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UNDERSTANDING AND IMPROVING MENTAL-IMAGERY BASED BRAIN-COMPUTER INTERFACE (MI-BCI) USER-TRAINING: *TOWARDS A NEW GENERATION OF RELIABLE, EFFICIENT & ACCESSIBLE BRAIN-COMPUTER INTERFACES.*

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UNDERSTANDING AND IMPROVING MENTAL-IMAGERY BASED BRAIN-COMPUTER INTERFACE (MI-BCI) USER-TRAINING: *TOWARDS A NEW GENERATION OF RELIABLE, EFFICIENT & ACCESSIBLE BRAIN-COMPUTER INTERFACES.*

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Defended on the: 2ND OF DECEMBER, 2016

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– October 2, 2016

This PhD project lasted 3 years, from the 01/10/2013 to the 30/09/2016. It was funded by the IdEx program of the University of Bordeaux and was co-supervised by F. Lotte, Pr. B. N'Kaoua, M. Hachet & Pr. S. Subramanian.

"Jeeves," I said. "A rummy communication has arrived. From Mr. Glossop."
"Indeed, sir?"
"I will read it to you. Handed in at Upper Bleaching.
Message runs as follows:

When you come tomorrow, bring my football boots. Also, if humanly possible, Irish water-spaniel. Urgent. Regards. Tuppy.

"What do you make of that, Jeeves?"
"As I interpret the document, sir, Mr. Glossop wishes you, when you come tomorrow, to bring his football boots. Also, if humanly possible, an Irish water-spaniel. He hints that the matter is urgent, and sends his regards."
"Yes, that is how I read it. But why football boots?"
"Perhaps Mr. Glossop wishes to play football, sir."

— P.G. Wodehouse, Very Good, Jeeves!

Dedicated to
my Sunshine, who makes me happy when skies are gray,

– October 2, 2016

ABSTRACT

Mental-imagery based brain-computer interfaces (MI-BCIs) enable users to interact with their environment using their brain-activity alone, by performing mental-imagery tasks. This thesis aims to contribute to the improvement of MI-BCIs in order to render them more usable.

MI-BCIs are bringing innovative prospects in many fields, ranging from stroke rehabilitation to video games. Unfortunately, most of the promising MI-BCI based applications are not yet available on the public market since an estimated 15 to 30% of users seem unable to control them.

A lot of research has focused on the improvement of signal processing algorithms. However, the potential role of user training in MI-BCI performance seems to be mostly neglected. Controlling an MI-BCI requires the acquisition of specific skills, and thus an appropriate training procedure. Yet, although current training protocols have been shown to be theoretically inappropriate, very little research is done towards their improvement.

Our main object is to understand and improve MI-BCI user-training. Thus, first we aim to acquire a better understanding of the processes underlying MI-BCI user-training. Next, based on this understanding, we aim at improving MI-BCI user-training so that it takes into account the relevant psychological and cognitive factors and complies with the principles of instructional design.

Therefore, we defined 3 research axes which consisted in investigating the impact of (1) cognitive factors, (2) personality and (3) feedback on MI-BCI performance. For each axis, we first describe the studies that enabled us to determine which factors impact MI-BCI performance; second, we describe the design and validation of new training approaches; the third part is dedicated to future work. Finally, we propose a solution that could enable the investigation of MI-BCI user-training using a multifactorial and dynamic approach: an Intelligent Tutoring System.

RÉSUMÉ

Les Interfaces Cerveau-Ordinateur basées sur l'Imagerie Mentale (IM-ICO) permettent aux utilisateurs d'interagir avec l'environnement uniquement via leur activité cérébrale, grâce à la réalisation de tâches d'imagerie mentale. Cette thèse se veut contribuer à l'amélioration des IM-ICO dans le but de les rendre plus utilisables. Les IM-ICO sont extrêmement prometteuses dans de nombreux domaines allant de la rééducation post-AVC aux jeux-vidéo. Malheureusement, leur développement est freiné par le fait que 15 à 30% des utilisateurs seraient incapables de les contrôler.

Nombre de travaux se sont focalisés sur l'amélioration des algorithmes de traitement du signal. Par contre, l'impact de l'entraînement des utilisateurs sur leur performance est souvent négligé. Contrôler une IM-ICO nécessite l'acquisition de compétences et donc un entraînement approprié. Or, malgré le fait qu'il ait été suggéré que les protocoles d'entraînement actuels sont théoriquement inappropriés, peu d'efforts sont mis en œuvre pour les améliorer.

Notre principal objectif est de comprendre et améliorer l'apprentissage des IM-ICO. Ainsi, nous cherchons d'abord à acquérir une meilleure compréhension des processus sous-tendant cet apprentissage avant de proposer une amélioration des protocoles d'entraînement afin qu'ils prennent en compte les facteurs cognitifs et psychologiques pertinents et qu'ils respectent les principes issus de l'ingénierie pédagogique.

Nous avons ainsi défini 3 axes de recherche visant à investiguer l'impact (1) de facteurs cognitifs, (2) de la personnalité et (3) du feedback sur la performance. Pour chacun de ces axes, nous décrivons d'abord les études nous ayant permis de déterminer les facteurs impactant la performance ; nous présentons ensuite le design et la validation de nouvelles approches d'entraînement avant de proposer des perspectives de travaux futurs. Enfin, nous proposons une solution qui permettrait d'étudier l'apprentissage de manière mutli-factorielle et dynamique : un système tutoriel intelligent.

PUBLICATIONS

Please find below a list of our publications, sorted by type and date.

JOURNAL PAPERS -

- Jeunet, C., Jahanpour, E., and Lotte, F. (2016). 'Why standard brain-computer interface (BCI) training protocols should be changed: an experimental study.' In: *Journal of neural engineering* 13.3, p. 036024.
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— Jeunet, C., N'Kaoua, B., N'Kambou, R., and Lotte, F. (2016). 'Why and how to use an intelligent tutoring system to adapt MI-BCI training to each user?' In: *6th International BCI Conference*.

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— Pillette, L., Jeunet, C., Mansencal, B., N'Kambou, R., N'Kaoua, B., and Lotte, F. 'PEANUT: Personalised Emotional Agent for Neurotechnology User-Training.' In: *Submitted*.

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CONTENTS

LIST OF FIGURES

ACRONYMS

BCI	Brain-Computer Interface
MI	Mental-Imagery
MI-BCI	Mental-Imagery based Brain-Computer Interface
SCP	Slow Cortical Potential
SCP-BCI	Slow Cortical Potential based Brain-Computer Interface
SMR	Sensori-Motor Rhythms
OC	Operant Conditioning
SMR-BCI	Sensory-Motor Rhythm based Brain-Computer Interface
PEANUT	Personalised Emotional Agent for Neurotechnology User-Training
TEEGI	Tangible EEG Interface
ITS	Intelligent Tutoring System
EEG	Electro-Encephalography
fMRI	functional Magnetic Resonance Imaging
fNIRS	functional Near Infra-Red Spectroscopy
SA	Spatial Abilities
VC	Verbal Comprehension
LSI	Learning Style Inventory
STAI	State Trait Anxiety Inventory
16 PF5	16 Personality Factors - Version 5
IPC	Internal, Power, Chance scale
WAIS-IV	Fourth Weschler Adult Intelligence Scale
IQ	Intelligence Quotient
CSP	Common Spatial Patterns
LDA	Linear Discriminant Analysis
SVM	Support Vector Machine
ANOVA	ANalysis Of VAriance
ANCOVA	ANalysis of COVAriance
SD	Standard Deviation
LM	Learnability-Memorability
EE	Efficiency-Effectiveness
ADHD	Attention Deficit Hyperactivity Disorder
COERLE	Comité Opérationnel d'Evaluation des Risques Légaux et Ethiques

INTRODUCTION

The story begins in 1875 when Richard Caton, a Medical Doctor from Liverpool (UK) made a fundamental discovery: the brain produces electrical activity (Caton, 1875). The experiment on which this discovery was based consisted in placing electrodes on a dog's brain: two on the surface of the cortex, or one inside the cortex and one on the skull. The electrical recordings revealed that the brain produces a current which increases in amplitude during sleep and disappears some time after death. The study of the brain's electrical activity is now called Cerebral Electrophysiology, and Richard Caton is often described as a pioneer in this field.

1875: Caton discovers that the brain produces electrical activity

Some years later, in 1924, the German Psychiatrist and Neurologist Hans Berger became the first person to record electrophysiological activity in a human brain(Scientific Biography, 2008). His motivation to lead research in this field stemmed from an accident that had occurred a few years earlier: one day, the story goes, when he found himself in mortal danger during a cavalry training exercise, his sister also reported that she had a feeling something bad had happened to her brother. Hans Berger assumed that he transmitted his thoughts to his sister by a kind of telepathy. From this moment, Hans Berger became fascinated by the *mind* and his ambition was to understand *the correlation between objective brain activity and subjective psychic phenomena*. Once he had managed to record his first human ElectroEncephaloGraph (EEG), he waited 5 years before publishing his work (Berger, 1929) due to a lack of confidence in his discovery. Besides, his European colleagues received the news with much scepticism, and he had to wait until 1937 before the importance of his work and its impact were finally recognised worldwide by the scientific community. Hans Berger is now considered the *Father of EEG*: among other discoveries, he was the first to describe alpha waves (and the way their amplitude increases during rest), as well as the alteration of brain signals during epileptic seizures.

1924: Berger records the first human EEG

Backed by this discovery, scientists, and especially Medical Doctors, were able to measure and visualise specific electrical currents. Indeed, the amplitude of these currents -in specific frequency bands- was known to undergo modifications in certain particular contexts. At the time, alpha waves (oscillations in the frequency range of 8-12Hz approx.) were certainly the most investigated brain patterns. It had been shown that their amplitude was low when people are awake and concentrating, and that their amplitude increased when they were relaxing or asleep. In the 1950s-early 1960s, using a simple reward system, Joe Kamiya (Professor of Psychology at the University of California in Berkeley) trained participants to find strategies, by themselves, in order to alterate their brain waves and *enter the alpha state*, i.e., to increase the amplitude of their alpha waves: this is considered the birth of *Neurofeedback* (Kamiya, 1969). The object of neurofeedback is to learn to control specific brain patterns (especially those involved in pathologies) in order to reach a certain mental state. For instance, neurofeedback can be used to train patients suffering from Attention Deficit Hyperactivity Disorder (ADHD) to relax by entering the alpha state (i.e., by increasing the amplitude of their alpha waves) (Milstein, Stevens, and Sachdev, 1969).

1960s: Kamiya develops neurofeedback paradigms

Some years later, the 1970s saw the development of computer sciences. These machines brought unhoped for computational power, and enabled users to control simple applications using neurofeedback by, for example, displaying on a screen a cursor that was gets bigger as the amplitude of the user's alpha waves increases. This work on neurofeedback led the scientific community to imagine a system enabling humans to communicate with a computer using their brain-activity alone. Such a system was first described in Pr. Jacques Vidal's paper entitled "Towards Direct Brain-Computer Communication" published in 1973 (Vidal, 1973). At the time, Jacques Vidal was working as Professor of Computer Sciences at the University of California Los Angeles. He was the first person to use the phrase "Brain-Computer Interfaces" to refer to these systems.

1973: Vidal describes the concept of "Brain-Computer Interface"

Brain-Computer Interfaces (BCIs) were later defined, in a reference paper entitled "Brain-Computer Interfaces for Communication and Control" (Wolpaw et al., 2002), as a hardware and software communication and control system that enables humans to interact with their surroundings without the involvement of peripheral nerves and muscles, i.e., by using brain signals alone.

Over the last thirty years, helped along by incredible technological advances, BCIs have undergone exponential development and great diversification. Current BCI systems can be classified in three main categories: active, reactive and passive BCIs [1] (Zander and Kothe, 2011).

Active BCIs are BCIs that require the user to intentionally perform tasks to control the system. Two main paradigms exist for active BCIs: Slow Cortical Potential based BCIs (SCP-BCI) and Mental-Imagery based BCIs (MI-BCI). Historically, BCIs were based on SCP, i.e., cognitive Event-Related Potentials (ERP) that are triggered, from the upper layer of the cortex, 300ms to several seconds after an internal or

1. It should be noted that this is not the only possible classification, and that no definition is unanimously accepted by the community yet. Indeed, what we call here *passive BCIs* (Zander and Kothe, 2011), for which there is no voluntary/conscious interaction between the user and the computer, may not be considered as proper BCIs by some, since the term BCI implies deliberate interaction. Nonetheless, based on Wolpaw and Wolpaw, 2012's definition, which characterises BCI as systems providing users with real-time feedback, passive BCI are indeed BCI.

external event (that the user is expecting) occurs (Birbaumer et al., 1990). These SCP are measurable using EEG. Because they can be triggered by internal events, people can train to modulate their SCP (positively or negatively with respect to the baseline) in a self-paced way. In their famous paper "A Spelling Device for the Paralysed" published in Nature, Birbaumer et al., 1999, describe the first SCP-BCI enabling locked-in patients to control a spelling device after having been trained through an operant conditioning approach. This approach consisted in asking the patients to find a strategy to modulate their SCP positively or negatively in order to select letters. Both of the patients who took part in this study reported using imagery strategies, at least at the beginning of their training . After several hundred sessions, they succeeded in efficiently controlling the device and spelling full texts reliably. This approach, although efficient for enabling such patients to communicate once again, presents several limitations (Birbaumer et al., 2006): user-training is a long process (which takes weeks or even months) and this is partly due to the fact that only the user can adapt to the machine (the machine does not adapt to the user). A second approach overcomes these limitations by shortening the user-training process, by focusing on other brain patterns and by adapting the system to each user. This approach consists in asking the BCI users to perform specific mental-imagery tasks (such as motor-imagery of the limbs, mental calculation or navigation). These mental tasks first induce an Event-Related Desynchronisation (ERD - while they are being performed) and then an Event-Related Synchronisation (ERS - once the user has stopped performing the MI task) (Pfurtscheller et al., 1997) in specific cortical regions that the machine is trained to identify using machine learning techniques. Once the the system is able to recognise the brain patterns associated with the MI task, these patterns are linked to specific commands: this approach is called MI-BCI. The specificity of this approach is the double adaptation between the user and the machine: the machine is trained to recognise the user's brain patterns associated with each MI task (using machine learning techniques) while the user has to train so that his MI tasks are correctly recognised by the machine. More details about this approach are provided in Chapter 1.

On the other hand, *reactive BCIs* are BCIs which depend on a cerebral response triggered by an external event on which the user is focusing. Such brain responses are called cognitive Event Related Potentials (ERPs). Many different types of reactive BCIs exist, based on different ERPs. For example, one of the most popular current paradigms is the P300 Speller, first introduced by Farwell and Donchin, 1988. The P300 is a positive cortical potential that appears around 300ms after the occurrence of a rare and relevant event (which can be either the appearance or absence of a stimulus) which is expected by the user. This potential is recognisable in the EEG signals. Thus, the

P300 speller consists of a matrix of symbols (e.g., letters and punctuation signs mostly) displayed on a screen. The rows and columns of the matrix light up in a random order but at a known moment in time. Users are asked to focus on the symbol they want to use. Approximately 300ms after the symbol is lit up, a P300 is generated in the EEG signal. By finding out which row or column triggered the P300, it is possible to infer which symbol the user was focusing on. Because they are based on *automatic* brain responses, this kind of reactive BCI has the advantage of not requiring much user-training and of being very reliable. Nonetheless, controlling the BCI still requires considerable attentional resources, thus preventing these reactive BCIs from being used in interactive situations (such as navigation and control) that require high levels of visual and auditory attention. Such systems are called time-locked or synchronous BCIs, because the user has to wait for an external stimulus to send a command.

Finally, the last type of BCIs are *passive BCIs* (Zander and Jatzev, 2009). Passive BCIs are systems that enable the user's mental state to be measured in order to adapt an application/interface accordingly. In other words, users do not voluntary interact with the BCI, they do not send commands. Instead, their cognitive (e.g., workload), emotional (e.g., frustration) or motivational states are inferred from their EEG signals, which can also be combined with other physiological and behavioural data. An application can then be adapted to the user's state. For instance, if an application proposes an exercise but the system detects that the user is not motivated and frustrated, the exercise can be modified so that the user returns to a more positive state. Here we focus on BCIs for communication and control and therefore passive BCIs do not enter within the scope of this work.

The object of this thesis is to contribute to the improvement of BCIs dedicated to communication and control in order to render them more usable and accessible for patients as well as for the general public. We focus on active BCIs as they have the potential to enable asynchronous control and do not require valuable attentional resources to be allocated to an interface, as opposed to reactive BCIs. As a reminder, two main paradigms exist for active BCIs: SCP and MI. We chose to focus on MI-BCIs because the training process is faster, making them both more suitable and more usable for BCI applications than SCP-BCIs. Furthermore, MI-BCI performance has a great potential for improvement, especially through the understanding and improvement of the user-training process. As a consequence, the object of this manuscript is to reach a better understanding of the mechanisms underlying MI-BCI user-training in order to improve MI-BCI training procedures. We hope this work will be a first step towards a new generation of reliable, efficient and accessible MI-BCI.

MI-BCIs function as a closed loop (see Figure 1). First, the user has to perform specific MI-tasks. These tasks are associated with specific

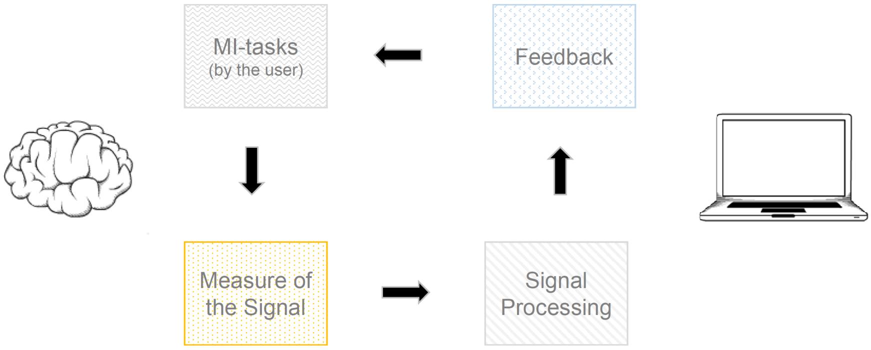


Figure 1 – Schematic representation of the BCI loop.

brain patterns, typically measured using EEG, which are sent to a computer. The system then has to extract the relevant information from the signal in order to infer which task the user was performing. The user is then provided with feedback which apprises them of the task recognised by the system. Based on this feedback, they should adapt their strategy so that the MI-tasks they are performing get recognised as often and as well as possible. A more elaborate description of MI-BCIs is provided in our first review of the literature, i.e., in Chapter 1. This chapter describes how MI-BCIs work, which MI-tasks are used, the machine training phase (also called calibration) and the user training phase. In this thesis, we focus on EEG based MI-BCIs despite the fact that more and more highly precise brain-imaging techniques are currently being developed. Indeed, in order to be usable for MI-BCIs, the device ought to be portable and affordable, thus excluding functional Magnetic Resonance Imagery (fMRI) and MagnetoEncephaloGraphy (MEG). Functional Near-InfraRed Spectroscopy complies with both these criteria and has good spatial resolution (around 5mm) but, because it is based on a haemodynamic response, it also has a poor temporal resolution (around 1000ms) compared to EEG (around 50ms). If we consider a BCI-based application for controlling a wheelchair, a neuro-prosthetic or a video game, temporal resolution is of utmost importance. This is why EEG is often preferred over fNIRS. Nevertheless, for more fundamental work the combination of EEG and fNIRS is very promising due to the complementarity of the two techniques (EEG having a modest spatial resolution of around 10mm) (Fazli et al., 2012).

Since the 1990s, MI-BCI have spread to a wide range of fields (Graimann, Allison, and Pfurtscheller, 2010). This paragraph deals with several of them. Originally, MI-BCIs were designed for the purpose of improving living standards of severely motor-impaired patients (e.g. patients in a locked-in state due to a stroke or brain injury) by enhancing their mobility autonomy and communication possibilities. In particular, smart wheelchairs and neuroprosthetics controlled by MI-BCIs were developed (Millán et al., 2010; Pfurtscheller and Neuper, 2001; Wolpaw et al., 2002 - for a review see Nicolas-Alonso and Gomez-Gil, 2012). Concretely, a standard MI-BCI-based wheelchair would work as follows: performing left-hand motor-imagery would make the wheelchair turn left while right-hand motor-imagery would make it turn right. Nowadays, these systems are often controlled using MI combined with a machine-based control system that relies on infrared sensors which enable obstacles to be detected and avoided automatically. In addition to these classic applications, several more recent fields for MI-BCI based applications are emerging. First, MI-BCI based stroke rehabilitation is growing in popularity, especially for motor rehabilitation of the upper limbs (Ang and Guan, 2013; Ramos-Murguialday et al., 2013). Indeed, MI-BCIs enable therapists to visualise patients' brain activity while they perform attempted movements during the rehabilitation process. More particularly, patients can then be provided with haptic feedback that closes the sensorimotor loop and helps brain-plasticity processes. For more details about this application, please refer to Section 5.7. Moreover, more and more MI-BCI-based applications for the general public are being designed, especially for multimedia, gaming and virtual reality (Coyle et al., 2013; Erp, Lotte, and Tangermann, 2012; Lécuyer et al., 2008). Some of these applications are depicted in Section 7.5.

To summarise, MI-BCIs are bringing innovative prospects both to patients and to the general public in many fields. Unfortunately, most of the promising technologies based on MI-BCIs are not yet available on the public market since an estimated 15 to 30% of users seem unable to control an MI-BCI based system (Allison and Neuper, 2010): this phenomenon is often called "BCI illiteracy" or "BCI deficiency". Even for MI-BCI users who are not "illiterate", average performance is generally rather low (Blankertz et al., 2010b; Guger et al., 2003), i.e., around 75% of classification accuracy for 2 class MI-BCIs (i.e., MI-BCIs which require users to perform 2 different MI tasks). Nevertheless, around 20% of users do manage to obtain performances ranging from 80% to 100% of classification accuracy (Hammer et al., 2014) after training for two MI-tasks.

Two main factors have been identified to explain the low reliability of MI-BCIs. The first, which has been extensively investigated, concerns brain signal processing. Indeed, current classification algorithms are still imperfect (Allison and Neuper, 2010). On the other hand, the potential role of user-training in MI-BCI performance seems to be mostly neglected. Controlling an MI-BCI requires the acquisition of specific skills, and particularly the ability to generate stable and distinct brain activity patterns while performing the different Mental-Imagery (MI) tasks (Neuper and Pfurtscheller, 2010; Wolpaw et al., 2002). An appropriate training procedure is required in order to acquire these skills (Neuper and Pfurtscheller, 2010) and an inefficient training protocol (which includes the instructions, training tasks, feedback and training environment) could consequently be partly responsible for users' modest performances. Yet, although current training protocols are theoretically inappropriate for skill-acquisition (as extensively investigated in Chapter 1), very little research is done towards their improvement (Lotte et al., 2013).

In order to improve MI-BCI user-training with the ultimate goal of increasing the reliability and thus accessibility of these technologies (for patients as well as for the general public), an interdisciplinary approach is crucial. Indeed, cognitive sciences, psychology and instructional design are necessary to understand how humans learn and how to adapt the training process accordingly. Neuroscience helps to investigate the neural processes underlying the acquisition of MI-BCI related skills, and more generally MI-BCI control. Finally, Human-Computer Interaction (HCI) and Human Factors (HF) are necessary to adapt the training protocol (instructions, tasks, feedback and environment) based on the recommendations from psychology and instructional design.

This thesis relies on these different disciplines with two main objects in view. The first is to acquire a better understanding of the psychological and neurophysiological processes underlying MI-BCI user-training, skill acquisition and control. Next, based on this understanding, we aim at improving MI-BCI user-training so that it takes into account the relevant psychological, cognitive and neurophysiological

Object: Understanding & Improving MI-BCI User-Training

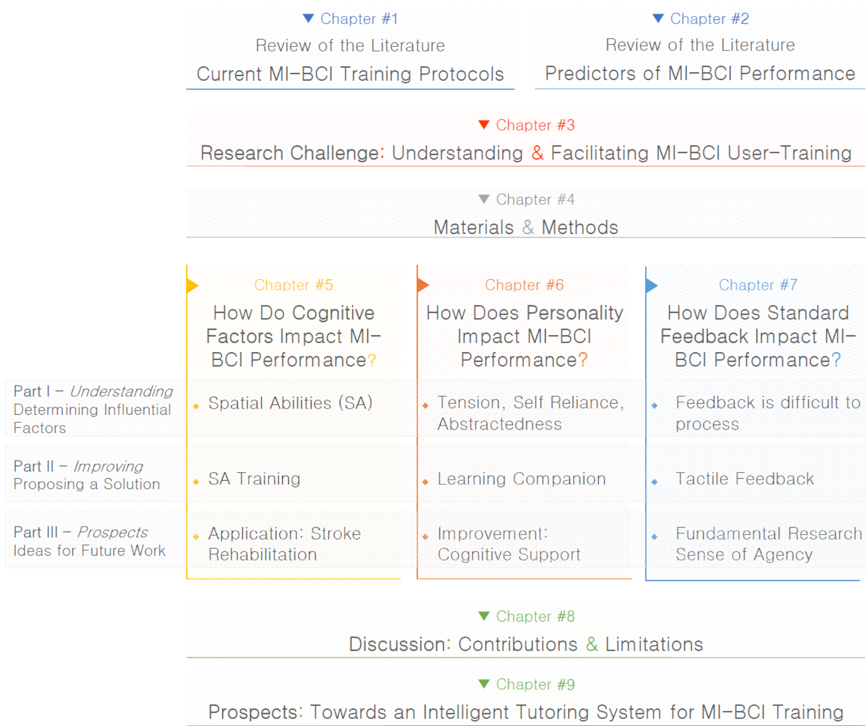


Figure 2 – Illustration of the Roadmap of this thesis. It will be completed step by step throughout the manuscript.

logical factors and complies with the principles of instructional design, HCI and HF.

The first part of this thesis comprises two reviews of the literature introducing (1) the current training protocols and their limitations, along with some design guidelines for future training protocols (i.e., Chapter 1), and (2) an overview of current MI-BCI performance predictors (i.e., Chapter 2). Then, the Research Challenges of this project are described in further detail in Chapter 3. As a reminder, the first object of this project was to reach a better understanding of the mechanisms underlying the MI-BCI user-training process. Secondly, our findings concerning these mechanisms enabled us to design and evaluate new training approaches aiming at improving MI-BCI performance and user-experience. Chapter 4 deals with the Materials and Methods used in the different experiments that were led to reach both of these goals. This section is followed by three research chapters, each of which investigates one aspect of the training process which has a potential impact on the efficiency of the process. Thus, the first chapter focuses on cognitive factors, the second deals with personality factors and the third investigates the impact of the feedback users are provided with during the training procedure. All three chapters follow the same structure: first we describe the studies that enabled us to determine which factors (cognitive factors, personality factors, aspects of the feedback) have an impact on MI-BCI performance ; Second, we describe the design and validation of new MI-BCI training approaches based on the results of the first part ; in the third and final part, some of the future prospects that await these new approaches are proposed. More details about the content of these three Research Chapters are provided in the Challenge Chapter. Finally, a General Discussion and Prospects are introduced in the last Chapter. Figure 2 is a schematic representation of this roadmap which will gradually be revealed throughout the manuscript.

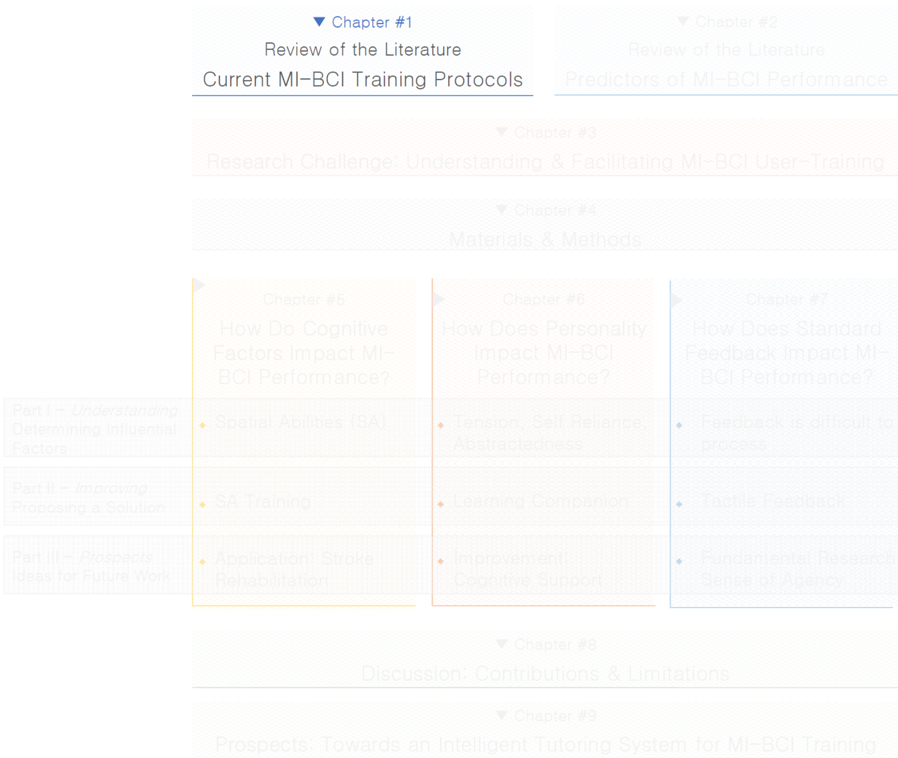
I

THEORETICAL BACKGROUND

The first part of this manuscript is dedicated to the exploration of the theoretical background that led us to the the definition of our research challenges. More precisely, in the first chapter we give a review of the literature of MI-BCI training protocols as well as their limitations and gather some guidelines suggested in the literature to design more appropriate training protocols. In the second chapter, we synthesise and classify predictors of MI-BCI performance found in the literature. We also explain how these predictors impact performance based on their neurophysiological correlates and on psychological theories. This theoretical work then leads us to define the research questions developed in this thesis, which are detailed in chapter 3.

1 STANDARD MI-BCI TRAINING PROTOCOLS, THEIR VARIANTS & THEIR LIMITATIONS - A STATE OF THE ART.

ROADMAP -



QUICK SUMMARY -

We provide a review of the literature of current user-training approaches for MI-BCI. We more specifically focus on the Graz protocol and its variants. The comparison of this protocol with recommendations from instructional design and psychology literature enabled us to determine the limitations of current user-training procedures and to propose guidelines for the design of future protocols. In particular, we argue that the user should be provided with *instructions* that explicitly specify the training objective; that the *training tasks* should be adaptive and allow a progression in terms of difficulty; that the *feedback* should be multi-modal, explanatory and supportive; and that the *training environment* should be motivating.

RELATED PAPER -

-1- Jeunet, C., N'Kaoua, B., and Lotte, F. (2016). 'Brain-Computer Interfaces.' In: Iste/Wiley. Chap. Human learning for Brain-Computer Interfaces.

1.1 INTRODUCTION

BCIs are defined by Wolpaw (Wolpaw et al., 2002) as tools of communication and control that allow users to interact with their environment by means of their cerebral activity alone. This definition highlights one fundamental aspect of BCIs, the interaction between two components: the user's brain and the computer. The challenge is to make sure that these two components (brain and computer) "understand each other", and adapt to each other so that the system performance (often measured using the classification accuracy) is optimal.

Thus, a BCI (Wolpaw et al., 2002) works as a loop with two major stages following the generation of a command by the users using their brain activity (which we shall denote STAGE 0). During STAGE I, the computer attempts to *understand* the command sent by the user, generally by extracting relevant information followed by classification. Next, during STAGE II, it is the user's turn to attempt to *understand* the meaning of the feedback generated by the computer, which indicates how the computer understood the command that it received. To see how this loop works, consider the case of a standard BCI protocol based on motor imagery (Pfurtscheller and Neuper, 2001). In this protocol, users can perform two motor imagery tasks, "imagine moving the left hand" and "imagine moving the right hand", which are associated with two distinct commands. To provide guidance to the user, the system also produces feedback, often in the form of a bar indicating the task recognised by the system. The direction of the bar depends on the task recognised by the system (e.g. the bar points left if the task "imagine moving the left hand" is recognised). The size of the bar also depends on the value of the classifier output (i.e. higher values indicate that the classifier is more confident in the task recognition, and so the bar will be larger) (see Figure 3). In this example, STAGE I of the loop is the computer's recognition of the motor imagery task performed by the user (Is the user imagining moving his left hand, or his right hand?). Then, in STAGE II, the user now has to understand the feedback generated by the system (What does this bar mean? Did the system correctly recognise the task that I performed? If so, how confident was it? What should I do so that it recognises more easily my commands?). Unfortunately, it appears that most current systems do not properly establish this mutual understanding, which might explain why users perform poorly when attempting to control the BCI, as well as the non-negligible fraction (between 15% and 30%) of users that find themselves completely incapable of controlling these systems (Allison and Neuper, 2010).

How can we facilitate this understanding? Over the last several years, there have been many studies on STAGE I of the loop: how to make the computer understand the task performed by the user. Signal processing algorithms and machine learning techniques have been developed to achieve this. But two fundamental factors for improving BCI performance have not yet been sufficiently explored:

— Stage 0, *the quality of the signals generated by the user*: for the classification algorithms to be effective (i.e. in order that they can be capable of recognising motor imagery tasks by extracting specific features from the cerebral signal), the user must be able to generate a *stable* cerebral signal each time that he performs the same task, and *distinct* cerebral signals when the tasks are different. These two elements are non-trivial skills, and require a training process that is both specific and adapted to each user. This is rarely taken into account in BCI teaching protocols (Neuper and Pfurtscheller, 2010).

— Stage II, *user comprehension of the feedback produced by the system*: The standard BCI protocols often provide the user with feedback in the form of a graphical representation of the classifier output (e.g. the bar described above). Although this is informative (and more importantly allows evaluation/correction), this feedback does not explain to the user why a certain task was or was not recognised, and even less what the user must do in order to improve performance. In their review, Lotte et al., 2013 show that to be effective feedback must provide an explanation (rather than just the possibility of correction), be multi-modal (and not just visual), and finally be clear and explicit (which is not the case with classifier output for non-experts).

These different ideas highlight a point that might allow user performance to be improved: facilitating the acquisition of skills by providing adapted training protocols. As we will see in this chapter, establishing a training protocol requires various elements to be taken into consideration: the instructions/indications given to the user, the training environment, the training tasks used to enable the acquisition of knowledge/skills, and the feedback provided after performing the various tasks.

In this chapter, we will explore the limitations of the standard protocols widely used by the BCI community. Next, we will analyse the alternative training protocols that have been suggested for BCIs. As stated in the Introduction, we will focus on protocols developed for training users to use BCIs based on Mental Imagery (MI), also known as spontaneous BCIs. Before we begin, however, let us describe two *historical* approaches that were used with BCIs, on which most of the current training protocols are based. One protocol was proposed by researchers in Graz (Pfurtscheller and Neuper, 2001), based on techniques of *machine learning* while the other was proposed by the researchers at the Wadsworth center (Wolpaw, McFarland, and Vaughan, 2000) based on an *operant conditioning* approach.

1.2 ILLUSTRATION : TWO HISTORICAL BCI PROTOCOLS

Principle of the Graz protocol (Pfurtscheller and Neuper, 2001) - This approach is organised into two stages: -I- training the system and -II- training the user. In stage I, the user is instructed to successively perform a certain series of MI tasks (for example, imagining movements of the left and right hands). Using the recordings of cerebral activity generated as these various MI tasks are performed, the system attempts to extract characteristic patterns of each of the mental tasks from the signal. These extracted features are used to train a *classifier* whose goal is to determine the *class* to which the signals belong (i.e. imagining a movement of the left hand or the right hand). This classifier is then typically adjusted over the course of the training session so that variations in the disposition of the EEG cap or in the user conditions (e.g., EEG non-stationarity or different cognitive state) between sessions are taken into account. When this stage is complete, stage -II- consists in training the user. The user is instructed to perform the MI tasks, but this time feedback (based on the training performed by the system in stage -I-) is provided to inform him or her of the MI task recognised by the system and the corresponding confidence level of the classifier. The user's goal is to develop effective *strategies* that will allow the system to easily recognise the MI tasks that the user is performing.

Concretely, this training protocol is generally organised over multiple sessions, each of which is comprised of sequences (often called *runs*) lasting approximately 7min. Each session generally has 4 to 6 runs to avoid fatigue, which is often observed after the 6th run. Finally, the runs themselves are divided into trials. One run contains 10 to 20 trials per class (i.e. per MI task) depending on the number of classes. A trial typically lasts for 8s, during which time a cross appears on the screen followed by a sound to attract the user's attention, further followed by an arrow symbolising the instruction (e.g. an arrow pointing to the left corresponds to the instruction "imagine moving the left hand") and then visual feedback shown as a bar indicating the recognised task and the corresponding confidence level of the classifier. The detailed chronology of a trial is shown in Figure 3.

Principle of the Wadsworth center protocol for 1D cursor control - The BCI system proposed by the Wadsworth center team is based on controlling the sensorimotor rhythms μ and β after a training process based on operant conditioning (Wolpaw, McFarland, and Vaughan, 2000). The initial version of this BCI system, which has now become standard, featured a cursor (or ball) on the screen moving continuously from the left to the right, at constant speed. The user can control the vertical position of the cursor by modulating the amplitude of his or her sensorimotor rhythms. On the right-hand section of the screen, several targets (generally between 2 and 4, represented by rectangles) are shown, aligned vertically, one-by-one. The user must adjust the vertical position of the cursor using the BCI so that the cursor hits the indicated target when it reaches the right-hand edge of the screen (see Figure 4). This kind of BCI, based on operant conditioning, does not impose any specific mental task on the user, unlike the BCI approach from Graz, nor does it make use of machine learning. Users must find the strategy that allows them to effectively modulate their cerebral rhythms to move the cursor across the screen, on their own. Typically, users utilise motor imagery tasks at the beginning of the training process, but with practice they report that they use these motor imagery tasks less and less (Wolpaw, McFarland, and Vaughan, 2000). Training to control the BCI takes time, generally several days, weeks or even months of practice. This principle has nonetheless enabled certain users to master controlling a cursor with this BCI in 1 dimension (1D) (Wolpaw, McFarland, and Vaughan, 2000, 2D Wolpaw, McFarland, and Vaughan, 2000), and more recently even 3D (McFarland, Sarnacki, and Wolpaw, 2010).

1.3 REVIEW OF THE LITERATURE ON STANDARD MI-BCI USER-TRAINING PROTOCOL & OF THEIR VARIANTS.

This section offers a review of the literature on existing BCI training protocols, that are variants of the Graz training protocol, with the objective of establishing guidelines that will be useful for the development of future BCI training protocols. These training protocols can be divided into 4 elements: the instructions the participant is provided with, the training tasks used to enable him acquire BCI-related skills, the feedback informing him about the task recognised by the system so that he can adapt, and the training environment in which the training process takes place.

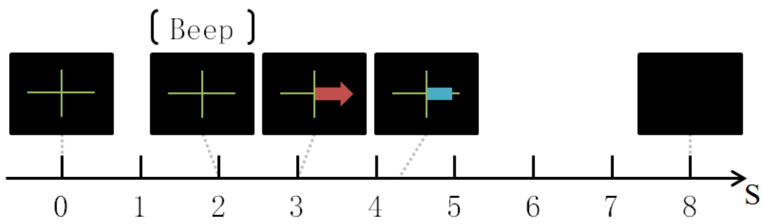


Figure 3 – Chronology of a trial: at the beginning of the trial, a cross appears at the center of the screen; after 2s, a sound is played to indicate that the instruction is imminent; at 3s, an arrow appears for 1.25s: the direction of the arrow indicates the MI task that should be performed; at 4.25s the feedback is shown for 4s, and is generally updated 16 times per second depending on classifier output.

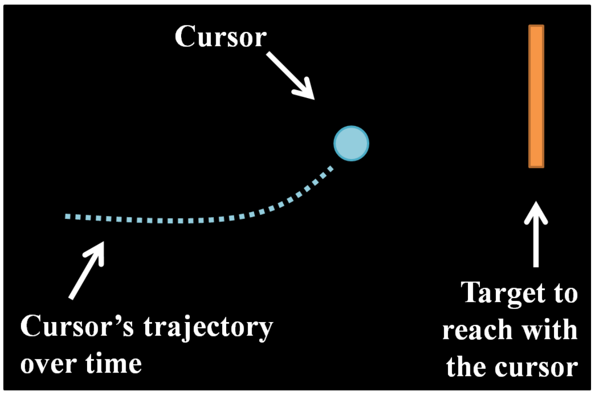


Figure 4 – Schematic illustration of a trial with the Wadsworth center protocol (Wolpaw, McFarland, and Vaughan, 2000).

1.3.1 *Instructions*

Very few studies have examined the instructions given to users learning to control a BCI. Yet this is a central element of the training process, since these instructions help users to understand their tasks. Often, these instructions consist only of a single directive indicating that the goal of the exercise is to move the cursor/bar in the correct direction. However, as pointed out by Lotte et al., 2013, the ultimate objective of the training protocol is not to move the bar, but to help the user to learn to generate a stable, specific signal for each of the mental imagery tasks that he or she performs. It seems therefore that the training objective should be made more explicit. One study shows that prompting users to attempt kinesthetic imagination of movements (i.e. to imagine performing the motion, feeling the same sensations, without actually moving anything) rather than simply visual imagination improves the performance (Neuper et al., 2005). On the other hand, another study shows that the users that obtained the best performances were those who were not given any specific strategy at the beginning of the training process (Kober et al., 2013). The authors reason that the success of the training process depends on subconscious training mechanisms, and that users who attempt to follow a strategy overload their cognitive resources (which does not result in a positive performance improvement).

1.3.2 *Training tasks*

Although most BCI training protocols only used one single training task, which is repeated identically multiple times, a few studies have explored a more varied selection of tasks. In particular, McFarland et al. successfully implemented a progressive sequence of training tasks; with operant conditioning, they taught users to first control a 1-dimensional (1D) cursor separately in three different dimensions, then in 2D (for each pair of dimensions), and finally in 3D (McFarland, Sarnacki, and Wolpaw, 2010). Vidaurre et al. experimented with adaptive training tasks by giving subjects a BCI that was initially generic in nature (i.e. independent of the subject, calibrated with the data from multiple other subjects), then progressively more and more adapted to the new user (by adapting the choice of sensors and classifier to this user) (Vidaurre and Blankertz, 2010). This progressive and co-adaptive approach (the user adapts to the machine and the machine adapts to the user) allowed users that were "illiterate" at first to eventually succeed in controlling the BCI. In a less formal and systematic setting, Neuper et al. also explored the idea of allowing the user to learning freely and asynchronously from time to time, with positive results (Neuper et al., 2003). Even though this approach has not been compared with the traditional approach (synchronous only), this nonetheless suggests that organising self-paced and asynchronous sessions can be beneficial to BCI training processes. Finally, Eskandari et al. taught their users to meditate before using a BCI, and demonstrated that this had a positive impact on the performance (Eskandari and Erfanian, 2008).

1.3.3 *Feedback*

In the standard training protocols (Pfurtscheller and Neuper, 2001), feedback is given in the form of a bar or a cursor shown on screen, whose direction depends on the task recognised by the classifier and whose size is proportional to the confidence of the classifier in the recognised task. Some studies have suggested other variants for displaying feedback. First of all, Kübler et al., 2001b developed a process that displays a smiley after each successful trial. In their own study, Leeb et al., 2007 replaced the cursor with a gray smiley that moves towards the left or the right depending on the classifier output. After each trial, the smiley becomes green and happy if the trial is successful, sad and red if not. According to the authors, this study revealed increasd motivation levels related to this feedback which led them to conclude that users' motivation is linked to improved performance. However, on the one hand neither of these studies offered a formal comparison with the standard feedback process, which unfortunately prevent us from affirming that these kinds of feedback are more effective than standard ones.
Although the feedback described above (all of which was visual in nature) is simple to implement and intuitive, its effectiveness is not optimal for BCIs. Indeed, it is a recognised fact that in situations of real-life interactions, the visual channel is often overloaded (Leeb et al., 2013), which prompted certain researchers to consider providing feedback via the other senses. Accordingly, several experiments were performed to evaluate the effectiveness of auditory feedback. In

the same way as the standard visual feedback, the auditory feedback provided usually represents the classifier output: instead of varying the size of a bar, the classifier output is represented by variations in the frequency of the sound (Gargiulo et al., 2012), or its volume (McCraedie, Coyle, and Prasad, 2014), or tone (Hinterberger et al., 2004; Nijboer et al., 2008). For example, with their *auditory BCI*, Nijboer et al., 2008 used the sounds of two different instruments to indicate the recognition of each of the MI tasks. Although its utility has been proven for patients suffering from locked-in syndrome (Smith and Delargy, 2005), because this syndrome is often linked with visual deficiencies and a loss of sensitivity, the performance achieved with auditory feedback has generally been significantly inferior to the performance achieved with visual feedback. One suggested explanation is that it is less intuitive, and thus is longer and more difficult to learn. Also, for real-life applications in open environments (e.g. navigating a wheelchair), the auditory channel is very frequently used (e.g., to perceive alert signals or to interact with other people) and must remain available (much like the visual channel). These factors suggest that auditory feedback is not ideal for applications involving navigation or general entertainment.

Given this context, tactile feedback may have many advantages. Firstly, the sense of touch is very infrequently used for interactions. So, sending additional information via this channel will have zero or limited effect on the workload (Lotte et al., 2013), and so will not affect performance. Secondly, unlike visual and auditory feedback, tactile feedback is personal, and is not perceived by others in the user's immediate environment. Motivated by this, various different types of tactile feedback were tested with BCIs. Tactile feedback for MI-BCIs has been mainly used in a medical context. Indeed, Wilson et al., 2012 explored lingual electro-tactile stimulation, as the tongue provides an excellent spatial resolution, and its sensitivity is preserved in the case of spinal cord injuries; while Gomez Rodriguez et al., 2011 and Ramos-Murguialday et al., 2012 focused on proprioceptive feedback (i.e., information about the limbs' position and about the strength developed while performing a movement) and showed that proprioceptive feedback allows increasing BCI performance, indicating that these alternative feedback are very promising for patients. However, these kinds of tactile feedback are quite cumbersome and expensive. Thus, they do not seem to be relevant for applications targeting the general public. A few studies explored tactile feedback for general public applications. Most of these studies in which haptic feedback has been chosen to inform the user about the classifier output used vibrotactile feedback with either a variation of the vibration patterns (e.g., different motor activation rhythms according to the classifier output) (Chatterjee et al., 2007) or variations in spatial location (Cincotti et al., 2007; McCraedie, Coyle, and Prasad, 2014).

Results show benefits when coupled with visual feedback, but only when the vibrotactile feedback maps the "stimulus" location (i.e., the MI task the participant has to perform). This relationship is known as "control-display mapping" (Thurlings et al., 2012). For example, when a right-hand MI is recognised, tactile feedback provided to the right part of the body will be more efficient (i.e., associated with better performance and user experience) than tactile feedback provided to the left side. Results also show similar performances between visual and tactile feedback, and the participants reported that tactile feedback was more natural than visual feedback, although negative feedback due to a misclassification of the mental task can be annoying. Nevertheless, Cincotti et al., 2007 and Leeb et al., 2013 suggest that although it is disturbing, negative vibrotactile feedback has no impact on classification (i.e., it does not affect the brain patterns used by the system to recognise the MI tasks). A few studies already attempted to use continuous vibrotactile feedback (Cincotti et al., 2007; Gwak et al., 2014; Leeb et al., 2013). For instance, Cincotti et al., 2007 propose a continuous tactile feedback in one of their studies: feedback is provided on the neck , updated every 2 seconds (as opposed to every 0.250s, see Section 7.6) and more importantly, . Unfortunately, this feedback has not been tested in a BCI control context. In Gwak et al., 2014, a comparison between visual and tactile feedback was proposed, and the findings showed that they are associated with equivalent performances in a BCI context. In Leeb et al., 2013, visual and tactile feedback were compared in the context of a visual attention task performed using a BCI. In the latter study, tactile feedback was shown to be associated with better performances than the visual one. Unfortunately, these studies present some limitations. First, the samples are small: 6-7 subjects. Second, and most importantly, as they used within subject comparisons and that the conditions were not counterbalanced (the visual feedback was always tested before the tactile feedback), one cannot rule out that these results are due to an order effect. Finally, while the feedbacks were tested in presence of distracters (Leeb et al., 2013), it is not a multitasking context as the visual attention task and the MI-BCI control task have been performed sequentially.

As well as using different senses, changes in the content of the feedback have also been investigated. For instance, Hwang, Kwon, and Im, 2009 suggested training based on neurofeedback. The feedback was represented in the form of a schematic map showing the various activated zones of the cortex in real time, which allowed users to improve their performance. Another study (Kaufmann et al., 2011) shows that increasing the level of required attention by using multimodal visual feedback (i.e., a visual feedback with more information) does not decrease the performance compared to traditional feedback.

Although these approaches are promising, they have not been yet been thoroughly explored.

Finally, some studies used a procedure that introduced a bias into the feedback (i.e. by leading users to believe that their performance was better than it actually was). For example, Barbero and Grosse-Wentrup, 2010 showed that expert users were hindered by biased feedback, but that this procedure could sometimes prove useful to new users. Another result showed that the users' perception of uniquely positive feedback was changing along training (for a large number of sessions): after a while, it could decrease the feeling of control and thus be detrimental (Kübler et al., 2001b). These results suggest that the experience level of the user needs to be taken into account when designing the optimal feedback system.

1.3.4 *Training Environment*

Most MI-BCI training protocols trigger a poor user motivation and are generally associated with an average user experience. *Gamified* training protocols were developed with the objective of maintaining motivation levels and improving the user experience. For example, McCraedie, Coyle, and Prasad, 2014 suggested two simple games based on the *ball-basket paradigm* (i.e. manoeuvring a ball to pass through a basketball hoop) and the concept of a spaceship that must avoid asteroids. Other studies, summarised in a review by Lécuyer et al., 2008, even suggested gamified BCI training protocols that integrated elements of virtual reality. In one of the games, the "Use The Force" application inspired by Star Wars allows users to levitate a spaceship by imagining moving their feet. Indeed, studies by Ron-Angevin and Diaz-Estrella, 2009 and Leeb et al., 2006 show that using entertaining protocols, in particular protocols based on virtual reality, achieves an increase in performance for controlling BCIs compared to traditional training protocols. Although these protocols are effective, they all use feedback that is visual in nature. However, as we have seen, the visual channel is often overloaded in interactive situations for which BCIs might be useful. It would therefore certainly be productive to combine these training environments with tactile feedback systems, and then compare the performance with training situations in traditional environments.

1.3.5 *In Summary: Guidelines for Designing More Effective Training Protocols*

In this section, we will provide a synthesis of the guidelines that arise from the studies presented above, the objective of which is to act as a guide for whoever wishes to implement more effective training protocols.

Instructions - It appears to be necessary to explicitly specify the training objective to the user, in particular the fact that the user must learn to generate a stable, specific signal when performing the different MI tasks in order to be able to control the BCI in the long term. Furthermore, it seems important to allow users to experiment independently rather than imposing any particular strategy for performing the tasks. On the other hand, for motor imagery, it appears that kinesthetic motor imagery is more effective than visual motor imagery.
Training tasks - Providing tasks that are designed to include a progression (increasing difficulty) and that are adaptive (specific to each user) appears to facilitate the acquisition of BCI-related skills. Including self-paced and asynchronous sessions and preparatory training tasks (e.g. meditation) also seems to help.
Feedback - Even though this has not been formally shown in a study, visual feedback with emotional connotations (e.g. smileys) seems to increase user motivation levels and consequently their performance. However, visual feedback is not ideal in interactive situations. The same is true for auditory feedback, which does not appear to be truly beneficial except for patients suffering from locked-in syndrome. Tactile feedback is promising, so long as the principles of *control-display mapping* are observed. Indeed, tactile feedback generally produces a level of performance equivalent to visual feedback, but relies on a channel that is much less saturated in interactive situations. Finally, increasing the quantity and the quality of the information provided (e.g. topography of cerebral activity) seems to be useful, as well as adapting the way that the feedback is presented to the experience level of the user.
Training environment - Several studies have shown that gamified training, especially including elements of virtual reality, increases the user motivation, and consequently performance.

1.4 LIMITATIONS OF CURRENT MI-BCI USER-TRAINING PROTOCOLS.

BCI control being a skill, it has to be learned to be mastered by the BCI user (Neuper and Pfurtscheller, 2010). Typically, a standard BCI training process is performed by asking the user to control an object on screen through the modulation of their brain activity in a specific way (e.g., by doing motor imagery of their hands). As depicted in the previous sections, the feedback provided to the user about his/her task performance is thus generally a uni-modal (generally visual) feedback indicating the mental task recognised by the classifier together with the confidence in this recognition. It is generally represented by an extending bar or a moving cursor (Neuper and Pfurtscheller, 2010). Typically, the bar/cursor extends in the required direction if the mental task is correctly recognised and extends in the opposite direction otherwise. The length of the bar or the speed of the cursor movement is also proportional to the classifier confidence in its decision. Besides, the user is generally trained following a synchronous protocol, i.e., the user is required to do specific tasks (e.g., imagining left hand movements) in specific time periods only. The same protocol (i.e., training tasks and feedback) is usually repeated until the user has learnt the BCI skill, i.e., until he/she has achieved a given performance, often measured in terms of classification accuracy (to know more about classification accuracy computation, please refer to Chapter 4, Section 4.2.3).

Unfortunately, such standard training approaches satisfy very few of the guidelines provided by psychology of human learning and instructional design principles to ensure an efficient acquisition of a skill (Lotte, Larrue, and Mühl, 2013). For instance, a typical BCI training session provides only corrective feedback (indicating whether the learner performed the task correctly), using fixed and (reported as) boring training tasks identically repeated until the user acquired the BCI skill, with these training tasks being provided in a synchronous way. In contrast, human learning and instructional design principles recommend to provide an explanatory feedback (indicating what was right or wrong about the task performed by the user) that is goal-oriented (i.e., indicating a gap between the current performance and the desired level of performance) and possibly multimodal, in an engaging and challenging environment, using varied training tasks with adaptive difficulty (Shute, 2008, Merrill, 2007) (see also Lotte, Larrue, and Mühl, 2013 for many other guidelines that are not satisfied by current BCI training approaches in terms of training environment, instructions, tasks and feedback). In short, current standard BCI training approaches are theoretically suboptimal, and are unlikely to enable efficient learning of BCI-related skills.

Moreover, according to Keller, 2008, it is necessary to consider the user motivational and cognitive states to ensure he/she can learn and perform efficiently, irrespectively of the task. Indeed, according to Keller's theory, optimising motivational factors - Attention (triggering a person's curiosity), Relevance (the compliance with a person's motives or values), Confidence (the expectancy for success), and Satisfaction (by intrinsic and extrinsic rewards) - leads to more user efforts towards the task and thereby a better performance. Additionally, considering cognitive constraints such as the limited user working memory (requiring to minimise the amount of skill-unrelated information), the way information is processed by him/her (requiring to make relevant information salient) and the pre-existing knowledge stocked in long-term memory (requiring to relate the to-be-learned skill to existing knowledge), leads to a more efficient skill acquisition. Again, these different factors are typically not considered in BCI training protocols, or only very few of them, leading to theoretically suboptimal training protocols (Mühl et al., 2014).

1.5 CONCLUSION

This chapter has allowed us to paint a picture of the current state of research of BCI training protocols. The BCI community now recognises that in order to achieve an improvement in performance, the user must be included in the loop, and so training protocols must be improved accordingly. We have seen that a few promising avenues regarding the various constituent elements of these training protocols (instructions, training tasks, feedback and training environments) have been explored. Unfortunately, these types of study remain few and far between and, critically, their results are insufficiently utilised by the BCI community. We have also shown that by building on theories in disciplines such as psychology and instructional design, it is possible to suggest new, promising approaches for improving user performance. One of the most important steps seems to be making the effort of understanding how each user works cognitively in order to offer training protocols adapted to their individual profiles.

2

PREDICTORS OF MI-BCI PERFORMANCE & THEIR NEURAL CORRELATES - A STATE OF THE ART.

ROADMAP -

QUICK SUMMARY -

We propose a review and classification of cognitive and psychological predictors of MI-BCI performance. Three categories are defined: the user-technology relationship, attention and spatial abilities. The description of these categories and of their neurophysiological correlates enables us to submit ideas to improve MI-BCI user-training. For instance, we explain how to reduce computer-anxiety and increase the sense of agency, notably through the use of a positively biased feedback for novice users. Also, we propose solutions to raise and improve attention, e.g., using neurofeedback or meditation. Finally, we argue that spatial abilities could be trained to improve users' capacity to perform mental imagery and consequently, potentially improve their MI-BCI performance.

RELATED PAPER -

-1- Jeunet, C., N'Kaoua, B., and Lotte, F. (2016). 'Advances in user-training for mental-imagery-based BCI control: Psychological and cognitive factors and their neural correlates.' In: *Progress in brain research*.

2.1 INTRODUCTION

A tremendous inter- and intra-subject variability has been observed in terms of performance (command classification accuracy) in virtually every MI-BCI paper, both with the machine learning and the operant conditioning approaches (Allison and Neuper, 2010, Wolpaw and Wolpaw, 2012, Kübler et al., 2013). Thus, it is now clear that one of the major aspects contributing to MI-BCI control performances is the individual characteristics of the BCI user (Kübler et al., 2013). However, it is neither entirely clear which characteristics do impact BCI performances, why they have such an impact nor what the extent of this impact is. This has led the BCI community to look for predictors of MI-BCI performance, i.e., individual characteristics that correlate with the command classification accuracy. Indeed, identifying such predictors would allow BCI designers to find the most suitable BCI for a given user. Alternatively, or additionally, identifying such predictors would enable BCI researchers to identify what makes some users fail to control MI-BCI and thus to work on designing specific solutions. In particular, a promising research direction would be to propose MI-BCI training approaches that are adapted to users, according to their characteristics (Lotte, Larrue, and Mühl, 2013, Lotte and Jeunet, 2015). Interestingly enough, a number of neurophysiological predictors have been identified, as reviewed in Ahn and Jun, 2015. Some psychological predictors have also been identified for P300-based BCI and BCI based on SensoriMotor Rhythms (SMR) (Kleih and Kübler, 2015). However, to the best of our knowledge, there is no comprehensive and up-to-date review that surveys the psychological and cognitive factors that impact MI-BCI performances, presents some cognitive mechanisms that could explain why they have such an impact, sheds light on the underlying neural correlates of these factors and proposes theoretical solutions that could take these factors into account to improve MI-BCI training. This is therefore what this chapter sets out to offer.

First, this chapter surveys the BCI literature in order to identify the psychological and cognitive factors that correlate with MI-BCI performance (Section 2.2). This survey allowed the identification of different predictors that can be organised into three main categories, each representing a higher-level cognitive concept. In particular, it was found that existing predictors of MI-BCI performance were mostly related to the relationship between users and technology, their attention and their spatial abilities. Thus, the following sections define each of these concepts in more detail, and describe their neural correlates: the user-technology relationship is dealt with in Section 2.3, attention is discussed in Section 2.4 and spatial abilities are attended to Section 2.5. Finally, Section 2.6 proposes some future prospects and theoretically promising levers to improve MI-BCI training by taking into account each of these three high-level factors.

2.2 Psychological and Cognitive Factors Related to MI-BCI Performance

This first section offers a review of the latest developments in our understanding of the psychological and cognitive factors reported to influence MI-BCI performance (i.e., control accuracy). These factors can be divided into three groups. The first group includes the factors associated with the States of the user. Users' states are described by Chaplin, John, and Goldberg, 1988 as "temporary, brief, and caused by external circumstances". The second group gathers the factors related to the users' Traits, characterised as "stable, long-lasting, and internally caused" with respect to one's environment and experience (Chaplin, John, and Goldberg, 1988). Finally, the third group comprises the factors that can be qualified neither as Traits nor as States, i.e., demographic characteristics, habits and environment-related factors.

2.2.1 *Emotional and Cognitive States that Impact MI-BCI Performance.*

Some aspects of users' states, and more specifically of their cognitive and emotional states, have been reported to influence their MI-BCI performance in terms of control accuracy. First, Nijboer et al., 2007 have shown that mood (measured using a subscale of the German Inventory to assess Quality of Life - Averbeck, 1997 -) correlates with BCI performance. On the other hand, both attention (Daum et al., 1993, Grosse-Wentrup, 2011, Grosse-Wentrup and Schölkopf, 2012), assessed for instance by means of digit spans or block taping spans (Daum et al., 1993), and motivation (Hammer et al., 2012, Neumann and Birbaumer, 2003, Nijboer et al., 2007) levels have repeatedly been shown to positively correlate with performance, both in the context of Slow Cortical Potential (SCP) and SMR based BCI. Furthermore, in their study, Nijboer et al., 2007 suggested that higher scores in mastery confidence, i.e., how confident the participant was that the training would be successful, were correlated to better SMR regulation abilities, whereas higher rates of fear of incompetence were correlated to lower SMR regulation abilities. This last point has also been suggested in Kleih et al., 2013 for stroke patients taking part in BCI-based rehabilitation. More generally speaking, fear of the BCI system has been shown to affect performance (Burde and Blankertz, 2006, Nijboer, Birbaumer, and Kübler, 2010, Witte et al., 2013). In the same vein, control beliefs (Witte et al., 2013), i.e., participants' beliefs that their efforts to learn would result in a positive outcome, and self-efficacy (Neumann and Birbaumer, 2003), which can be defined as participants' beliefs in their own abilities to manage future events, have been suggested to play a role in BCI performance, in an SMR and an SCP paradigm, respectively. Mastery confidence, control beliefs and self-efficacy can be classed as context-specific states, i.e., states triggered each time a person faces a specific situation.

2.2.2 *Personality and Cognitive Traits that Influence MI-BCI Performance*

On the one hand, several aspects of the cognitive profile have been related to BCI control ability. Memory span and attentional abilities have been shown to correlate with the capacity to regulate SCP in patients with epilepsy (Daum et al., 1993). Hammer et al., 2012 also showed that attention span played a role in one-session SMR-BCI control performance. Furthermore, Hammer et al., 2012 have proposed a model for predicting SMR-BCI performance - which includes visuo-motor coordination (assessed with the Two-Hand Coordination Test) and the degree of concentration (assessed with the Attitudes Towards Work) - that reaches significance. More recently, Hammer et al., 2014 tested this model in a 4 session experiment (one calibration and three training sessions) within a neurofeedback based SMR-BCI context (i.e., involving no machine learning). Their results showed that these parameters explained almost 20% of SMR-BCI performance in a linear regression. However, the first predictor, i.e., visual-motor coordination, failed significance. With this model, the average prediction error was less than 10%. Finally, kinesthetic imagination and visual-motor imagination scores have both been shown to be related to BCI performance by Vuckovic and Osuagwu, 2013. On the other hand, concerning personality traits, Burde and Blankertz, 2006 have obtained a positive correlation between a Locus of control score related to dealing with technology and the accuracy of BCI control.

2.2.3 *Other Factors impacting MI-BCI Performance: Demographic Characteristics, Experience & Environment.*

Some other factors that have also been related to the ability to control a BCI, cannot be classified as either traits or states. These factors can be divided into three categories: (1) demographic characteristics, (2) experience/habits and (3) environment. Concerning the first point, demographic characteristics, age and gender have been related to SMR-BCI performance (Randolph, 2012): women being more capable than men and over 25 year-old being more competent than their younger counterparts. On the other hand, some habits or experiences have been shown to increase SMR-BCI control abilities (Randolph, Jackson, and Karmakar, 2010, Randolph, 2012). More specifically, playing a musical instrument, practicing a large number of sports, playing video games (Randolph, 2012), as well as spending time typing and the ability to perform hand and arm or full-body movements (Randolph, Jackson, and Karmakar, 2010) positively impact SMR-BCI performance. However, the consumption of affective drugs seems to have the opposite effect (Randolph, Jackson, and Karmakar, 2010). Finally, the user's environment, and more particularly the quality of caregiving for patients, has been suggested in an anonymous report to play a role in SMR-BCI performance (Kleih and Kübler, 2015).

2.2.4 *To Summarise - MI-BCI Performance is Affected by the Users' (1) Relationship with Technology, (2) Attention and (3) Spatial Abilities.*

To summarise, the predictors of MI-BCI performance can be gathered into the three following categories, as depicted in , Figure 5:

— Category 1 - The user-technology relationship & the notion of control (in orange - spades, see Figure 5): indeed, based on

STATES	EMOTIONAL STATE	♣	Mood (Nijboer et al. 2008)
	COGNITIVE STATE	♣	Attention level (Grosse-Wentrup et al., 2011; Grosse-Wentrup and Scholkopf, 2012)
		♣	Motivation (Hammer et al., 2012; Neumann and Birbaumer, 2003; Nijboer et al., 2008)
		♠	Mastery confidence (Nijboer et al., 2008)
		♠	Fear of the BCI (Burde and Blankertz, 2006; Nijboer et al., 2010, Witte et al., 2013)
		♠	Control beliefs (Witte et al., 2013)
		♠	Fear of incompetence (Kleih et al., 2013; Nijboer et al., 2008)
		♠	Self-efficacy (Neumann and Birbaumer, 2003)
TRAITS	PERSONALITY	♠	Locus of control for dealing with technology (Burde and Blankertz, 2006)
	COGNITIVE PROFILE	♣	Attention span (Hammer et al., 2012)
		♣	Attentional abilities (Daum et al. 1993)
		♣	Attitude towards work (Hammer et al., 2012)
		♣	Memory span (Daum et al., 2013)
		♦	Visual-motor coordination (Hammer et al., 2014, 2012)
		♦	Kinaesthetic imagination score (Vuckovic and Osuagwu, 2013)
		♦	Visual motor imagination score (Vuckovic and Osuagwu, 2013)
OTHER FACTORS	DEMOGRAPHIC DATA	·	Age (Randolph, 2012)
		·	Gender (Randolph, 2012)
	EXPERIENCE	♦	Playing a music instrument (Randolph, 2012)
		♦	Practicing sports (Randolph, 2012)
		♦	Playing video-games (Randolph, 2012)
		♦	Hand & arm movements (Randolph et al., 2010)
		♦	Time spent typing (Randolph et al., 2010)
		♦	Full body movements (Randolph et al., 2010)
		♣	Consumption of affective drugs (Randolph et al. 2010)
	ENVIRONMENT	·	Quality of caregiving (Kleih and Kübler, 2015)

Figure 5 – This table summarises the different predictors which have been related to MI-BCI performance in the literature, i.e. the predictors related to the user-technology relationship (orange spades), to attention (green clubs) and to spatial abilities (blue diamonds).

the literature, it appears that people who apprehend the use of technologies (and more specifically the use of BCIs) and who do not feel in control, experience more trouble controlling BCIs.

— Category 2 - Attention (in green - clubs, see Figure 5): this category includes both attentional abilities (trait) and attention level (state). The latter can fluctuate with respect to different parameters such as environmental factors, mood or motivation. Both these aspects of attention have been repeatedly evoked as being predictors of BCI performance.

— Category 3 - Spatial Abilities (in blue - diamonds, see Figure 5): many predictors depicted in the previous brief review are related to motor abilities (e.g., 2-hand coordination, sports or music practice) or to the ability to produce mental images (e.g., kinaesthetic imagination scores). These predictors can be gathered under the label of "spatial abilities".

It is noteworthy that in the vast majority of the experiments during which the predictors were computed, users were BCI-naïve and thus novices. Indeed, as stated earlier, predictors were generally computed during the first training session, whereas learning to control an MI-BCI requires several training sessions (McFarland, Sarnacki, and Wolpaw, 2010, Neuper and Pfurtscheller, 2010, Pfurtscheller and Neuper, 2001). In the next paragraph, we will argue that the involvement of the predictors in Category 1, i.e., the User-Technology Relationship & the Notion of Control, can be explained by the fact that users were BCI-naïve while the involvement of the predictors in Categories 2 & 3, i.e., Attention & Spatial Abilities, can be explained by the fact they were novices.

First, when confronted with a new technology, and even more so when this technology is associated with a new interaction paradigm (as is the case here with MI), users are likely to experience anxiety and a related low feeling of control during their first interaction attempts. Yet, the level of control perceived by a user (i.e., to what extent they consider being responsible for the perceived outcome of their actions) has been shown to positively correlate with motivation, performance and general skill acquisition (Achim and Al Kassim, 2015, Saadé and Kira, 2009, Simsek, 2011). These elements, which will be described in further detail in Section 2.3, both explain why the notions of anxiety and control are involved in BCI performance and how they are related to other predictors. Second, the definition of attention and spatial abilities as two major categories of MI-BCI performance predictors is consistent with Phase ♯1 of the Ackerman model of inter-individual differences during skill acquisition (Ackerman, 1988). In his model, Ackerman argues that skill acquisition is divided into three phases and that inter-individual differences are explained by different factors according to the phase in which the user is (Neumann and Birbaumer, 2003):

— Phase ♯1: Slow and error prone performance - During this phase, inter-individual differences are mainly explained (1) by task-appropriate abilities and (2) by "cognitive-intellectual general ability, involving a strong demand on the cognitive attentional system" (Neumann and Birbaumer, 2003).
— Phase ♯2: Redefinition and strengthening of the stimulus - response connections of the skill - During this second phase, speed of perception plays a major role in inter-individual differences.
— Phase ♯3: Automatic phase - During this third phase, non - cognitive psycho-motor abilities are mostly responsible for inter-individual differences (Wander et al., 2013).

As stated earlier, BCI users were in an early stage of learning, i.e., in Phase ♯1 of the Ackerman model, when the predictors were computed. This is coherent with the fact that BCI literature reports a strong involvement of (1) spatial abilities and (2) attention. Spatial abilities correspond to the ability to produce, transform and interpret mental images (Poltrock and Brown, 1984). Thus, they can be defined as "task-appropriate abilities" for an MI-BCI control task. On the other hand, the involvement of attentional state and trait is consistent with the second factor responsible for inter-individual differences in Phase ♯1, namely, "cognitive-intellectual general ability" and the "cognitive attentional system".

The concepts associated with each of the three categories of predictors, i.e., relationship with technology, attention and spatial abilities are introduced, and their neural correlates are described in the following sections.

2.3 THE USER-TECHNOLOGY RELATIONSHIP: INTRODUCING THE CONCEPTS OF COMPUTER-ANXIETY AND SENSE OF AGENCY - DEFINITION & NEURAL CORRELATES

In the previous section, we stated that some predictors of MI-BCI performance could be gathered under the label "user - technology relationship". These factors can be divided into 2 categories: (1) the apprehension of the use of technology and (2) the notion of control.

On the one hand, the fear of the BCI system (Burde and Blankertz, 2006, Nijboer, Birbaumer, and Kübler, 2010, Witte et al., 2013) and the fear of incompetence (Kleih et al., 2013, Nijboer et al., 2008), all having been shown to negatively impact MI-BCI performance, reflect a certain apprehension of the user towards BCI use. This apprehension can be defined as computer-anxiety.

On the other hand, the locus of control related with dealing with the technology (Burde and Blankertz, 2006) will influence the extent to which users feel in control while using the BCI. In the same vein, levels of mastery confidence (Nijboer et al., 2008), control beliefs (Witte et al., 2013) and self-efficacy (Neumann and Birbaumer, 2003) will impact the experience of control of the technology. An experimental study (Brosnan, 1998) suggested that self-efficacy would determine the way the person attempts to solve the task and that it would explain around 50% of the variance in the task performance. Besides, self-efficacy has been suggested to be related to motivation, work engagement and performance (Achim and Al Kassim, 2015). This would be consistent with the MI-BCI literature as both self-efficacy and motivation were involved in MI-BCI users' control abilities. It appears that people with a high self-efficacy level perceive failure as a challenge, and not as a threat (Achim and Al Kassim, 2015) which could explain why they are prone to persevere, and thus more likely to reach good performances. Furthermore, Vlek et al., 2014 indicate that when users feel in control, their attitude towards the BCI system is more positive which enables them to replenish mental resources and increase motivation which in turn induces a better task engagement. Both these studies and the predictors stress the importance of the notion of control to reach better MI-BCI control abilities. This notion of control can be conceptualised as the sense of agency.

These two aspects of the user - technology relationship, namely the apprehension of the technology and the notion of control, are much related. In the following sections, we will further detail these two phenomena and the neural correlates associated to the sense of agency (indeed, to our knowledge, no studies have investigated the neural correlates of the specific concept of computer anxiety). We will notably see that the sense of agency (i.e., the feeling of being in control) actually mediates computer anxiety (i.e., the apprehension of the technology).

2.3.1 *Apprehension of Technology: the Concept of Computer Anxiety - Definition*

Computer Anxiety (CA), also called "Tech-Stress" (Achim and Al Kassim, 2015), can be classed as a context-specific anxiety, i.e., a transitory neurotic anxiety ranging between anxiety trait and anxiety state (Saadé and Kira, 2009). Indeed, it is a kind of anxiety specifically associated to one context: the use of a computer or of a computer-based technology.

Brosnan, 1998 has shown that CA has a direct influence over performance when an unforeseen or unknown event occurs during the interaction process. Moreover, CA has been shown to impact the perceived ease-of-use of the technology, i.e., high computer anxiety will result when perceived difficulty is high. Both these elements explain why CA plays a major part when people are first exposed to new technologies, especially when the paradigm of interaction is new for them, as is the case for MI-BCI control. Brosnan, 1998 insists on the fact that even those who do not usually experience it, may undergo CA when confronted with a piece of technology that is new to them. Besides, around one third of the population is thought to experience CA to some degree: from preferring not to use the technology to palpitations while using it (Brosnan, 1998). The relationship between anxiety and performance could be explained, according to Brosnan, 1998, by the fact that anxious people devote more cognitive resources to "off-task" efforts (such as worrying about their performance), which induces shifts in attention between task and "off-task" considerations. As a consequence, the focused attention level dedicated to the task is decreased and fewer resources are available to perform the task. Thus, the task takes longer to complete, and performances drop in the case of tasks in which a limited amount of time is allocated. Furthermore, Simsek, 2011 identifies CA as being an affective response due to one's beliefs about one's lack of ability to control the technology. This perception of the level of control that one can exert on the task corresponds to the concept of self-efficacy. Simsek, 2011 argues that decreasing CA, and thus increasing self-efficacy, would lead to a better skill acquisition.

To summarise, based on empirical and theoretical studies, it seems that CA levels could enable to predict one's level of self-efficacy, which in turn could enable prediction of one's performance. More specifically, self-efficacy mediates the impact of CA on performance (Saadé and Kira, 2009).

2.3.2 *"I did that!": The Concept of Sense of Agency - Definition*

The sense of agency can be defined as "the sense that I am the one who is causing or generating an action" (Gallagher, 2000). The sense of agency is of utmost importance when a person is controlling an external device, since it will influence their affect towards the technology, and thus their commitment to the task and their performance (Vlek et al., 2014). However, in the context of MI-BCI, experiencing this sense of agency is not straightforward. Indeed, as a component of the "who" system (De Vignemont and Fourneret, 2004, Farrer and Frith, 2002), i.e. a mechanism which allows one to attribute one's own actions to oneself, the sense of agency depends on the sensory feedback resulting from the action. In other words, it depends upon a bodily experience (Damasio, 1999). Yet, the absence of proprioceptive feedback when performing mental imagery tasks prevents this bodily experience from occurring (Haselager, 2013), and should theoretically inhibit the sense of agency. However, evidence exists that the sense of agency does not only depend on the outcome of an action, but also that it is triggered before the action takes place (Gallagher, 2012, Synofzik, Vosgerau, and Newen, 2008) which explains why mental imagery, under certain conditions, can be associated with a sense of agency (Perez-Marcos, Slater, and Sanchez-Vives, 2009).

The sense of agency can be divided into 2 components (Farrer and Frith, 2002, Gallagher, 2012, Synofzik, Vosgerau, and Newen, 2008): (1) the feeling of agency and (2) the judgement of agency (also called feeling of ownership). The feeling of agency is pre-reflective, implicit, low-level and non-conceptual while the judgement of agency is reflective, explicit, high-order, belief-like and conceptual. In other words, the feeling of agency precedes the action, and is triggered during the preparation of the action, while the judgement of agency results from the computation of the comparison between the predicted and actual outcomes of the action. Synofzik, Vosgerau, and Newen, 2008 explains that a feeling of agency must be conceptually processed for a judgement or an attribution of agency to occur. The judgement of agency has been investigated in more depth than the feeling of agency in the literature (Chambon et al., 2012).

In order to experience a judgement of agency, three principles must be respected (Vlek et al., 2014): (1) the priority principle: the conscious intention to perform an act must immediately precede the action, (2) the consistency principle: the sensory outcome must fit the predicted outcome and (3) the exclusivity principle: one's thoughts must be the only apparent cause of the outcome (i.e. one must not believe there to be an outside influence). Moreover, several indicators influencing the judgement of agency have been proposed (Wegner, 2004, Wegner, Sparrow, and Winerman, 2004): bodily and environmental cues ("Where am I?"), bodily feedback (proprioceptive and kinesthetic information), bodily feedforward (i.e., the predicted sensory feedback), sensory feedback, social cues, action consequences and action-relevant thoughts (thinking about doing beforehand, in other words: the feeling of agency). On the one hand, the absence of some of these markers can lead to "a case of automatism" (Wegner, 2004), that is to say to the absence of judgement of agency: the agent is "doing without feeling". On the other hand, the manipulation of the same markers can lead to "an illusion of agency/ownership" (Wegner, 2004): agents who are "feeling without doing", and thus think they are in control although they are not.

2.3.3 *"I did that!": The Concept of Sense of Agency - Neural Correlates*

As stated by Ehrsson, Geyer, and Naito, 2003, the neural correlates underlying the sense of agency remain poorly understood. However, some brain regions have been repeatedly associated with this phenomenon. More specifically, here we will focus on the premotor cortex (PMC), and more precisely on its ventral part i.e., the supplementary motor area (SMA), as well as on the Angular Gyrus (AG) which is part of the posterior parietal cortex (PPC), on the anterior insula and on the cerebellum. All of the aforementioned brain areas have been reported to be involved in sensorimotor transformation and motor control as well as in the sense of agency (David, Newen, and Vogeley, 2008).

Self-agency has been shown to be underlain by an increased activity in the PMC (Farrer and Frith, 2002, Ehrsson, Geyer, and Naito, 2003) and more specifically in its ventral part, the SMA (Farrer and Frith, 2002, Kühn, Brass, and Haggard, 2013). The neural populations in the ventral PMC (SMA) and parietal PMC have been stated to represent both the seen and felt position of the limbs (Ehrsson, Geyer, and Naito, 2003). Thus, it is thought that the PMC enables a multi-sensory integration and thus provides a mechanism for bodily attribution (Ehrsson, Geyer, and Naito, 2003). Farrer and Frith, 2002 have also suggested that the insula may play a role in the experience or agency. More specifically, they measured an increase in activity in the anterior insula when a person was aware of causing an action. The authors justify this implication by the fact that the insula's role is to integrate all the concordant multi-modal sensory signals associated with voluntary movements. This result seems very consistent with the literature, since the activation of both these regions has been linked to awareness and execution of self-generated actions, to action preparation and to subjects' own intention to act (David, Newen, and Vogeley, 2008).

Contrariwise, the activation of the posterior parietal cortex (PPC) has been shown to negatively correlate with the sense of agency: the more a person tends to attribute the action to another person, the more the PPC is activated (Farrer and Frith, 2002). In other words, the activity in the PPC - and more specifically in the AG - increases when discrepancies are noticed between the predicted and the actual sensory outcomes of the action (Chambon et al., 2012). Indeed, PPC activation is linked to the processing of visual-motor incongruence during self-generated actions (David, Newen, and Vogeley, 2008). In this process, the cerebellum acts as a relay to inform about the sensorimotor discrepancies between the predicted and actual outcomes of the action (David, Newen, and Vogeley, 2008). But it seems that the AG also monitors the signals linked to action selection in the dorsolateral Pre-Frontal Cortex (dlPFC) to prospectively provide information about the subjective feeling of control over action outcomes (Chambon et al., 2012). Thus, the online monitoring of these signals by the AG may provide the subject with "a subjective marker of volition, prior to the action itself" (Chambon et al., 2012). While consistent, these correlates are still discussed. For instance, Kühn, Brass, and Haggard, 2013 report no correlation between AG activation and their subjective measure of agency.

The fact that these brain areas belong to different functional brain networks could explain their role in self-agency. For instance, the insula and the PPC have been shown to be involved in complex representations of the self (Farrer and Frith, 2002). Farrer and Frith, 2002 suggested that the relocation from the insula (when experiencing self-agency) to the PPC (when attributing the outcome to another person) could correspond to a shift in the attentional process from the egocentric to the allocentric point of view. In a similar vein, the PPC and the SMA are the key nodes in the human mirror neuron system: they encode motor aspects of actions performed by oneself or by another person (David, Newen, and Vogeley, 2008).

To summarise, the sense of agency seems to be related to complex interconnections between several brain areas enabling one to experience (1) a feeling of agency before the action outcome (through the involvement of the PMC/SMA and cerebellum among others) but also (2) a judgement of agency by comparing the predicted and perceived outcomes (notably through the activation of the insula and the AG/PPC). However, the neural processes involved in each of these phenomena, namely the feeling and judgement of agency, as well as the differences between both, require further investigation (David, Newen, and Vogeley, 2008).

2.4 ATTENTION - DEFINITION & NEURAL CORRELATES

The second category of factors that have been found to correlate with BCI performances contains attention-related predictors. Indeed, both attentional traits, i.e., the BCI user's intrinsic attentional capacities, and attentional states, i.e., the amount of the user's attentional resources dedicated to the BCI task, were found to be correlated to BCI performances. To summarise (see Figure 5), the attentional traits predicting BCI performances include attention span (Hammer et al., 2012), attentional abilities (Daum et al., 1993), attitude towards work (Hammer et al., 2012) which also measures the capacity to concentrate on a task, and memory span (Daum et al., 1993) which measures the ability to maintain attention (Engle, Kane, and Tuholski, 1999). The higher the attentional abilities of BCI users, the better the BCI classification accuracy they will reach. There is also some evidence that the attentional state of BCI users seems to be correlated to their BCI performances. Indeed, two different neurophysiological markers based on neural correlates of the attentional state were defined and measured in single-trial EEG signals. They were both found to be significantly correlated to the classification accuracy obtained for these trials (Grosse-Wentrup, Schölkopf, and Hill, 2011, Grosse-Wentrup and Schölkopf, 2012, Bamdadian et al., 2014) (see Section 2.4.2 for more details on these two EEG predictors based on attentional states).

Another factor, which is not a result of attention alone but is however related to it, is the user's motivation for a given BCI session, which has also been found to be predictive of their BCI performances (Hammer et al., 2012, Neumann and Birbaumer, 2003, Nijboer et al., 2008). Indeed, attention appears to be a critical factor in many models of motivation (Keller, 2008, Keller, 2010).

Finally, there are a number of other factors that have been found to be correlated to BCI performances that are not related to attention per se, but that are likely to impact the attentional resources that users devote to the BCI task. These include mood (Nijboer et al., 2008), the consumption of affective drugs (Randolph, Jackson, and Karmakar, 2010), as well as environmental factors for patients such as room temperature, sleep quality or headaches (Neumann and Birbaumer, 2003).

The following sections define and describe in more detail some of the cognitive mechanisms of attention, their associated neural correlates and their relevance to BCI control.

2.4.1 *Attention - Definition*

Attention could be defined as the "the ability to focus cognitive resources on a particular stimulus" Frey et al., 2014a. According to Posner and Petersen, 1989, the attention system can be divided into three main sub-systems, each of which corresponds to a major attentional function. These three sub-systems are the alerting system, the orienting system and the executive control system. The alerting function is responsible for maintaining a state of vigilance over long periods of time, i.e., it is responsible for sustained attention. Sustained attention (or vigilance) is necessary to perform long and usually tedious tasks. The orienting function is involved in selecting information among different information streams, such as different modalities (sounds, images) or different spatial or temporal locations. It is implicated in ignoring distracting events, and is thus involved in what is known as selective attention. The third function, executive control, is involved in the awareness of events and in the management of attentional resources, which are limited. Indeed, two tasks competing for attention will interfere with each other, thus possibly reducing performances for these tasks. Executive control is therefore involved in what is known as focal attention. For further details concerning the different components of attention, the interested reader can refer to (Posner and Boies, 1971, Posner and Petersen, 1989, Petersen and Posner, 2012). It is also important to note that attentional abilities and resources vary between individuals (Petersen and Posner, 2012).

Attention has been known for many years to be necessary in ensuring successful learning (Nissen and Bullemer, 1987). Indeed, if learners do not assign enough attentional resources to a given learning task, e.g., because they have to perform dual-attentional tasks (i.e., split their attentional resources between two tasks), their learning performance will be greatly reduced, or they may even fail to be aware of relevant learning material and fail the learning task al-together (Nissen and Bullemer, 1987). Keller even stated that "attention is a prerequisite for learning" (Keller, 1987). This gave birth to the ARCS model of instructional design, a well-known model used to design learning material and training tasks (Keller, 1987, Keller, 2008). ARCS stands for Attention, Relevance, Confidence and Satisfaction, which are the four main components of human motivation that are necessary to ensure successful learning. In order to ensure an efficient instruction and training, the ARCS model states that it is necessary to get the attention of students on the relevant learning stimulus (thus ignoring distracters), and to sustain this attention over the duration of the instruction, in order to focus the attentional resources on training-relevant problems (Keller, 1987). We can see here that the three sub-systems of attention (sustained attention, selective attention and focal attention) are therefore involved in the learning process. Since MI-BCI control requires training, it therefore makes sense that it also requires the user's attentional resources, and thus that attention and motivation are predictors of MI-BCI performance.

2.4.2 *Attention - Neural Correlates*

Interestingly enough, the attention system is associated with specific anatomical structures in the brain that are different than those dedicated to information processing (Posner and Petersen, 1989). Each of the three attention subsystems (alerting, orienting and executive control) corresponds to a specific brain network (Posner and Petersen, 1989, Petersen and Posner, 2012). The alerting network, although still not fully understood, seems to primarily involve the right hemisphere (frontal and parietal lobes), including the right inferior parietal lobule with the Angular Gyrus (AG) and thalamic areas (Seghier, 2013, Petersen and Posner, 2012). The orienting network notably involves the Frontal Eye Fields, the intraparietal sulcus and the superior parietal lobe, the temporo-parietal junction, the AG and the ventral frontal cortex (Seghier, 2013, Petersen and Posner, 2012). Finally, the Executive Network involves multiple brain areas, including the medial frontal cortex, the Anterior Cingulate Cortex (ACC), the dorsolateral prefrontal cortex, the anterior prefrontal cortex, the precuneus, the thalamus, the anterior insula, the intraparietal sulcus and the intraparietal lobule. There is large inter-individual variability in the efficiency of these networks which explains, at least in part, the inter-individual variations in attentional abilities, i.e., attentional traits (Petersen and Posner, 2012).

There are also a number of electrophysiological neural correlates, in particular spectral variations in EEG signals that are related to change in attention levels. Regarding the alerting system, decreased vigilance levels are associated with a slowing of EEG frequencies, i.e., in an increased power for low frequency EEG rhythms (delta - ~1-4z, theta ~4-7Hz, low alpha ~7-10Hz), and a decreased power for higher frequency EEG rhythms (Frey et al., 2014a, Roy, 2015). The amplitude of Event Related Potentials such as the P300 or the parietal N100 also decreases with lower vigilance. Concerning the orienting system, alpha activity (~8-12Hz) has also been shown to be related to selective attention, with higher alpha power indicating lower attention, and occipital alpha providing information on the location of spatial visual attention (Frey et al., 2014a). A delta (~3-8Hz) over beta (~16-24Hz) power ratio has also been used as a marker of sustained attention (Bamdadian et al., 2014). Finally, it seems that the Gamma (~55-85Hz) power in attentional networks related to the executive control system also correlates with the attentional level (Grosse-Wentrup, 2011).

Consistent with the literature in cognitive sciences stressing the impact of attention on success in task-learning, the BCI community has also identified a number of neural correlates of attention that are related to BCI performance. For instance, variation in Gamma power, notably in executive control attentional brain networks, have been found to be correlated to SMR-BCI performance and can be used to predict successful or unsuccessful classification both for SMR-BCI (Grosse-Wentrup, 2011, Grosse-Wentrup and Schölkopf, 2012) and for general MI-BCI (Schumacher, Jeunet, and Lotte, 2015). Moreover, the extent of activation of the dorsolateral prefrontal cortex (involved in executive control as seen above), was also found to differ between SMR-BCI users with high performances and SMR-BCI users with low performances (Halder et al., 2011). Finally, an EEG predictor based on frontal Theta, occipital Alpha and midline Beta power, which are all neural correlates of sustained attention (thus involving the alerting system) as described previously, has been shown to correlate with SMR-BCI performances (Bamdadian et al., 2014).

2.5 SPATIAL ABILITIES - DEFINITION & NEURAL CORRELATES

As already seen, many studies have highlighted the role of spatial abilities on BCI performance variation across subjects. The general hypothesis is that low BCI performers have less-developed abilities to generate or maintain mental images.

For example, Vuckovic and Osuagwu, 2013 relate the results of kinaesthetic and visual motor imagery questionnaires to performances obtained with a BCI based on object oriented motor imagery. They show that the kinaesthetic score could be a relevant predictor of performance for an SMR-BCI. Moreover, the physical presence of the object of an action facilitates motor imagination in poor imagers. It is important to note that the impact of imagery abilities on BCI performances might be mediated by differences in brain activation. Guillot et al., 2008 attempted to identify the functional neuroanatomical networks that dissociate able versus poor imagers. They used functional magnetic resonance imaging (fMRI), to compare the patterns of cerebral activations in able and poor imagers during both the physical execution and mental imagery of a sequence of finger movements. Results show that good imagers activated the parietal and ventrolateral premotor regions to a greater degree, both having been shown to play a critical role in the generation of mental images.

Furthermore, Randolph, 2012 has shown that video game experience is likely to enhance BCI performance. Many studies have noted a link between video game experience and spatial abilities. For example, spatial abilities can be improved through playing action video game (Dorval and Pepin, 1986, Subrahmanyam and Greenfield, 1994). Feng, Spence, and Pratt, 2007 observe that performances in a mental rotation test (Vandenberg and Kuse, 1978, that is often used to measure spatial abilities) are enhanced after only 10 hours of training with an action video game. More remarkably, these authors found that playing an action video game can decrease the well-known gender disparity in mental rotation tasks (see also Ventura, Shute, and Zhao, 2013). All these elements strongly suggest that the link between video game experience and BCI performance could be mediated by spatial ability levels.

Moreover, Randolph, 2012 showed that using hand-and-arm movements, or full body movements (such as playing sports or musical instruments) also favors BCI performance. Many authors have also observed a link between spatial abilities and motor processes (Hoyek et al., 2014). For example, Moreau et al., 2011 compared elite and novice athletes and found a significant relationship between sports performance, activity, sport-specific training and mental rotation abilities. In the Hoyek et al., 2014 study, the motor performance of 7 to 8 year old and 11 to 12 year old children was measured in a steeple race and an equivalent straight distance sprint. Data revealed that the time taken to complete the race was influenced by speed and sex, but also by the individual mental rotation abilities. These links between motor performances and spatial abilities are also attested by neuroimaging studies which provide evidence that motor areas are involved in mental rotation (e.g., Lamm et al., 2007). Thus, it can be assumed that the relationship between BCI performance and motor processes are mediated by spatial ability levels.

Finally, Hammer et al., 2012 found that visual-motor coordination abilities constitute a predictor of BCI efficiency, and Scordella et al., 2015 showed a relationship between motor coordination and visual-spatial skills (measured by a visual-constructive task). We can again assume that the link between visual-motor coordination and BCI efficiency is mediated by visual-spatial abilities.

2.5.1 *Spatial Abilities - Definition*

As mentioned above, spatial abilities embody the ability to produce, transform and interpret mental images (Poltrock and Brown, 1984). Lohman, 1996 greatly highlighted the pivotal role of spatial abilities and particularly mental imagery in all models of human abilities. This author reports that high levels of spatial abilities have frequently been linked to creativity in many domains (arts, but also science and mathematics) (see also Shepard, 1978). He also indicates that Albert Einstein, as well as other well-known physicists and inventors (such as James Clerk Maxwell, Michael Faraday and Herman von Helmholtz) , have been reported to have had high spatial abilities, and that these abilities played an important role in their creativity. Furthermore, studies on developmental cognitive skills have consistently shown that spatial aptitude and mathematical aptitude are closely related (Geary et al., 2000). Moreover, the importance of spatial ability in educational pursuits and in the professional world was examined by Wai, Lubinski, and Benbow, 2009, with particular attention devoted to STEM (science, technology, engineering, and mathematics) domains. Participants (Grades 9-12, N=400 000) were tracked for 11 years. Results showed that spatial abilities were a significant predictor of achievement in STEM, even after taking into account possible third variables such as mathematical and verbal skills (see also Humphreys, Lubinski, and Yao, 1993, Shea, Lubinski, and Benbow, 2001).

The key role of mental imagery in human cognition has also been highlighted by the fact that it is involved in certain pathological situations such as Post-Traumatic Stress Disorders (Brewin, Dalgleish, and Joseph, 1996), schizophrenia (Oertel-Knöchel et al., 2013), depression (Rogers et al., 2002) social phobia (Clark and Wells, 1995) and bipolar disorder (Holmes et al., 2008). For example, impairment in image generation or in mental rotation of letters has been shown in unipolar major depression (Rogers et al., 2002).

Furthermore, the potential role of imagery for motor skill learning has been demonstrated in many situations, such as learning new skills in sports (Murphy, 1994), improving performance both in novice and expert surgeons (Cocks et al., 2014) and in Paralympics athletes (Martin, 2012).

Today, it is common to distinguish between large scale and small scale spatial abilities (Hegarty et al., 2006). Large scale abilities refer to the notion of way-finding (or spatial navigation) defined as “the process of determining and following a path or route between origin and destination” (Golledge, 1999). Way-finding is assessed by tasks such as search, exploration, route following, or route planning in contexts including outdoor and urban environments, indoor spaces and virtual reality simulations (Wiener, Büchner, and Hölscher, 2009).

By contrast, small-scale spatial abilities are usually assessed by paper-and pencil tests which involve perceptually examining, imagining, or mentally transforming representations of small shapes or easy-to-handle objects (Hegarty et al., 2006). These abilities also refer to the notion of mental imagery consisting of several component processes. For example, the classical model of Kosslyn (Kosslyn, 1980, Kosslyn, 1996) proposes a distinction between four components, namely image generation (the ability to form mental images), image maintenance (the ability to retain images over time), image scanning (the ability to shift one's attention over an imaged object), and image manipulation (the ability to rotate or otherwise transform images) (see also Marusan, Kulistak, and Zara, 2006).

2.5.2 *Spatial Abilities - Neural Correlates*

The neural correlates of visual mental imagery are subject to much debate. Some authors claim a functional equivalence between visual perception and visual mental imagery, with the retinotopic areas in the occipital lobe acting as common substrate (for a review, see Bartolomeo, 2008). However, some brain lesion studies indicate that visual imagery is possible without the involvement of primary visual areas (Chatterjee and Southwood, 1995). Nevertheless, the frontal eye fields and the superior parietal lobule seem to play a crucial role in generating visual mental images (Mechelli et al., 2004). These results have been confirmed by Zvyagintsev et al., 2013 showing that the visual network comprises the Fusiform Gyrus bilaterally and a Fronto-Parietal network involving the Superior Parietal Lobule and Frontal Eye Field bilaterally.

Motor imagery is a particular case of mental imagery defined as the mental simulation of a specific action without any corresponding motor output (Jeannerod, 1994). The neural substrate that underlies motor imagery has also been subject to many debates. Miller et al., 2010 measured cortical surface potentials in subjects during overt action and imagery of the same movement. They demonstrated the role of primary motor areas in movement imagery and showed that imagery activated the same brain areas as actual motor movement. In their study, the magnitude of imagery-induced cortical activity was reduced compared to real movement, but this magnitude was largely enhanced when subjects learned to use imagery to control a cursor in a feedback task. It is important to note that a distinction has been made between two types of motor imagery depending on the point of view adopted to imagine an action: the third-person perspective point-of-view consists in self-visualizing an action, whereas the first-person point of view perspective implies somesthetic sensations elicited by the action. Some evidence suggested that visual (third person) and somesthetic/kinaesthetic (first person) motor imagery recruit distinct neural networks. Guillot, Collet, and Dittmar, 2004 showed that visual imagery predominantly activated the occipital regions and the superior parietal lobules, whereas kinaesthetic imagery preferentially activated the motor-associated structures and the inferior parietal lobule. Finally, Ridderinkhof and Brass, 2015 specify that activation during kinaesthetic mental imagery is not just a subliminal activation of the same brain areas involved in the real action. For these authors the activation during kinaesthetic imagery is similar to the activation associated with the preparatory planning stages that eventually lead to the action (Jeannerod, 2006).

Interestingly enough, it has been shown that kinaesthetic motor imagery leads to better MI-BCI performances than visual motor imagery (Neuper et al., 2005). Nevertheless, the distinction between these different forms of mental imagery, their neural correlates and their relationships with the neural circuits involved in motor processes remain to be elucidated.

To conclude this section, spatial skills play a crucial role in human cognition as they are involved in many activities including art, music, mathematics, engineering, literature, etc. Many skills related to spatial abilities (such as playing sports, musical instruments, action video games, etc.) have been shown to be likely to improve BCI performance. It is an attractive hypothesis to consider that imagery abilities could contribute to explaining the "BCI illiteracy" phenomenon, but further investigations are needed to make a more systematic study of the relationship between certain cognitive and personality predictors, spatial abilities and BCI efficiency.

2.6 PROSPECTS: THE USER-TECHNOLOGY RELATIONSHIP, ATTENTION AND SPATIAL ABILITIES AS THREE LEVERS TO IMPROVE MI-BCI USER-TRAINING

2.6.1 *Demonstrating the Impact of the Protocol on Computer Anxiety & Sense of Agency*

In Section 2.3, we stressed the impact of the notion of control on performance, notably through its mediating role on computer anxiety. The notion of control can be conceptualised as a Sense of Agency, i.e., "the sense that I am the one who is causing or generating an action" (Gallagher, 2000). Given the strong impact that the sense of agency has on performance, it seems important to increase it as far as possible. Yet, in the context of MI-BCI control, it is not straightforward. Indeed, the sense of agency is mainly based on a bodily experience, whereas performing MI tasks does not provide the participant with any sensory feedback. Thus, here we would like to insist on the importance of the feedback, especially during the primary training phases of the user (McFarland, McCane, and Wolpaw, 1998). Indeed, in the first stages, the fact that the technology and the interaction paradigm (through MI tasks) are both new for the users is likely to induce a pronounced computer anxiety associated with a low sense of agency. Providing the users with a sensory feedback informing them about the outcome of their "action" (MI task) seems necessary in order to trigger a certain sense of agency at the beginning of their training. This sense of agency will in turn unconsciously encourage users to persevere, increase their motivation, and thus promote the acquisition of MI-BCI related skills, which is likely to lead to better performances (Achim and Al Kassim, 2015, Saadé and Kira, 2009, Simsek, 2011). This process could underlie the (experimentally proven) efficiency of biased feedback for MI-BCI user-training. Indeed, literature (Barbero and Grosse-Wentrup, 2010; Kübler et al., 2001b) reports that providing MI-BCI users with a biased (only positive) feedback is associated with improved performances while they are novices. However that is no longer the case once they have progressed to the level of expert users. This result could be due to the fact that positive feedback provides users with an illusion of control which increases their motivation and will to succeed. As explained by Achim and Al Kassim, 2015, once users reach a higher level of performance, they also experience a high level of self-efficacy which leads them to consider failure no longer as a threat (Kleih et al., 2013) but as a challenge. And facing these challenges leads to improvement.

However, to be efficient, this feedback must follow certain principles (Vlek et al., 2014). First, the priority principle, i.e., the conscious intention to perform an act must immediately precede the act: here, the feedback must appear after the users become conscious they have to perform the act and have started to do it. Second, the consistency principle, i.e., the sensory outcome must fit the predicted outcome. And third, the exclusivity principle, i.e., one's thoughts must be the only apparent cause of the outcome. This last point suggests that the user should not think that another person is controlling the feedback. Thus, if the feedback is biased, it has to be subtle enough so that the user is not aware of it. Otherwise, the user will not feel in control anymore. The two latter principles could explain why biased feedback is efficient for novices but not for experts. Indeed, experts develop the ability to generate a precise predicted outcome that usually matches the actual outcome (when the feedback is not biased). This explains why when the feedback is biased, and therefore the predicted and actual outcomes do not match, expert users attribute the discrepancy to external causes more easily. In other words, it can be hypothesised that experts might be disturbed by a biased feedback because they can perceive that it does not truly reflect their actions, thus decreasing their sense of being in control.

Furthermore, Beursken, 2012 tested the impact of the concept of transparent mapping in a pseudo-BCI experiment. A protocol is said to be transparent when the task and the feedback are consistent. In the experiment, the sense of agency of the participants was tested in two conditions: one transparent and one non-transparent. The participants had to imagine movements of their left and right hands. In the transparent condition, a virtual left or right hand moved on the screen when left or right hand imagination was recognised, respectively. In the non-transparent condition however, the same tasks were associated with both hands making "thumbs-up" or "okay" movements. Participants felt more in control in the transparent condition and reported that less effort was required to understand the instructions and remember the meaning of the feedback. Consequently, more resources were available to perform the task. This result means that when designing the feedback, researchers must be careful to propose a feedback that fits the mental task. Yet, in standard training protocols such as Pfurtscheller and Neuper, 2001, MI-tasks are associated with a bar extending in a specific direction. Although the direction of the bar is consistent with the task when participants are asked to perform left- and right-hand motor imagery, it is not particularly natural. Thus, the feedback-task transparency could be improved. With reference to the Ackerman model (1988), when the outcome (the feedback) is consistent with the task, during the Phase ♯1 the "task-appropriate" abilities, here spatial abilities, decrease in influence and thus the between-subject variability in terms of performance also decreases. However, when the outcome is inconsistent with the task, the requirements for information processing are important and the impact of the user-profile, here in terms of attentional abilities and spatial abilities, remains constant (Neumann and Birbaumer, 2003) which makes the between-subject variability due to these factors stable even in advanced phases of the training. To summarise, we can derive three guidelines for MI-BCI protocol design that could enable users to experience a better sense of agency. First, providing the users, especially novices, with a sensory feedback is essential as it will increase their potential sense of agency. While positively biasing the feedback can improve novice users' sense of agency, motivation and will to succeed, this is not the case for expert users who can be disturbed by biased feedback. Second, in order to be efficient the feedback must follow the principles of priority, consistency and exclusivity. And finally, transparent protocols, i.e., protocols in which the feedback fits with the MI-task, should be associated with better MI-BCI performance as (1) they induce a greater sense of agency and (2) they require less workload to be processed and thus grant more cognitive resources to be devoted to the task.

2.6.2 *Raising and Improving Attention*

As mentioned previously, attention is a major predictor of BCI performances, and it has been shown that the better the users' attentional abilities and the more attentional resources they devote to BCI training, the better their BCI performances. Therefore, BCI performances could be improved by designing BCI training protocols that 1) train users to increase their attentional abilities and 2) ensure the attentional resources of users are directed towards and maintained on the BCI training tasks. A first suggestion to improve BCI training is to include attention training tasks, to improve users' attentional abilities and thus their BCI performance. A number of approaches may be used, but recently researchers have identified meditation and neurofeedback as promising approaches for attention training (Brandmeyer and Delorme, 2013). Indeed, it has been shown that meditation is actually a successful form of attention training that improves the ability of practitioners to focus their attentional resources on a given task, possibly for long periods of time, as well as their ability to ignore distractors. Expert meditators have been found to show different activation levels than non-meditators in the fronto-parietal and the default mode networks, in functional Magnetic Resonance Imaging (fMRI) studies (Braboszcz, Hahusseau, and Delorme, 2010). The Gamma EEG power in these areas also differs between expert meditators and non-meditators (Lutz et al., 2008). Such brain networks are notably involved in sustained attention. Interestingly enough, these areas, and gamma activity originating from there, have both been identified as being related to BCI performance (Grosse-Wentrup and Schölkopf, 2012, Halder et al., 2011). The promising usefulness of meditation practice for BCI training is further supported by research from a number of groups who have found that meditation increases SMR-BCI performances (e.g., Eskandari and Erfanian, 2008, He et al., 2015). In other words, meditation seems to improve attentional abilities, which in turn would improve BCI performances.

Attentional capabilities can also be improved using neurofeedback training, e.g., by providing users with games in which they have to increase an EEG measure of their attentional level to win (Lim et al., 2010, Lim et al., 2012). For instance, in Lim et al., 2012, children with Attention Deficit Hyperactivity Disorder (ADHD) were asked to play a game in which the speed of the character they were controlling was directly proportional to their attentional level, as measured by EEG. Thus, they had to focus as much attention as possible on the game in order to move fast enough to complete it in the allotted time. This was shown to be a successful form of attention training which reduced the children's ADHD symptoms (Lim et al., 2010, Lim et al., 2012). Gamma neurofeedback was also shown to be useful in improving visual attention abilities (Zander et al., 2013). To the best of our knowledge, such neurofeedback training of attentional capabilities has not been explored with the aim of improving MI-BCI control abilities, and thus could be a promising direction to investigate.

A second suggestion to improve BCI training is to design BCI training tasks, feedbacks and environments that capture and maintain the attention of the user on the BCI training. In the ARCS model for instructional design, Keller suggests a number of approaches to get and maintain users' attention (Keller, 1987). In particular, this includes ensuring the active participation of the learners, adding game-like training, having a variety of supports, training materials and tasks, ensuring concrete training tasks and feedbacks as well as encouraging inquiry and curiosity from the learners (Keller, 1987). In practice, for MI-BCI, this could be achieved by having BCI users control video games or Virtual Reality (VR) applications with their BCI, hence ensuring game-like training, active user participation and concrete training tasks. The fact that VR and game-based BCI training were actually shown to improve BCI performances (Lotte et al., 2013) further supports this suggestion. Moreover, rather than using the same standard training protocol continuously and repeatedly, variety in training can be obtained by adding other training tasks, with different objectives. For instance, users can be asked to practice each MI task separately, or to perform a given MI-task as fast as possible as in (Ramsey et al., 2009) for instance. Finally, to encourage enquiry and add concreteness to the training, BCI users could be provided with richer and more motivating visualisation and feedbacks that enable them to see the impact of a given MI-task on their EEG signals in real-time, thus motivating them to explore different strategies. This could be achieved using recently proposed EEG visualisation techniques such as Teegi (Frey et al., 2014c). With this approach, users can see their own brain activity and EEG features in real-time, displayed in a user-friendly way on the head of a physical puppet they can manipulate. Other considerations could be taken into account to ensure users assign an appropriate amount of attentional resources to the BCI training. For instance, the training protocol should avoid requiring split attention, i.e., requiring users to divide their attentional resources between two different subtasks, especially if these tasks involve the same modality, e.g., two visual processing tasks. This would indeed deplete the user's cognitive resources and lead to poorer performances and lower learning efficiency for any training task (Sweller, Van Merrienboer, and Paas, 1998). This is a relevant point to consider as BCI feedback is often provided on the visual modality, while the controlled BCI application generally also requires visual processing, e.g., to control a game or a visual speller. Thus, it would be interesting to explore other modalities of feebdack such as the tactile or the auditory modalities. Finally, since it is possible to measure users' attentional level from EEG signals, this could be used in real-time to detect whether they are paying enough attention, and warn them to refocus their attention, if necessary, as suggested in Schumacher, Jeunet, and Lotte, 2015.

2.6.3 *Increasing Spatial Abilities*

If it appears that the training of spatial abilities could improve BCI performance, it is necessary to review the studies that have tried to better understand the effects of training on spatial skills. For instance, it is well known that men perform better than women in spatial perception and mental rotation tests (see for example, Linn and Petersen, 1985). In a meta-analysis, Baenninger and Newcombe, 1989 found that improvements in men and women remain parallel in response to practice and training, so that gender differences remain constant. However, others studies have shown greater performance improvement in women than in men (Okagaki and Frensch, 1994), or a waning of gender differences (Kass, Ahlers, and Dugger, 1998). In a meta-analysis of training studies, Uttal et al., 2013 indicated that spatial skills are highly malleable and that training in spatial thinking is effective, durable, and transferable (to skills that have not been subject to specific training). The authors outline that many studies in which transfer effects were present administered large numbers of trials during training, which allowed to conclude that such a transfer is possible if sufficient training or experience is provided. The meta-analysis did not show a significant effect of age or a significant effect of the type of training on the degree of improvement. Finally, the initial level of spatial skills affected the degree of malleability. Participants who started at lower levels of performance improved more in response to training than those who started at higher levels (Uttal et al., 2013). Terlecki, Newcombe, and Little, 2008 confirmed the impact of long-term practice or repeated testing, and training capacity to improve mental rotation performances. However, neither mental rotation practice nor video game training reduced gender differences. It is also important to note that these effects can last over several months and the effects of video game experience are transferable to tasks that have not been trained for. All these results are extremely interesting as they show that training and practice can improve spatial skills. Mental training has been used to improve performances in many domains such as sports, surgery, music, etc. However, very few studies have focused on BCI practice. Erfanian and Mahmoudi, 2003 have investigated the role of mental practice and concentration on a natural EEG-based Brain-computer interface for hand grasp control. The imagery task used was the imagination of hand grasping and opening. For imagery training, the authors used a video based method where subjects watched themselves performing hand-closing and -opening while undertaking imagery. The results showed that mental and concentration practice increased the classification accuracy of the EEG patterns. Moreover, mental practice more specifically affected the motor areas. This study shows very promising results on the way spatial training could improve BCI performances. Thus, it is a challenging project to study the impact of spatial training on reducing the "BCI deficiency" phenomenon, and thus enabling BCI to be more systematically used outside laboratories.

2.7 CONCLUSION

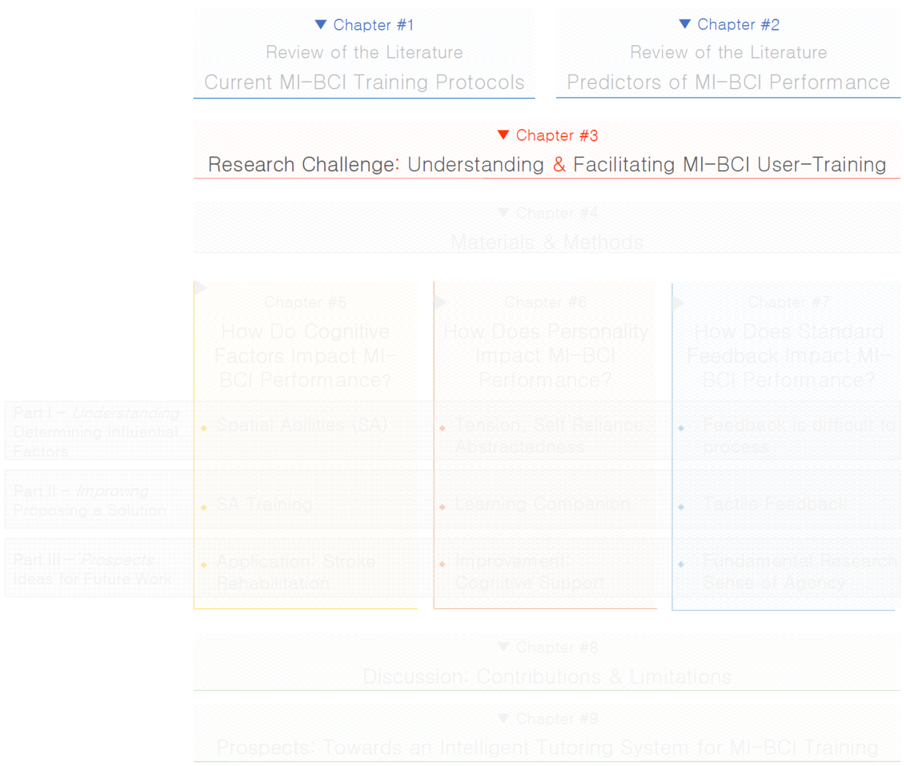
In this chapter, we performed a literature survey in order to identify the psychological and cognitive factors related to MI-BCI performance. This survey enabled us to classify most of the predictors into three categories representing higher-level cognitive concepts: (1) the user - technology relationship (comprising the notions of anxiety and control during the interaction), (2) attention and (3) spatial abilities. These three categories appear to be extremely relevant in the context of MI-BCI training. Indeed, the predictors were computed during the early stages of training, i.e., during the first or first few sessions. Moreover, most studies were performed on BCI-naïve users who were confronted with a BCI for the first time. Yet, the literature suggests that this situation (early training phase and first exposition to the technology) can induce an important level of anxiety associated to a low sense of agency, both having potential negative repercussions on performance (Achim and Al Kassim, 2015, Saadé and Kira, 2009, Simsek, 2011). This first point justifies the involvement of the category 1 predictors, i.e., those related to the users' relationship with the technology. Besides, the Ackerman model (Ackerman, 1988) suggests that during the early stages of learning (phase ♯ 1), the inter-user variability in terms of performance in mainly due to (1) differences in "task-appropriate" abilities and (2) high-level cognitive abilities such as attention. These two aspects correspond to the two other predictor categories that we identified. Indeed, spatial abilities (category 3), i.e., the ability to produce, transform and interpret mental images (Poltrock and Brown, 1984) can be considered as "task appropriate" abilities in the context of MI-BCI training, while attention (category 2) clearly corresponds to the second parameter influencing inter-user variability in Ackerman's model. Hence the elaboration of these three categories: the inclusion of the predictors in different categories was justified, the associated cognitive models were introduced and the neural correlates related to each concept were described. This work was intended to provide a better understanding of the different factors impacting MI-BCI training and thus to provide, in the Prospects section (i.e., Section 2.6), a discussion about how these factors could be taken into account when designing future protocols in order to optimise user-training. More specifically, the impact of the training protocol on users' computer anxiety and sense of agency was demonstrated. It has been suggested that a biased positive feedback could increase novice users' sense of agency and thus increase their performance. Also, the significance of respecting the principles of priority, consistency, exclusivity and a transparent mapping between the task and the feedback was emphasised. Furthermore, it should also be possible to increase BCI training efficiency by considering the user's attention. In particular, attention capabilities can be improved using meditation or neurofeedback. Moreover, attentional resources can be optimally directed towards BCI training by using gamified BCI training tasks, varied tasks, rich and friendly feedback as well as multimodal feedbacks. BCI efficiency could also be improved by using training procedures of spatial skills, since spatial ability training has proved to enhance performances in many domains (sport, music, surgical practice, etc.). Moreover, this improvement has been shown to be effective, durable, and transferable (to skills that have not been subject to specific training) when the training duration is long enough.

To conclude, we hope that this work will be useful to guide the design of new protocols and improve MI-BCI user-training so that these technologies become more accessible to their end-users.

3

RESEARCH CHALLENGE: UNDERSTANDING AND FACILITATING BCI USER-TRAINING.

ROADMAP -



QUICK SUMMARY -

We first explain the rationale of our research challenge. We argue that to make BCIs more reliable, efficient and accessible, it is necessary to *understand and improve MI-BCI user-training*. In order to face this challenge, we defined 3 research axes which consisted in investigating the impact of (1) cognitive factors, (2) personality and (3) feedback on MI-BCI performance. Each of these 3 axes was then investigated in 3 parts. First, experiments were performed to determine specific factors that impact performance. Second, a solution taking into account these factors and aiming at improving MI-BCI user-training was designed, implemented and tested. Third, ideas for future work were introduced.

RELATED PAPER -

-1- Lotte, F. and Jeunet, C. (2015). 'Towards Improved BCI based on Human Learning Principles.' In: *3rd International Brain-Computer Interfaces Winter Conference*, pp. 1–4 - Invited paper.

3.1 INTRODUCTION

As stated in the introductory chapter, EEG-based BCIs make computer control possible without any physical activity (Wolpaw and Wolpaw, 2012). As such, they have promised to revolutionise many application areas, including assistive devices and human-computer interaction (Erp, Lotte, and Tangermann, 2012, Wolpaw and Wolpaw, 2012). Despite this promising potential, the revolutions that were anticipated have not yet occurred, and BCIs are still barely used outside laboratories (Wolpaw and Wolpaw, 2012). The main reason for this is the substantial lack of reliability of current BCIs (Wolpaw and Wolpaw, 2012). In particular, BCIs often fail to correctly recognise the mental commands sent by the user. As an example, for BCIs that use imagined movements as mental commands, a study showed that the average rate of correct command recognition was only 74.4% (Blankertz et al., 2010a). Moreover, it is estimated that roughly 10 to 30% of BCI users cannot control the system at all (so-called BCI illiteracy/deficiency) (Allison and Neuper, 2010). Such poor reliability makes current BCIs unable to compete with alternative input devices (e.g., eye trackers), which are faster and more reliable (Wolpaw and Wolpaw, 2012).

To operate a BCI, the user must produce EEG patterns, typically using mental imagery tasks, which the machine can recognise with signal processing techniques. So far, to address the reliability issue of BCIs, most research efforts have been focused on EEG signal processing alone (Allison and Neuper, 2010, Bashashati et al., 2007). While this has contributed to increasing performance, improvements have been rather modest. Indeed, BCI accuracy rates are still relatively low and BCI deficiency rates still high (Allison and Neuper, 2010, Wolpaw and Wolpaw, 2012). Thus, the reliability issue of BCIs is unlikely to be solved by focusing on signal processing alone. Rather, there is a need for a new paradigm in BCI design, to enable both EEG signal processing and the user to work in synergy to optimise BCI performance.

Indeed, BCI control is known to be a skill that must be acquired and then mastered by the user (Wolpaw and Wolpaw, 2012). This means that 1) a user's BCI performances improve with practice and thus that 2) the user must learn how to produce stable, clear and distinct brain activity patterns to successfully control a BCI. This can be achieved so long as users are able to understand the feedback provided by the system, and can use it to improve their strategy. Even the very best signal processing algorithms will fail to recognise the user's mental commands if that user's BCI control skills are too poor. Unfortunately, the question of how to train users to control a BCI has been rather scarcely studied in the BCI literature so far, and consequently the currently used training protocols are theoretically inappropriate for acquiring skills (see Chapter 1). Thus, the best way to train users to master BCI control skills remains unknown (Allison and Neuper, 2010, Wolpaw and Wolpaw, 2012).

The stance of this thesis is that changing the design of BCIs in order to enable users to master BCI control skills is a very promising step towards improving BCI reliability. Thus, the aim of this chapter is to more precisely define the research challenges that have been addressed along our project in order to reach this goal.

The theoretical limitations mentioned in Chapter 1 coupled with users' modest BCI control performances motivated our choice to explore the concrete/practical impact of the training protocol on BCI performance. There is, however, a large inter-individual variability between BCI users despite the fact they are trained with the same protocol. Some users are indeed able to reach high BCI performances. This observation suggests that inter-user differences, and thus users' personalities and cognitive profiles, could impact BCI performance and should therefore be considered for the design of BCI training protocols. Thus, in line with the recommendations from psychology (Lotte et al., 2013), these training protocols could be adapted to each user.

To summarise, since current training protocols are suboptimal, it appears necessary to redefine them so that they comply with theoretical guidelines such as the ones introduced in Section 1.4. In order to manage this, it is necessary to understand the factors impacting the MI-BCI user training process and to improve the training protocols accordingly.

Therefore, three research challenges were defined. The first research challenge consisted in "Considering Cognitive Factors to Understand and Improve MI-BCI User-Training". The results of this first challenge are introduced in Chapter 5. The second research challenge was about "Considering Personality Factors to Understand and Improve MI-BCI User-Training", all the work related to this second challenge being introduced in Chapter 6. Finally, the third challenge was "Considering the Impact of the Feedback to Understand and Improve MI-BCI User-Training". This last challenge led to different studies that are presented in Chapter7. User-training improvements can manifest themselves in different ways: better performances (classification accuracy), shorter/easier training process, better user-experience, etc. In this thesis we mainly use classification accuracy as a metric of improvement, but we also pay attention to user-experience in order to judge the relevance of our propositions. Each research challenge is dealt with in three steps/parts:

— "Which factors influence MI-BCI user-training?" - This first part aims at experimentally determining the factors (cognitive factors, personality factors, aspects of the feedback) that could influence user-training, positively or negatively.

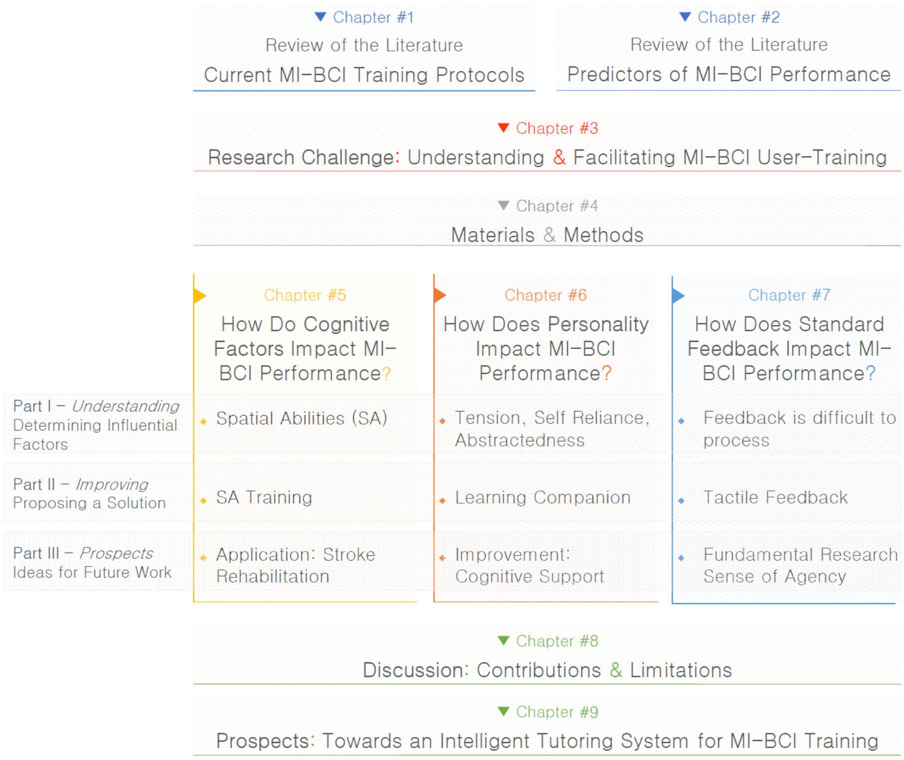


Figure 6 – Schematic representation of the roadmap of this Thesis.

— "How could MI-BCI user-training be improved based on these factors?" - This second part consisted of proposing solutions that take the relevant factors (cognitive factors, personality factors, aspects of the feedback) into account in order to improve the user-training process. First, the theoretical background behind the proposed solution's rationale is provided. Then, how we came to design that solution is introduced. Finally, our solutions were tested in a BCI experiment, and their efficiency for improving user-training was assessed.

— "Prospects: further study" - This last part contains future work ideas that could enable 1) the solutions we propose to be applied in MI-BCI user-training 2) the neurophysiological and psychological correlates of these solutions to be investigated, which could help to explain their efficiency for improving MI-BCI user-training.

Figure 6 is a schematic representation of this roadmap. Further details about each part of these three challenges are provided in the following sections.

3.2 *research challenge* #1: considering cognitive factors to understand and improve bci user-training

BCI deficiency, and more generally the huge variability in users' ability to control an MI-BCI, led to several studies searching for psychological (Hammer et al., 2012, Nijboer et al., 2008) and neurophysiological (Blankertz et al., 2010a, Grosse-Wentrup and Schölkopf, 2012) predictors of MI-BCI performance (for a review of these predictors, see Chapter 2). Unfortunately, no widely accepted and reliable predictive model of performance exists yet. This could be partly due to the fact that most of the predictors are based on one-session experiments, while several sessions are required to learn to master an MI-BCI and that several sessions are necessary to flatten the inter-session variability due to external factors unrelated to the user's control abilities. Another limitation of these predictors is the fact that they only consider motor-imagery, even though other mental imagery tasks have been shown to be associated to better performance in terms of classification accuracy (Friedrich, Scherer, and Neuper, 2013).

Our first research challenge is to consider cognitive and neurophysiological factors in order to understand and improve MI-BCI user-training.

Therefore the first part of this chapter aims at understanding which cognitive factors influence performance. We looked for predictors based on data collected over several sessions, during which participants were asked to learn to perform a combination of mental-imagery tasks shown to be associated with the best performance across subjects. These tasks include both motor-imagery and non motor- imagery tasks; Friedrich, Scherer, and Neuper, 2013. This study revealed, amongst other things, a strong correlation between Spatial Abilities (measured using the mental rotation test -Vandenberg and Kuse, 1978-) and MI-BCI performance. This correlation was replicated in a following purely motor-imagery based study.

Then, based on the results of these first studies, a new training paradigm was proposed with the object of improving MI-BCI user training. This new paradigm aimed at testing the hypothesis of a causal relationship between spatial abilities and MI-BCI performance, or in other words: Would improving spatial abilities (by specifically training these abilities) lead to an improvement in MI-BCI control abilities? In this second part of the chapter, we depict the theoretical background justifying this hypothesis, we describe the way the spatial ability training protocol was designed and validated, and finally we present the experiment that enabled us to test the efficiency of this spatial ability training protocol to improve MI-BCI user-training.

Finally, in the third and last part of this chapter, we examine a potential application for this work on Spatial Abilities: stroke rehabilitation. BCIs are used increasingly to improve motor rehabilitation after a stroke: the patient is asked to attempt movements of his limbs; the patient's brain activity is recorded so that the therapist knows when the attempt at movement is performed, enabling him to provide the patient with an appropriate feedback. Nevertheless, this has several disadvantages such as reminding the patient that he has lost the ability to move. Spatial ability exercises trigger activity in the motor cortex and could thus be used to supplement the rehabilitation process. It would be a more "transparent" therapy, which could help to avoid worsening the patient's depressive state.

3.3 *research challenge* #2: CONSIDERING PERSONALITY FACTORS TO UNDERSTAND AND IMPROVE BCI USER-TRAINING

In a similar way as for Challenge #1 with the cognitive factors, some aspects of the personality have been shown to impact the ability of a person to acquire new skills in many fields. However, until now, the impact of personality on MI-BCI training has remained unclear: no predictive model had ever been developed. We thus led a first experiment which aimed at determining the aspects of the user's personality that have an impact on MI-BCI performance. This resulted in a model which is able to predict approximately 80% of the performance variance of our participants. This model includes 4 factors: tension (negative impact), abstractness abilities, self-reliance and one dimension of the learning-style (active learners perform better than reflective ones). Interestingly, the fact that these dimensions are the ones which contribute the most to MI-BCI performance is in line with the scientific literature. This is explained in more detail in the first part of Chapter 6.

Particularly, the tension and self-reliance dimensions can be found in the literature as predictors of a person's ability to acquire skills in a Distance Learning environment (i.e., with no teacher or classmates). Indeed, students who are anxious and those who lack autonomy struggle to follow distance training processes. This led us to the solution that is proposed in the second part of this chapter: we developped a Learning Companion that would provide users with a social presence and emotional support. We named this companion PEANUT, for Personalised Emotional Agent for Neurotechnology User-Training. Thus, in this second part, we detail the theoretical background that led us to PEANUT. Then, we describe PEANUT's design and validation process, as well as the experiment that was performed to assess its efficiency for improving MI-BCI user-training. Finally, in a third part, we propose future developments for PEANUT that could enable users to be provided with cognitive support in order to help MI-BCI users improve their control abilities.

3.4 *research challenge* #3: CONSIDERING THE FEEDBACK TO UNDERSTAND AND IMPROVE BCI USER-TRAINING

The review introduced in Chapter 1 enabled the limitations of current standard feedback (an extending bar that represents the classifier output) to be demonstrated. While relevant, these limitations are *only* theoretical limitations, and one may wonder whether they translate into actual practical limitations. Indeed, this standard feedback still enables many users to gain control of a BCI system. It would therefore be interesting to evaluate the impact of the current standard feedback on BCI performance and deficiency. Unfortunately, there are many reasons why a given user may not gain BCI control: poor EEG signal-to-noise ratio, non-stationarity of the signals or non-access to the relevant brain signals due to the orientation of the user's cortical neurons, among many other factors. As such, failure to control the BCI may stem from several EEG signal-related causes, but may not be related to the feedback.

Therefore, we had to work around these issues to determine the aspect(s) of the feedback that could impact on BCI performance. To do so, in the first part of the chapter, we examine the relevance of a standard BCI feedback for acquiring a non-BCI related skill. In particular, the results of this study suggest that the feedback is difficult to process and requires considerable cognitive resources to be dealt with, potentially leading to poor performance.

On these grounds, in the second part of the chapter, a solution is proposed to modify the feedback in order to improve user-training.

Appropriate feedback has repeatedly been shown to be a key element during the skill acquisition process (Lotte et al., 2013). Indeed, in order to be able to learn efficiently, the user must be provided with feedback that is meaningful and explanatory (Shute, 2008). This feedback should also be engaging and could benefit from multi-modality (Shute, 2008, Lotte, Larrue, and Mühl, 2013). Yet, training protocols most often associated with visual feedback, despite the fact that both theoretical (Lotte, Larrue, and Mühl, 2013) and practical (Leeb et al., 2013) evidence argues for the use of other sensory modalities that could be more adapted to BCI-based applications (for more information, see Chapter 1). Among these modalities, the tactile channel is an interesting candidate as it is often not overtaxed in interaction contexts, contrary to the visual and auditory channels, and thus could provide users with relevant information without increasing their cognitive workload. We then explored this "tactile feedback" hypothesis, and the results of the BCI experiment suggest that, as expected, tactile feedback was more efficient than the equivalent visual feedback both in terms of classification accuracy and in terms of performance in a secondary (simultaneous) task, thus suggesting it requires less cognitive resources to be processed.

Finally, in the third part of the chapter, we present several other hypotheses to explain the efficiency of tactile feedback to improve MI-BCI performance (in addition to the fact that is requires less cognitive resources to be processed). The first hypothesis is that stimulating the hands with vibrations triggers the motor cortex, which in turn contributes to the classification and leads to better classification accuracy. Our second hypothesis is that tactile feedback is associated to a greater sense of agency. The sense of agency, as elaborated in Chapter 2,is a predictor of BCI performance and is underlain by an activation of the premotor cortex (which, as explained previously, could improve classification accuracy). Thus, in this final part, we explain the theoretical background that led to these hypotheses and introduce a future experiment that would enable to test these hypotheses.

3.5 *prospects*: TOWARDS AN INTELLIGENT TUTORING SYSTEM FOR AN ADAPTIVE & USER-SPECIFIC MI-BCI TRAINING.

Modest performances as well as flaws in the training protocols led us to investigate solutions to improve MI-BCI training by adapting it to each user. Some interesting insights have been gained (see Chapter 2). Nonetheless, learning is a complex multi-factorial process, and studying one aspect independently from the rest is likely to result in non-ecological conclusions. It is necessary to study MI-BCI user-training in its globality. Such an approach is possible using Intelligent Tutoring Systems (ITS) [1] (Nkambou, Bourdeau, and Mizoguchi, 2010). In this chapter, we show why ITS are relevant for MI-BCI training and how this technology could be used. Indeed, we developed a conceptual architecture of such a system and specified the requirements (e.g., deeper theoretical knowledge and technical improvements) so that it could be adapted for MI-BCI user-training.

3.6 TO SUMMARISE

Although EEG-based BCIs are very promising for numerous applications, they mostly remain prototypes that are unused outside laboratories, due to their low reliability. Poor BCI performances are partly due to imperfect EEG signal processing algorithms but also to the user, who may not be able to produce reliable EEG patterns. Indeed, BCI use is a skill, requiring the user to be properly trained to achieve BCI control. Therefore, rather than improving EEG signal processing alone, the research direction defended in this thesis is to also guide users to learn to master BCI control. Therefore, this the-

1. An Intelligent Tutoring System is a computerised training procedure aiming at teaching specific skills with the particularity of being able to dynamically adapt the sequence of exercises and the support provided to the users depending on their profile and cognitive state.

sis addresses the general challenge of understanding and improving BCI user-training through the consideration of 3 levers: (1) cognitive factors, (2) personality and (3) feedback. Challenges #1 and #2 attend to cognitive factors and personality, respectively, to understand and improve MI-BCI user training. Then, Challenge #3 considers the impact of the feedback to understand and improve MI-BCI user-training. Each of these challenges is processed in 3 steps, namely (1) understanding which factors impact BCI performance, (2) proposing solutions to improve MI-BCI user-training and (3) introducing prospects for future applications, further work or theoretical work aiming at understanding why these solutions are efficient.

Figure 6 is a schematic representation of this roadmap.

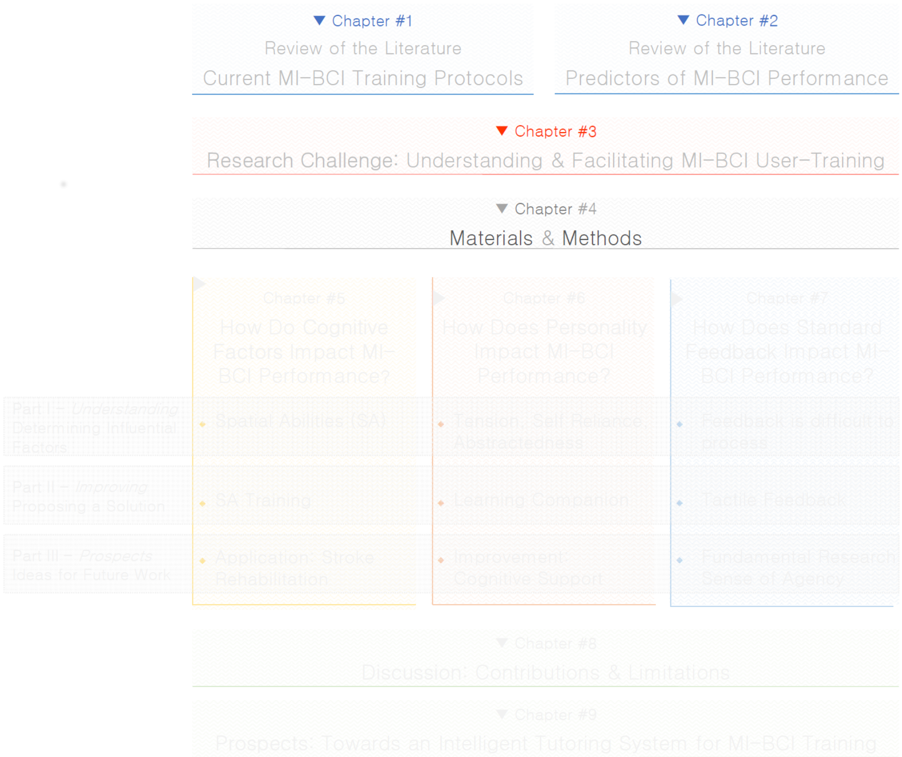
II

RESEARCH CONTRIBUTIONS

In the following chapters, the different studies we led over the course of this PhD project are introduced. As explained in chapter 3, the work performed to understand and improve MI-BCI user-training is divided into three axes. The first focuses on Cognitive Factors, the second on Personality Factors and the third on aspects of the Feedback. Each of these three axes is detailed in a specific chapter. As a preamble, the materials and methods of the different studies are introduced.

4 MATERIALS & METHODS.

ROADMAP -



QUICK SUMMARY -

This chapter describes the entirety of the materials and methods used in our different experiments. Thus, in the following chapters, for each experiment, a brief table will present the materials and methods used in that study. The reader can then refer back to this chapter for a detailed explanation of each element presented in the table. In this way we hope to avoid repetition which would otherwise have been rather tedious for the reader. More precisely, these tables comprise 4 sections. The first provides a quick description of the pipeline of the experiment. Then, all the psychometric and neurophysiological evaluations are described. The third part is dedicated to details concerning the BCI training protocol (tasks, feedback, environment) while the fourth details the hardware and software used to record and process the brain signals.

INTRODUCTION

In this section are introduced the materials and methods used in the different experiments led in the context of this project. First, all the tests applied for psychometric and neurophysiological evaluations (used in the different experiments) are introduced. Then, the materials and methods used for the BCI experiments themselves are described. Thus, the training protocols, the software and hardware used for brain signal recordings as well as the processing techniques are introduced. One may note that while the general principle of all the experiments was the same (i.e., it was based on the Graz training protocol), each experiment had some specificities in terms of evaluations, training protocol and signal processing. Thus, in a last section, the way the specific materials and methods of each experiment will be presented in the following research chapters is introduced.

4.1 PSYCHOMETRIC EVALUATIONS

The psychometric evaluations aimed at determining potential relationships between the users' profile/state and their BCI performance. Depending on the purpose of each experiment, some of the evaluations introduced hereafter were considered.

4.1.1 *Personality Assessment*

Three tests have been used to assess different aspects of the personality of the users. They are described hereafter.

— the *Learning Style Inventory* (LSI) (Kolb, 1999) enables to identify the students' preferred learning styles according to four dimensions: visual/verbal, active/reflective, sensitive/intuitive and sequential/global.

— the *16 Personality Factors - 5* (16 PF-5) (Cattell and Cattell, 1995) measures sixteen primary factors of personality (warmth, reasoning, emotional stability, dominance, liveliness, rule consciousness, social boldness, sensitivity, vigilance, abstractness, privateness, apprehension, openness to change, self-reliance, perfectionism and tension) as well as five global factors of personality (extraversion, anxiety/neuroticism, tough mindedness, indepedence and self control).

— the *Internal, Powerful others and Chance scale* (IPC) (Levenson, 1974) is a multi-dimensional locus of control assessment.

The first two tests, namely the Learning Style Inventory and the 16 Personality Factors - 5, have been chosen for covering a wide range of personality aspects. The locus of control has been measured as it had been shown to correlate with BCI performance.

4.1.2 *Cognitive Profile Assessment*

Different tests were used in order to evaluate high level cognitive functions such as comprehension, reasoning, speed of processing, memory, spatial abilities, motor skills, etc. These dimensions have been shown in the literature to potentially impact users' ability to acquire new skills. The tests are described hereafter.

— 6 subscales of the *Wechsler Adult Intelligence Scale* (WAIS-IV) (Wechsler, 2008), assessing the four IQ dimensions: similarities & vocabulary (measuring verbal comprehension abilities), digit span (measuring verbal working memory abilities), matrix reasoning (measuring perceptive reasoning abilities), coding & symbol search (measuring speed of processing abilities).

— the *Corsi Block task* (Berch, Krikorian, and Huha, 1998) focuses on visuo-spatial short term and working memory abilities.

— the *Revised Visual retention test* (Benton, 1963) quantifies visual retention abilities as well as perceptive organisation.

— the *State Trait Anxiety Inventory Y-B* (STAI) (Spielberger, Gorsuch, and Lushene, 1970) This subscale, STAI Y-B, measures anxiety as a trait.

— the *Bruininks-Oseretsky Test of Motor Proficiency* (BOT-2) (Bruininks, 1978) evaluates motor abilities; based on Hammer et al., 2012. We considered only some subtests evaluating bilateral and upper limb coordination as well as fine motor skills.

— the *Mental Rotation test* (Vandenberg and Kuse, 1978) measures spatial abilities.

— the *Arithmetic test* (Wechsler, 2008) is one of the WAIS-IV sub scales, measuring working memory abilities and more specifically the ability to concentrate while manipulating mental mathematical problems.

4.1.3 *Cognitive & Emotional State Measure*

The *State Trait Anxiety Inventory Y-A* (STAI Y-A) (Spielberger, Gorsuch, and Lushene, 1970) measures anxiety as a state. When used, participants had to complete it at the beginning of each session. Seven-point Likert scale were also used to determine the levels of fatigue and arousal after the runs. The flow, i.e., the optimal cognitive state for skill acquisition, was measured using the EduFlow Questionnaire (Heutte et al., 2016).

4.1.4 *Neurophysiological Profile Assessment*

Different neurophysiological patterns were explored. These patterns have been proposed in the literature as being predictors of motor imagery based BCI performance. They are introduced below:

— α-power [8-13Hz] over each electrode, measured pre-trial (2500 ms to 500 ms before the instruction) and in-trial (500 ms to 3500 ms after the feedback start). Low α-power in fronto-parietal networks has been shown to be associated to a high attentional level (Bamdadian et al., 2014; Klimesch, 1999).
— β-power [16-24Hz] over each electrode, measured pre-trial and in-trial. In the paper of Ahn et al. (Ahn et al., 2013), it is stated that "BCI-illiterates" have low β-power.
— θ-power [3-8Hz] over each electrode, measured pre-trial and in-trial. Low θ-power was related to internalised attention in (Aftanas and Golocheikine, 2001). High θ-power has also been shown to be related to cognitive, and more specifically to memory performance, when combined with high α power (Klimesch, 1999).
— γ-power over each electrode, measured in pre-trial and in-trial. High pre-trial fronto-parietal γ-power has been associated with attentional processes (Grosse-Wentrup and Schölkopf, 2012). Moreover, the ability to modulate SMR has been shown to be negatively correlated to γ power in occipital areas (Grosse-Wentrup, 2011). It has to be noted that muscular activity can represent a confounding factor as it is also correlated with γ power (Grosse-Wentrup, 2011).
— the predictor proposed by Bambadian et al. (Bamdadian et al., 2014) was calculated on pre-trial (2500ms to 500ms before the instruction). It is claimed to reflect the participant's attentional level, this state being, according to the literature, positively correlated to the θ-power and negatively correlated to both the α and β-power:

$$F = \frac{\sum_{c \in C_\theta} P_c^\theta}{\sum_{c \in C_\alpha} P_c^\alpha + \sum_{c \in C_\beta} P_c^\beta}$$

with C_θ =[F3, Fz, F4], C_α=[P7, P3, PZ, P4, P8] and C_β=[CZ, CpZ].
— the predictor proposed by Ahn et al., 2013 was computed on electrodes C3 and C4 on the data of each trial (500ms to 3500ms after the feedback start) :

$$F = \frac{w_1 \alpha + w_2 \beta}{w_3 \theta + w_4 \gamma}$$

with all the w_i=1.
— the Blankertz's SMR-predictor (Blankertz et al., 2010b) certainly is the most reliable (correlation of r = 0.53 with SMR performance over a large dataset, N = 80). It is computed from a 2 min baseline in a "rest with eyes open" state using two Laplacians over the motor cortex, i.e., C3 and C4. This predictor allows to

quantify the potential for desynchronisation of the SMRs at rest, which can be used as an indicator of SMR strength during the performance of motor-imagery tasks. As no 2 min baseline had been recorded with our protocol, we used all the 3 sec. pre-trial time windows of the run (3000ms before the instruction) and computed the predictor on this sequence. More precisely, we computed the power spectrum of each 2 sec time window, averaged these spectrums (i.e., over time windows), and computed the predictor on this average spectrum.

All these neurophysiological predictors except the Blankertz's SMR-predictor were computed for each trial, then averaged over all trials, runs and sessions for each subject. The Blankertz's SMR-predictor was computed for each run and then averaged over all runs and sessions for each subject. The relationship between these predictor values and MI-BCI performance was then investigated.

4.1.5 *Post-Experiment Evaluations: Usability Questionnaires*

After the experiments, participants were asked to complete questionnaires measuring the usability of the system. The usability was assessed based on four standard dimensions: learnability/memorability, efficiency/effectiveness, satisfaction and safety. Given that no validated questionnaire corresponded to our needs, we made our own ones. Being specific to each study, these questionnaires will be described in the research chapters when relevant.

4.2 BRAIN-COMPUTER INTERFACE EXPERIMENTS: TRAINING PROTOCOLS, BRAIN SIGNAL RECORDINGS & PROCESSING

In the following section are first introduced the specificities of the training protocols used in the experiments, in terms of instructions, training tasks, feedback and environment. Then, the brain signal recording and processing techniques are depicted.

4.2.1 *Training Protocol*

The research studies introduced in this thesis are all based on the currently most used training protocol, namely the Graz BCI Training Protocol. Thus, in this section, the general pipeline of this protocol is first introduced. Then, the specificities or variants of this protocol (in terms of (1) instructions, (2) training tasks, (3) feedback and (4) training environment) used in our studies are described.

4.2.1.1 *The Standard Graz BCI Training Protocol*

This protocol was first proposed by the Graz BCI group as an alternative to the Operand Conditioning (OC) approach (Wolpaw et al., 2000), enabling to provide the participants with a shorter training. Indeed, because in the OC approach the user has to adapt to the system, training can take several weeks. In the Graz approach however, which is based on Machine Learning, the system adapts to the user, thus enabling training time to be reduced from weeks to few days (Pfurtscheller, Flotzinger, and Kalcher, 1993). The Graz protocol also has the specificity of being externally paced, since it is based on stimuli, and of being specific, since EEG is recorded on specific areas, i.e., most commonly over the sensori-motor cortex (while for the OC approach, undefined mental processes can be used for control). Indeed, the most used tasks in the context of the Graz protocol are motor-imagery tasks (such as the imagination of hand movements) which are known to be associated with an activation of the motor cortex.

The Graz protocol is divided into two steps: (1) training of the system and (2) training of the user.

During the first step, the user is instructed to perform several successive motor imagery tasks such as the imagination of left- and right-hand movements. From the recorded EEG signals collected during the different MI tasks, the system extracts characteristic EEG patterns which are specific to each MI task. These extracted patterns are then used to train a classifier the goal of which is to determine the class to which the EEG signals belong (i.e., imagination of left- or right-hand movements). For MI-BCI training protocols that last over several sessions (i.e., days), it is common to regularly retrain the classifier on newly acquired data in order to take into account cap variations and the condition/state in which the user is (which can change from one session to another). For more information about these steps of EEG signal processing, see Section 4.2.3.

Step 2 consists in training the user. To do so, the user is instructed to perform the same MI tasks, but this time feedback (provided by the classifier, which was optimised in Step 1) is provided to inform the user which MI-task the system has recognised and how confident the system is that the task it has recognised is the one being performed by the user. Thus, the goal of the user will be to find strategies so that the system recognises the mental task he/she is performing. This training protocol is most often performed over different sessions divided into runs of approximatively 7 minutes each. One session typically includes 4 to 6 runs, in order to avoid the fatigue which is usually felt after more runs. Runs are themselves divided into trials, usually between 10 to 20 per class (i.e., per MI-task). One trial typically lasts 8s. At the beginning of each trial, a fixation cross is displayed to announce the start of the trial and to avoid eye movements during the following 2-second long rest period (which is usually used as a reference period for event-related synchronisation and desynchronisation calculation). Then, after 2s, a beep is used to trigger the attention of the user and prepare him/her for the oncoming instruction. One second later, at t = 3s, the instruction appears as an arrow the direction of which indicates the MI task to be performed, i.e., an arrow pointing left indicates a left hand MI and an arrow pointing right a right hand MI. From t = 3.250s, a feedback is provided for 4s in the shape of a bar the direction of which indicates the mental task that has been recognised and the length of which represents the confidence of the system in the recognition of the MI-task. This sequence of events is depicted in Figure 7.

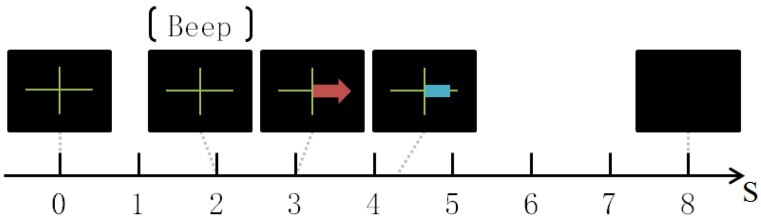


Figure 7 – Timing of one trial in the Graz Protocol.

4.2.1.2 *Instructions*

At the beginning of the experiments, the experimenter was always providing all the users with the same instruction pipeline. A typical script of instructions in presented below, with “XX" replacing the elements varying from one experiment to another.

“ Hello. Thank your very much for volunteering to take part to this study. This study is about *XX*. This experiment lasts *XX* sessions of around *XX* hours each. Each of these sessions will be divided into two parts: (1) you will be asked to complete different (online and/or paper and pen) questionnaires and (2) you will be asked to perform mental-imagery tasks to control a Brain-Computer Interface (BCI). In order to do the BCI part, we will first equip you with an EEG cap (which does not hurt) that enables to measure the electrical activity generated by your brain. Then, there will be, once more, two steps. First, we will train the BCI system to recognise how your brain activity is modified when you perform the different mental-imagery tasks; and then you will be trained to improve the way you perform the mental imagery tasks so that they are better recognised by the BCI system. *[description of the mental tasks and of how to perform them, see next paragraph]*. Thus, during each session, you will perform *XX* runs. Each run will be divided into trials. There will be *XX* trials per run, i.e., *XX* trial of each of the mental task, displayed in a randomised order. At the beginning of each trial, a fixation cross will appear and will be followed by the instruction, on the shape of *XX*, indicating the task that has to be performed. From this moment, you start performing the mental imagery task, and you do it continuously until the end of the trial. After the instruction, you will be provided with a feedback, on the shape of *XX*, indicating the task recognised by the system as well as the confidence of the system in this recognition. This feedback will be displayed for *XX* seconds. Once it disappears, it is the end of the trial, you can stop the imagery and rest until the next trial that will start 1.5 to 3.5 seconds later. The first run will be used to train the system. As the system is not trained yet, it cannot provide you with a feedback, we will thus display a sham feedback: do not take it into account. It does not represent your performance. It is just here so that this run is visually similar to the following runs. Also, as the rest of the training will be based on this run, please try to produce a signal as stable as possible, i.e., do exactly the same imagination each time you do a specific task. After this first run, we will use machine learning algorithms that will extract characteristic patterns from your brain activity for each mental imagery task. Once trained, the system will be able to provide you with a feedback about the task it recognises in the following runs. Your goal will be to find the right strategy so that you have the best feedback possible for all the tasks. It is very important that you stay still during the runs, i.e., that you do not speak or move so that we do not record muscular activity that could "polluate" the recorded brain activity. Do you have any question?".

When the experiment was composed of several sessions, on different days, the instructions about the BCI were repeated at the beginning of each of them.

4.2.1.3 *Training Tasks*

Depending on the study, participants were asked to learn to perform either (1) 2 motor-imagery tasks, namely left-hand motor-imagery and right-hand motor imagery, which are the most commonly used tasks or (2) 3 mental imagery tasks, namely left-hand motor imagery, mental rotation and mental subtraction, which were chosen according to Friedrich, Scherer, and Neuper, 2013, who showed that these tasks were associated with the best performance on average across BCI-users. “Left-hand motor imagery" (*L-HAND*) and “Right-hand motor imagery" (*R-HAND*) refer to the kinaesthetic continuous imagination of a left- or right-hand movement (respectively), chosen by the participant, without any actual movement (Friedrich, Scherer, and Neuper, 2013). The participant is allowed to chose either the same imagined movement for the left and right hand or two different ones. “Mental rotation" (*ROTATION*) and “mental subtraction" (*SUBTRACTION*) correspond respectively to the mental visualisation of a 3 Dimensional shape rotating in a 3 Dimensional space (Friedrich, Scherer, and Neuper, 2013) and to successive subtractions of a 3-digit number by a 2-digit number (ranging between 11 and 19), both being randomly generated and displayed on a screen (Friedrich, Scherer, and Neuper, 2013).

Link to a video of the 3 tasks: here!

Furthermore, as an alternative of mental-imagery tasks, the efficiency of other kinds of training tasks to improve MI-BCI performance has been explored. More precisely, we designed a spatial ability training containing different exercises based on the principle of the Vandenberg and Kuse, 1978 mental rotation test. The justification and design of this spatial ability training, as well as a control verbal comprehension training, are depicted in Section 5.4.

4.2.1.4 *Feedback*

In most of the studies introduced in the following research Chapters, a standard visual feedback updated at 16Hz has been used. More specifically, after the instruction had been provided, a blue bar was displayed on screen for 4 seconds (as shown in Figure 7). The direction of the bar corresponded to the task recognised by the classifier while its length corresponded to the confidence of the classifier in its decision. Every 0.0625s (i.e., at a frequency of 16Hz), a new classifier output was provided and the feedback (i.e., the direction and the length of the bar) was updated accordingly.

In the different studies we led, some variants of this standard feedback were used. The modifications concerned:

— the *modality* of the feedback: *visual* vs. *tactile* – The feedback was either displayed as a bar on screen, as described in the previous paragraph, or it was provided on the palms of the hands using vibrotactile motors embedded in gloves (this feedback was used in case of hand motor imagery only). The same way the feedback bar was extending towards the left/right, the motors of the left/right hand glove were activated upon the recognition of a left/right hand MI, respectively. Moreover, the more confident the classifier, the more the motors near the thumbs were activated. More details about the design of this feedback are provided in Chapter 7.

— the *update rate* of the feedback: *16Hz* vs. *4Hz* – In the experiments aiming at comparing a visual vs. a tactile feedback, the later was updated at 4Hz rather than 16Hz (as it was the case in the other studies). Indeed, so that two tactile stimuli are distinguishable on the palms, they have to last for at least 200ms (Gescheider, Wright, and Verrillo, 2010).

— the *information provided* through the feedback: *pure classifier output* vs. *positively biased classifier output* vs. *only positive classifier output* / *social presence & emotional support* – In the standard Graz training protocol, the feedback provided corresponds to the classifier output. On the one hand, in some of the studies introduced hereafter however, the participants were provided with *only* positive feedback only: meaning that the classifier output was displayed only when the correct task (i.e., the task the participant had been asked to perform) was recognised by the system. On the other hand, in other studies the feedback was positively biased, meaning that the classifier output was shifted towards the right direction so that the participants thought they were doing better than they were actually doing. More details about the justification and implementation of this biased feedback are provided in Chapter 7. Furthermore, we implemented a social companion made to provide BCI users with social presence and emotional support during the training process. The justification and description of this feedback are described in Chapter 6.

4.2.1.5 *Training Environment*

Two different training environments have been used in the studies: a standard one (inspired from the Graz protocol) and a game-like environment including distractors.

Concerning the standard training environment, it was just black as shown in Figure 7, with red arrows indicating the instructions and extending blue bars representing the feedback (in case of a visual feedback).

The second training environment we used was designed in the context of the evaluation of a tactile feedback for motor-imagery of the left- and right-hands. Indeed, we wanted to evaluate the efficiency, in terms of BCI performance, of this tactile feedback (in comparison to a visual feedback) in a multitasking environment. Therefore, we created an environment: a green planet, protected by a space craft (steered by the participant through motor-imagery), that was threatened by asteroids. The red arrows (instructions) were replaced by asteroids falling from the left or the right of the screen, indicating the users they had to imagine left- or right-hand movements, respectively, so that they can face the asteroids with the spacecraft and destroy them. Distractors, on the shape of rabbits, rockets and clouds, were also displayed. More details about this environment, and more generally about this experiment, are provided in Chapter 7.

4.2.2 *Brain Signal Recordings*

4.2.2.1 *EEG Recordings: Hardware and Set up*

The EEG signals were recorded from either a g.USBamp amplifier (g.tec, Graz, Austria) or a BrainVision actiCHamp amplifier (Brain Products,Germany), using 30 scalp electrodes (F3, Fz, F4, FT7,FC5, FC3, FCz, FC4, FC6, FT8, C5, C3, C1, Cz, C2, C4, C6, CP3, CPz, CP4, P5, P3, P1, Pz, P2, P4, P6, PO7, PO8, 10-20 system) (Friedrich, Scherer, and Neuper, 2013), referenced to the left ear (g.USBamp) or right mastoid (actiCHamp) and grounded to AFz. EEG data were sampled at 256Hz.

4.2.2.2 *EEG Recordings: Software - OpenViBE*

All the data were recorded, processed and visually inspected with OpenViBE (Renard et al., 2010).OpenViBE is a free and open source software enabling to design a BCI without programming: through the use of pre-existing signal processing and machine learning functions that can be connected using graphical programming.

4.2.3 *EEG Signal Processing & Machine Learning*

4.2.3.1 *General Pipeline*

The data obtained after the first run of the first session (15 or 20 trials per MI task, depending on the experiment) were used to train the classifier. While 15/20 trials per class is not much, it has been shown to be sufficient to set up a motor imagery classifier (Blankertz et al., 2008; Lotte et al., 2015). For instance, in Friedrich, Scherer, and Neuper, 2013, a successful mental imagery BCI classifier was setup with only 10 trials per class.

Thus, the following EEG signal processing pipeline was used to train the classifier in order to classify the mental-imagery tasks online in the next runs.

First, EEG signals were band-pass filtered in 8-30Hz, using a Butterworth filter of order 4. Then a Common Spatial Pattern algorithm was applied to spatially filter the signals (see Section 4.2.3.2 for more details). The band power of the spatially filtered EEG signals was then computed by squaring the signals, averaging them over the last 1 second time window (with 15/16s or 3/4 s overlap between consecutive time windows, depending on the frequency of update of the feedback, namely 16Hz or 4Hz, respectively) and log-transformed. The resulting band-power features we fed to a classifier (see Section 4.2.3.3 for more details). The classifier was then used online to differentiate between the mental-imagery tasks during the rest of the session. To reduce between session variability, in paradigms including several sessions, the classifiers' biases were re-calculated after the first run of the other sessions (from session 2), based on the data from this first run, as in Friedrich, Scherer, and Neuper, 2013.

4.2.3.2 *Common Spatial Patterns (CSP)*

The CSP algorithm aims at finding spatial filters whose resulting EEG band power is maximally different between two classes. Thus, in the case of experiments with 2 mental-imagery tasks, one CSP was used to find 6 spatial filters whose resulting EEG power was maximally different between these two MI tasks. However, in the case of experiments with 3 mental-imagery tasks, the EEG signals were spatially filtered using 3 sets of Common Spatial Pattern (CSP) filters (Ramoser, Muller-Gerking, and Pfurtscheller, 2000). Each set of CSP filters was optimised to discriminate EEG signals for a given class from the other two classes. Hence, 2 pairs of spatial filters were optimised for each class, corresponding to the 2 largest and lowest eigen values of the CSP optimisation problem for that class, thus leading to 12 CSP filters. The resulting band-power features we fed to a classifier (see Section 4.2.3.3 for more details).

4.2.3.3 *Classifiers: Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM)*

In most of the studies reported below shrinkage Linear Discriminant Analysis (sLDA) (Müller et al., 2008, Lotte and Guan, 2010) was used. However, for practical reasons, for the studies in which a tactile feedback is tested a Support Vector Machine (SVM) was used as a classifier. Indeed, on the one hand the SVM provides a probability value in (0;1) easier to convert into activations of the motors for the tactile feedback (more explanations about this point are provided in Chapter 7). While on the other hand, the sLDA classifier output corresponds to the distance of the feature vector from the LDA separating hyperplane.

In the case of a 2-class experiment (i.e., with 2 different mental-imagery tasks) the classifier was trained based on the 6 band-power

	EXPERIMENTAL PARADIGM
Description of the pipeline of the experiment (number of sessions, etc.)	
	EVALUATIONS
PSYCHOMETRIC EVALUATIONS	List of the psychometric evaluations
NEUROPHYSIOLOGICAL EVALUATIONS	List of the neurophysiological evaluations
	BCI EXPERIMENTS – TRAINING PROTOCOL
TRAINING TASKS	List of the training tasks
FEEDBACK	Type of feedback (modality, frequency, information provided)
TRAINING ENVIRONMENT	Standard Graz Environment vs. Game-like environment / Multitasking or not
	BCI EXPERIMENTS – BRAIN SIGNAL RECORDINGS & PROCESSING
HARDWARE & EEG SET-UP	Description of the hardware & list of the electrodes
SIGNAL PROCESSING PIPELINE	Description of the signal processing pipeline (CSP, LDA/SVM)

features generated by the CSP. However, in the case of a 3-class experiment, the resulting 12 band-power features (from the CSP) were fed to a multi-class shrinkage Linear Discriminant Analysis (sLDA), built by combining three sLDA in a one-versus-the-rest scheme.

As for the CSP filters, the sLDA were optimised on the EEG signals collected during the calibration run, i.e., during the first run of the first session.

The resulting classifier was then used online to differentiate between the mental-imagery tasks.

4.3 PRESENTATION OF THE MATERIALS AND METHODS SECTION IN THE FOLLOWING CHAPTERS

Now all the different elements of the materials and methods used in our studies have been introduced, the next sections will report the experiments themselves. For each of these experiments, the materials and methods will be reported using a table as the one that follows.

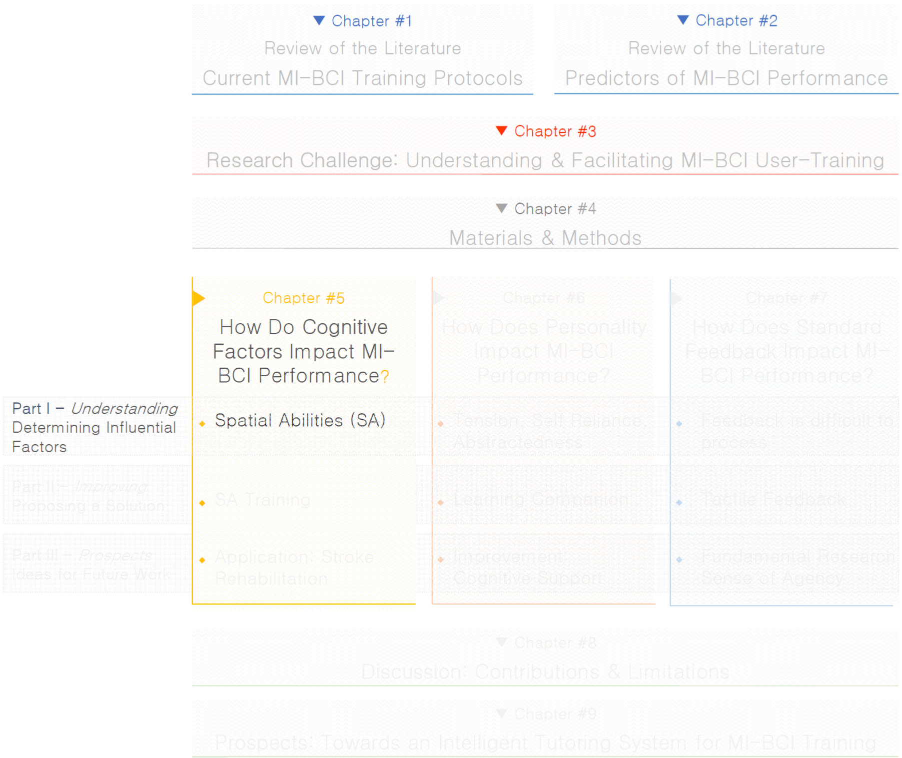
5 CONSIDERING COGNITIVE FACTORS TO UNDERSTAND & IMPROVE MI-BCI USER-TRAINING.

5.1 RESEARCH QUESTION

The review of the literature introduced in Chapter 2 shows that all the studies concerning BCI-performance predictors considered either SMR or Slow Cortical Potentials (SCP). Nonetheless, as stated by Grosse-Wentrup, Schölkopf, and Hill, 2011, "it remains to be seen if similar results can be obtained for BCI systems not [only] based on motor paradigms". Furthermore, most of these studies were based on very few runs, often recorded during a one-session experiment (an exception being Hammer et al., 2014). Yet, except for SCP-BCI (Neumann and Birbaumer, 2003), first session performance has not been shown to be representative of long-term MI-BCI control performance. Indeed, first session performance can differ greatly from subsequent sessions due to several factors: (1) the fact that the classifier is often trained only during the first session, (2) the fact that the position of the cap can change, (3) EEG-signal non-stationnarity or (4) the novelty effect. Finally, there is only one study, by Hammer et al., 2012, in which psychological factors were combined with a neurophysiological predictor (Blankertz et al., 2010b) to determine a predictive-model of motor-imagery based BCI performance. Thus, the aim of *Part I* of this Chapter is to investigate predictors of BCI performance (1) for Mental-Imagery tasks that are not purely based on motor imagery and (2) over a longer-term experiment. Then *Part II* proposes novel training paradigms which aim to improve MI-BCI performance indirectly, i.e., by increasing specific cognitive abilities. Finally, in *Part III*, we argue that such training paradigms could be of utmost interest to improve post-stroke rehabilitation therapies.

PART I - WHICH COGNITIVE FACTORS INFLUENCE MI-BCI USER-TRAINING?

ROADMAP -



QUICK SUMMARY -

Two user studies are described. In the first, 18 participants trained to perform 3 MI-tasks during 6 sessions while in the second, 20 other participants trained to perform 2 motor-imagery tasks during 1 session. Both studies reveal a strong correlation between MI-BCI performance (in terms of classification accuracy) and mental rotations scores (Vandenberg and Kuse, 1978). Mental rotation scores enable users' spatial abilities to be assessed, i.e., their capacity to produce, transform and manipulate mental images (Poltrock and Brown, 1984).

COLLABORATORS -

Morgane Sueur & Emilie Jahanpour (Master Students).

RELATED PAPERS -

-1- Jeunet, C., N'Kaoua, B., Subramanian, S., Hachet, M., and Lotte, F. (2015). 'Predicting Mental Imagery-Based BCI Performance from Personality, Cognitive Profile and Neurophysiological Patterns.' In: *PLOS ONE* 10.12, e0143962. [please refer to Chapter 6 for other aspects, related to personality]

-2- Jeunet, C., Jahanpour, E., and Lotte, F. (2016). 'Why standard brain computer interface (BCI) training protocols should be changed: an experimental study.' In: *Journal of neural engineering* 13.3, p. 036024. [please refer to Chapter 7 for other aspects, related to the feedback]

5.2 Study 1 - Which cognitive factors could predict mental imagery based BCI performance?

The main contribution of this chapter is to propose predictors of MI-BCI control performance, which was designed considering the possibility of combining several psychological and neurophysiological factors. Indeed, participants were asked to learn to perform three MI tasks, namely one motor-imagery task, i.e., left-hand movement imagination, and two non motor tasks, i.e., mental rotation and mental subtraction. The analyses consisted in looking for correlations between (1) the average performance over the six sessions they attended and (2) the scores obtained at the different psychometric tests as well as neurophysiological predictors.

5.2.1 *Materials & Methods*

5.2.1.1 *Participants*

Eighteen BCI-naive participants (9 females; aged 21.5 ± 1.2) took part in this study, which was conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki. This study was also approved by the legal authorities of Inria Bordeaux Sud-Ouest (the COERLE, approval number: 2015-004) as it satisfied the ethical rules and principles of the institute. All the participants signed an informed consent form at the beginning of the experiment and received a compensation of 100 euros at the end. Furthermore, in the aim of avoiding confounding factors, age [21.5 ± 1.2 year old] and educational level [14.5 ± 1.8 years of education] were controlled, which means that the ranges of these variables were low: participants were in the [20;25] year old interval and were studying at the University, for a Bachelor or Master degree. All of the participants were healthy and right handed (Harris lateralisation test - Harris, 1958).

5.2.1.2 *Experimental Paradigm*

Please refer to Figure 8.

5.2.1.3 *Variables and Factors*

The aim of this study was to evaluate the impact of different psychological and neurophysiological factors on MI-BCI performance in healthy participants. Thus, the effect of the scores obtained at different neuropsychological questionnaires and of the values of neurophysiological markers on the variable "MI-BCI classification performance" was evaluated.

EXPERIMENTAL PARADIGM	
This experiment was composed of 6 mental-imagery based BCI sessions of 2.00 hours each. Each session was divided into 5 runs, with 45 trials per run.	
EVALUATIONS	
PSYCHOMETRIC EVALUATIONS	*Personality assessment* ▾ Learning Style Inventory ▾ 16 Personality Factors-5 ▾ Internal, Powerful others and Chance scale *Cognitive profile assessment* ▾ Wechsler Adult Intelligence Scale (WAIS-IV) ▾ Corsi block task ▾ State Trait Anxiety Inventory Y-B ▾ Bruininks-Oseretsky Test of Motor Proficiency ▾ Revised Visual Retention Test ▾ Mental Rotation test *Cognitive State measure* ▾ State Trait Anxiety Inventory Y-A (at the beginning of each session) ▾ Fatigue and Arousal Likert scales (after each run)
NEUROPHYSIOLOGICAL EVALUATIONS	▾ α-power, β-power, γ-power & θ-power over each electrode, measured pre-trial (2500ms to 500ms before the instruction) and in-trial (500ms to 3500ms after the feedback start) ▾ Ahn's predictor: ratio: (α + β) / (θ + γ) over the sensori-motor areas ▾ Bamdadian's predictor: ratio: frontal-θ / (parietal-α + central-β) ▾ Blankertz's SMR predictor: μ amplitude at rest, over the sensori-motor areas
BCI EXPERIMENTS – TRAINING PROTOCOL	
TRAINING TASKS	▾ Left-Hand Motor Imagery ▾ Mental Subtraction ▾ Mental Rotation
FEEDBACK	▾ *Modality:* Visual [standard Graz blue bar feedback] ▾ *Update Frequency:* 16Hz ▾ *Content:* Only positive
TRAINING ENVIRONMENT	▾ Standard Graz Training Environment, adapted for 3 classes
BCI EXPERIMENTS – BRAIN SIGNAL RECORDINGS & PROCESSING	
HARDWARE & EEG SET-UP	▾ g.USBamp amplifier (g.tec, Graz, Austria) ▾ See the list in the Materiels & Methods Chapter ▾ Referenced to the left ear, grounded to Afz ▾ Sampling of the EEG data: 256Hz
SIGNAL PROCESSING PIPELINE	▾ Band-pass filtering of the EEG data: 8-30Hz *Session 1: the classifier & CSP are trained on the run 1* ▾ 3 CSP «one class vs. the others» → 12 band-power features ▾ Combination of 3 sLDA in a one-versus-the-rest scheme ▾ Use of the resulting classifier to discriminate between the 3 tasks for the runs 2 to 5 *Sessions 2 to 6* ▾ Run 1 with the classifier trained during Session 1 ▾ Re-computation of the sLDA's bias ▾ Use of the resulting classifier to discriminate between the 3 tasks for the runs 2 to 5

Figure 8 – Materials & Methods of the Study 1 of Section 5.2

5.2.1.4 *Analyses*

During each of the 6 sessions, participants performed 5 runs. However, as the classifier was updated after the first run of each session, we only used the 4 last runs (of each session) for the analyses. Thus, we considered 360 trials (15 trials x 4 runs x 6 sessions) per mental task, i.e. 1080 trials (360 x 3 MI-tasks) for each of the 18 participants. EEG data were analysed using Matlab (http://www.mathworks.com) in order to compute the different neurophysiological patterns that could predict MI-BCI performance according to the literature. Then, these features as well as the psychometric-test results were analysed using SPSS (http://www-01.ibm.com/software/analytics/spss) in order to find relevant MI-BCI performance predictors. In particular, correlation analyses were computed as descriptive analyses.

5.2.2 *Results*

5.2.2.1 *Mental-Imagery Task Performance*

Eighteen participants took part in this experiment. The data of one outlier participant were rejected since, with a mean performance of 67.21%, he outperformed (by more than two SDs) the group's mean performance over the six sessions ($\bar{X}_{group}$ = 52.50%; *SD* = 5.62). Thus, the following analyses were based on the data of 17 subjects.

Over the six sessions, participants achieved a mean performance of $\bar{X}$ = 51.63% (*SD* = 4.39; *range*: [43.04, 60.14]). All the participants obtained performances higher than chance level, this chance level being estimated to be 37.7% of correct classification accuracy for three classes and more than 160 trials per class and α=5% (Müller-Putz et al., 2008). In the first session, mean performance was $\bar{X}$ = 51.72% (*SD* = 8.14), in the second $\bar{X}$ = 51.18% (*SD* = 6.96), in the third, $\bar{X}$ = 53.06% (*SD* = 6.04), in the fourth $\bar{X}$ = 51.57% (*SD* = 5.64), in the fifth $\bar{X}$ = 51.78% (*SD* = 6.97) and in the sixth session $\bar{X}$ = 50.49% (*SD* = 6.25). The one-way ANOVA with the *session number* as the intra-subject factor revealed no learning effect [$F_{5,96}$ = 0.270, p = 0.928], as was generally observed for 6 sessions of training in Kübler et al., 2010. Moreover, no gender effect [t_{15} = -1.733, p = 0.104] was noticed.

5.2.2.2 *Correlations Between Performance and Neurophysiological Predictors*

Bivariate Pearson correlation analyses between MI-BCI performance and different neurophysiological patterns (i.e., α-power, β-power, θ-power, γ-power, Bamdadian, Ahn and Blankertz predictors) were performed. First, results showed no correlations between MI-BCI performance and the Bamdadian predictor, the Ahn predictor and the γ-power. Second, a tendency towards correlation was found between BCI performance and the Blankertz SMR-predictor [r = 0.428, p = 0.087]. Finally, these analyses revealed some correlations between MI-BCI performance and (1) parietal θ-power in both pre-trial and in-trial measurements, (2) frontal and occipital α-power in both pre-trial and

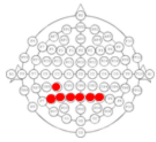
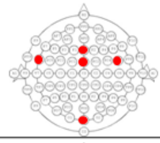
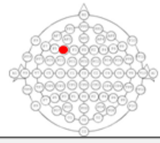
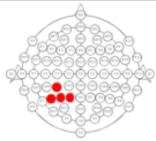
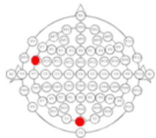
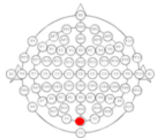
Pre-Trial					
Θ	[3-8Hz]	CP3 P5 P3 P1 Pz P2 P4	r = -.490 r = -.485 r = -.529 r = -.504 r = -.506 r = -.490 r = -.486	p = .046 p = .048 p = .029 p = .039 p = .038 p = .046 p = .048	
α	[8-13Hz]	Oz Fz FC6 FCz FT7	r = -.525 r = -.487 r = -.484 r = -.502 r = -.492	p = .030 p = .047 p = .049 p = .040 p = .045	
β	[16-24Hz]	F3	r = -.586	p = .014	
During Trial					
Θ	[3-8Hz]	CP3 P5 P3 P1	r = -.504 r = -.528 r = -.517 r = -.512	p = .047 p = .036 p = .040 p = .043	
α	[8-13Hz]	Oz FT7	r = -.525 r = -.504	p = .039 p = .046	
β	[16-24Hz]	Oz	r = -.525	p = .037	

Figure 9 – Correlations between MI-BCI performance and neurophysiological markers. Stastistically significant correlations (before the correction for multiple comparisons) between MI-BCI performances and the average signal power recorded on the electrodes for the different frequency bands (θ, α and β) as a function of the period: pre-trial (from 2500ms to 500ms before the instruction) or during trial (from 500ms to 3500ms after the feedback start). None of these predictors reached significance after the correction for multiple comparisons.

in-trial measurements and (3) β-power: FT7 in pre-trial and Oz in in-trial measurements. These results are depicted in Fig. 9. However, all these correlations failed to reach significance after a Positive False Discovery Rate (pFDR) correction for multiple comparisons (Noble, 2009).

5.2.2.3 *Correlations Between Performance and Psychometric Tests*

Bivariate Pearson correlation analyses revealed a correlation between MI-BCI performance and Mental Rotation scores [$r = 0.696$, $p < 0.005$]. This correlation reached significance after the Positive

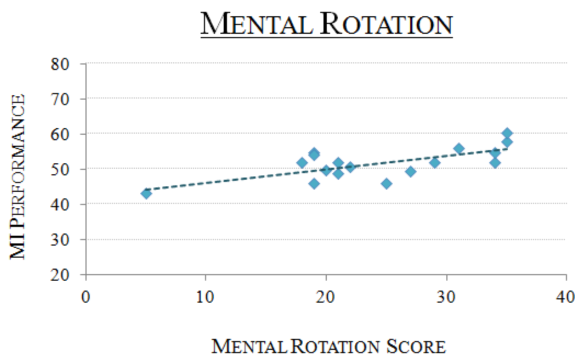


Figure 10 – MI-BCI Performance as a function of mental rotation scores (r=0.696).

False Discovery Rate correction for multiple comparisons [$p < 0.05$] (Noble, 2009). Other correlations between MI-BCI Performance and personality factors were revealed. They are described in Chapter 6.

5.2.3 *Discussion*

In this section, we explored possible predictors of MI-BCI performance based on the data of 17 participants. The important number of runs (30, spread over 6 sessions) attenuated the between-session variability (which could be due, to fatigue or motivation fluctuation, cap position variation, etc.) and thus enabled to more precisely estimate the participants' actual long-term ability to control an MI-BCI. For the first time, performance predictors were not determined in a context of pure motor-imagery, since participants were asked to perform one motor imagery task -left-hand movement imagination- as well as two non-motor MI-tasks -mental rotation and mental subtraction.

Different major results were obtained. The first is the strong correlation between MI-BCI performance and mental rotation scores. The second major result is the fact that, despite an apparent consistent relation between MI-BCI performance and frontal α and parietal θ-power which could suggest a role of attention processes, no significant correlation was revealed after the correction for multiple comparisons. Thus, in the context of this experiment, the considered predictors seem not to be robust nor relevant enough to predict MI-BCI performance over multiple sessions. Two plausible explanations of this result are the fact we considered 6 sessions whereas these neurophysiological predictors were computed, on the literature, based on one single session, and also the fact our paradigm involves three different MI-tasks, whereas only motor-imagery was considered in the studies from which the neurophysiological predictors were extracted. What is more, since participants were asked to perform one motor imagery task, it is interesting to notice the tendency towards a correlation between the Blankertz's SMR-predictor and MI-BCI performances which strenghtens the reliability of this predictor for SMR modulation abilities. The fact this predictor is not significantly correlated with MI-BCI performance could also be partly due to our experimental protocol. Indeed, as no 2 minute-long baseline was recorded the predictor was computed based on the concatenation of all the 3 second-long pre-trials of the runs, which could impact its performance.

A very interesting result is the prominent role of mental rotation scores: this factor is highly correlated with MI-BCI performance. Mental rotation scores reflect spatial abilities (Poltrock and Brown, 1984), i.e., the capacity to understand, manipulate and remember spatial relations between objects. Mental rotation, and thus spatial abilities, are intimately related with the three mental imagery tasks considered in this study. First, the MI-BCI task "mental rotation" consists in mentally rotating a 3D shape, which is actually the same task as the one participants are asked to perform during the mental rotation test. Second, Rourke and Finlayson, 1978 showed that children confronted with difficulties to perform arithmetics also had low spatial abilities. Third, the mental rotation test is actually used to evaluate motor imagery abilities in healthy subjects and patients with brain injuries (Vromen et al., 2011). The close relationship between mental rotation and the three MI tasks, that is described in Chapter 2, could explain the strong implication of spatial abilities in participants' capacity to perform the MI tasks proposed to control a BCI system. This relationship suggests that it would be interesting to consider each MI task independently. However, given the protocol and the kind of classifier used, doing so would most probably provide biased results and/or results that make little sense. Indeed, 3 "one vs all" linear discriminant analysis (LDA) classifiers were used, which means that each classifier was trained to discriminate the targeted MI task from the other two. Thus, the feedback (blue bar) was not informing the user about how well he was performing the target MI task, but how much this target MI task was distinguishable from the other two. Thus, analysing the performances "one MI task vs. one MI task" would make little sense, as this was not what the user was trained to do. We could have trained offline new classifiers to discriminate "one MI task vs. rest" to know how well the different MI tasks were performed independently from the others. But the performances could be very different from the ones presented to the user. For instance, an MI-task could be associated with good performances when using a "one vs. all" classifier (because it is well distinguishable from the other MI tasks) and at the same time associated with bad performances when using a "one vs. rest" classifier (because the brain activity associated with this MI task is close to the resting state). In such a case, the participant would not have put much effort in trying to improve his performance while doing this MI task because he thought he was managing well and so it does not make sense to study his performance in another context (i.e., with another classifier) as the participant did not receive any feedback enabling him to know that he had to adapt his strategy.

It now remains to validate this Spatial Ability predictor, i.e. to test if it would still predict performance with a different set of participants and with different mental-imagery tasks. Indeed, among the three tasks used in the study introduced above, was a mental rotation task that is close to the exercises proposed in the mental rotation test (used to assess Spatial Abilities). Thus, one could argue that BCI performance correlate to Spatial Abilities due to this task.

5.3 Study 2 - Do Spatial Abilities also influence pure motor-imagery based BCI performance?

This second study (the other results of which are introduced in Chapter 7) aimed, among others, at determining if the Spatial Ability predictor was relevant in a context of pure Motor-Imagery (of the left and right hands). Indeed, it would be argued that the relationship between mental rotation scores (reflecting SA) and MI-BCI performance could be due to the mental rotation task the participants are asked to perform during the MI-BCI training protocol and which is similar to the mental rotation test task. A second argument justifying this study is the fact that motor-imagery based BCI are certainly the most used MI-BCI. Therefore, it would be interesting to determine specific predictors of performance. We also investigated the relationship between participants' motor-imagery based BCI performance and the Blankertz SMR-predictor as this predictor is especially relevant for motor-imagery paradigms and was close to correlate with MI-BCI performance in our previous study.

5.3.1 *Materials & Methods*

5.3.1.1 *Participants*

20 BCI-naive participants (10 females; aged 24.7 ± 4.0 year-old) took part in this study, which was conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki. This study was also approved by the legal authorities of Inria Bordeaux Sud-Ouest (the COERLE, approval number: 2015-004) as it satisfied the ethical rules and principles of the institute. All of the participants were healthy and right handed (Harris lateralisation test - Harris, 1958).

5.3.1.2 *Experimental Paradigm*

Please refer to Figure 11.

5.3.1.3 *Variables and Factors*

The aim of this study was to evaluate the impact of spatial abilities on motor-imagery based BCI performance in healthy participants. Thus, the effect of the scores obtained at the mental rotation test on the variable "MI-BCI classification performance" was evaluated, depending on the gender of the user. Indeed, as stated above, literature shows an important gender effect for mental rotation scores (Vandenberg and Kuse, 1978). We also studied the correlations between participants' MI-BCI performance and the Blankertz SMR-predictor.

5.3.1.4 *Analyses*

A t-test has first been performed to assess a potential gender effect. Then, Pearson correlation tests have been performed in order to evaluate the relationship between spatial abilities (measured through the mental rotation test) or the Blankertz SMR-predictor and motor-

	EXPERIMENTAL PARADIGM
This experiment was composed of 1 mental-imagery based BCI session of 2.00 hours. The session was divided into 5 runs, with 40 trials per run.	
	EVALUATIONS
PSYCHOMETRIC EVALUATIONS	*Cognitive profile assessment* ▼ Mental Rotation test
NEUROPHYSIOLOGICAL EVALUATIONS	▼ Blankertz's SMR predictor: μ amplitude at rest, over the sensori-motor areas
	BCI EXPERIMENTS – TRAINING PROTOCOL
TRAINING TASKS	▼ Left-Hand Motor Imagery ▼ Right-Hand Motor Imagery
FEEDBACK	▼ *Modality:* Visual [standard Graz blue bar feedback] ▼ *Update Frequency:* 16Hz ▼ *Content:* Classifier output
TRAINING ENVIRONMENT	▼ Standard Graz Training Environment
	BCI EXPERIMENTS – BRAIN SIGNAL RECORDINGS & PROCESSING
HARDWARE & EEG SET-UP	▼ g.USBamp amplifier (g.tec, Graz, Austria) ▼ See the list in the Materiels & Methods Chapter ▼ Referenced to the left ear, grounded to Afz ▼ Sampling of the EEG data: 256Hz
SIGNAL PROCESSING PIPELINE	▼ Band-pass filtering of the EEG data: 8-30Hz *The classifier & CSP are trained on the run 1* ▼ CSP → 6 band-power features ▼ LDA (fed with the band-power features computed after CSP spatial filtering)

Figure 11 – Materials & Methods of the Study 2 of Section 5.3

imagery based BCI control abilities (assessed by the classification accuracy).

5.3.2 *Results*

In these analyses, we considered two different measures of MI-BCI performance: (1) the **peak** classification accuracy (measured at the time window of the feedback period for which the classification accuracy over all trials is maximal), which is the typical performance measure used with the Graz protocol, see, e.g., Scherer et al., 2013 and (2) the **mean** classification accuracy over the whole feedback period of all trials.

First, there was a clear gender effect on the mental rotation score, consistent with the literature: $mean_{men}$=30.5 $\pm$ 7.12 - $mean_{women}$= 20.7 $\pm$ 7.21 [t-test - t=3.058; p$\leqslant$ 0.01]. Moreover, while Mental Rotation scores were not correlated with mean motor-imagery based BCI performance [r=0.266; p=0.257], they were correlated with the peak mean motor-imagery based BCI performance [r=0.464; p=0.039]. These results confirm the important impact of SA on mean motor-imagery based BCI performance which was demonstrated in Jeunet et al., 2015b. More specifically, the positive correlation indicates that people with better spatial abilities (i.e., higher mental rotation scores in this instance) obtain higher MI-BCI control performance. Besides, results revealed no significant correlation between the Blankertz SMR-predictor and the **mean** MI-BCI performance [r = 0.151; p = 0.525] nor with the **peak** MI-BCI performance [r = 0.078; p = 0.743].

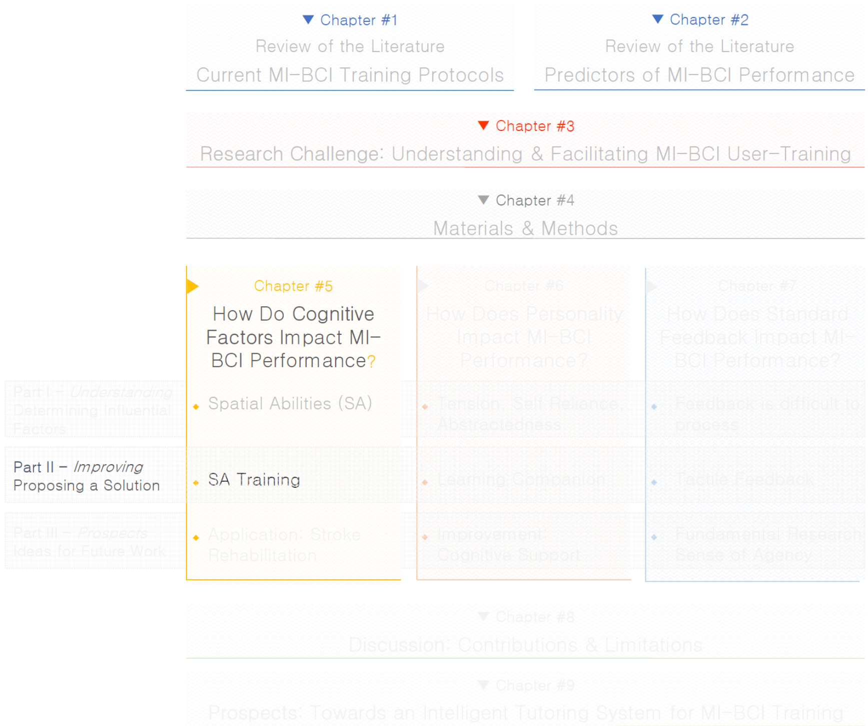
5.3.3 *Discussion*

These results confirm that spatial abilities are related to mental imagery-based BCI performances. We have shown such a relationship before for a mental imagery based BCI that was not based purely on motor imagery, but on left-hand motor imagery, mental geometric figure rotation and mental subtraction. The study introduced in this section suggests that spatial abilities also play a role in purely motor imagery based BCI performances, in which no mental rotation tasks are involved. It thus confirms the importance of spatial abilities for successful BCI control that were suggested in the literature and by the results introduced in Section 5.2 but that we were the first to explicitely measure the impact in both thesee studies, and reinforces the idea that spatial ability training should be explored to improve BCI control abilities. Concerning the Blankertz SMR-predictor, as was the case in the study introduced in the previous section, the fact that this predictor is not significantly correlated with MI-BCI performance could be partly due to our experimental protocol. Indeed, as no 2 minute-long baseline was recorded the predictor was computed based on the concatenation of all the 3 second-long pre-trials of the runs, which could haved impacted its performance.

Now a correlation between SA and MI-BCI control abilities seems to be confirmed, the next step will consist in exploring new solutions to improve MI-BCI user-training based on this lever. This is the aim of the second part of this chapter.

PART II - HOW COULD MI-BCI USER-TRAINING BE IMPROVED BASED ON THESE FACTORS?

ROADMAP -



QUICK SUMMARY -

We investigated the effects of training spatial abilities (SA) on MI-BCI user-training. Thus, the design and implementation of this SA training procedure are detailed. Then, the 2 user studies performed to validate the SA training procedure are described: results suggest that it efficiently improve participants' SA. Consequently, we included this SA training procedure in an MI-BCI protocol. Results (N=24) showed no difference in classification accuracy between participants performing 6 MI-BCI sessions and those performing 3 SA and 3 MI-BCI sessions. Nonetheless, SA training duration impacted users' progression, and neurophysiological analyses provided us with valuable insights into brain pattern evolution throughout the training process.

COLLABORATOR -

Suzy Teillet (Engineering Student).

RELATED PAPERS -

-1- Jeunet, C. (2015). 'Training Users' Spatial Abilities to Improve BCI Performance: A Theoretical Approach.' In: *CJCSC* - **Best Paper Award**.
-2-Jeunet, C., Lotte, F., Hachet, M., Subramanian, S., and N'Kaoua, B. (2016). 'Spatial Abilities Play a Major Role in BCI Performance.' In: *BCI Meeting*.
-3- Teillet, S., Lotte, F., N'Kaoua, B., and Jeunet, C. (2016).'Towards a Spatial Ability Training to Improve MI-BCI Performance: a Pilot Study.' In: *SMC*.

5.4 THEORY - INCREASING SPATIAL ABILITIES TO IMPROVE MI-BCI USER-TRAINING.

5.4.1 *Definition of Spatial Abilities & Relationship with Mental-Imagery*

As mentioned earlier, SA can be defined as mental capacities involving the construction, transformation and interpretation of mental images (Poltrock and Brown, 1984). They reflect the use of MI to manipulate spatial representations. Many studies have been led in order to determine the different factors composing SA (for a review, see Poltrock and Brown, 1984). Numerous models of these SA factors have been proposed, the relevance of many of them being still discussed. Nonetheless, some factors are redundant in most studies: *Visualisation, Orientation and Spatial Relations*. *Visualisation* is the ability to mentally manipulate a pictorially presented object. *Orientation* corresponds to the ability to comprehend the arrangement of elements. Finally, the *Spatial Relation* ability corresponds to the capacity to rapidly and accurately rotate a mental image. Considering the BCI experiments described in Sections 5.2 and 5.3, one can notice that SA are linked with all the MI tasks proposed, as was discussed in Section 5.2.3. These links between SA and the three MI tasks led to consider the potential positive impact an SA training could have on MI-BCI performance.

5.4.2 *Why Propose a Spatial Ability Training?*

SA training has been shown to be efficient to improve performance in many different areas such as surgery, mathematics or engineering education, thus suggesting its potential positive impact on MI-BCI control abilities. A large majority of these SA trainings are based on the Vandenberg and Kuse, 1978 Mental Rotation test. This test is composed of two sets of 10 items (see an example in Figure 12). Each set has to be completed in 3 minutes maximum. An item consists in a 3D shape on the left and four 3D shapes on the right. Among the four 3D shapes, two are similar to the left one with a rotation of 60°, 120° or 180° around the vertical axis. The other two are mirrored reversed and rotated images of the left 3D shape. For each item, the participant has to find the two 3D shapes similar to the left one.

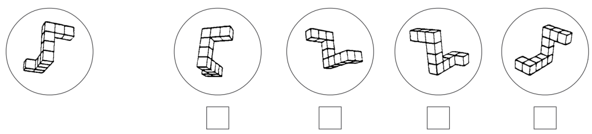


Figure 12 – A item of the Vandenberg and Kuse, 1978 mental rotation test.

Hoyek et al., 2009 used a computerised version of this Mental Rotation test to train students' SA and showed an improvement in their ability to learn anatomy. Indeed, SA were shown to impact capacities in scientific learning (Bishop, 1980). This is why Wiedenbauer and Jansen-Osmann, 2008 developed a manual version of the Mental Rotation test for children. This manual version appeared to be efficient to improve children SA. On the other hand, Mental Rotation test scores have also been shown to be improved through different activities such as sport (Moreau et al., 2012), juggling (Jansen, Titze, and Heil, 2009) or engineering courses (Baenninger and Newcombe, 1989). Training SA through the administration of Mental Rotation tests is considered as a *specific* training (as it enables to train one aspect of SA: the *Spatial Relations*) by opposition to *general* trainings (focusing on several aspects of SA) and *indirect* trainings (i.e., improving SA through different activities such as sport of engineering classes).

In a meta-analysis, Baenninger and Newcombe, 1989 revealed that to obtain the best performances, the SA training should be *specific* and have a medium duration, i.e., 3 to 5 sessions spread over at least 3 weeks. In Section 5.2, participants followed a standard MI-BCI training protocol composed of 6 identical sessions during which they had to learn to perform 3 MI-tasks: mental rotation, mental subtraction and left-hand motor imagery. On the one hand, no improvement in performance was noticed between the 1^{st} and 6^{th} session on average across participants. It suggests that despite the large number of sessions, participants did not learn during this experiment. On the other hand, the mean MI-BCI performance appeared to be strongly correlated with users' mental rotation scores. This correlation added to the relationship between SA and the MI-tasks led to question a potential causal relationship between both of them. In other words, the question is: would an increase in mental rotation scores be associated with an improvement of MI-BCI performance? In accordance with the literature, it thus seems worth exploring the effect of the inclusion of a specific and medium duration SA training, based on 3 to 5 sessions of Mental Rotation tests (Vandenberg and Kuse, 1978), in standard MI-BCI training protocols. These SA training sessions could replace some of the MI-BCI training sessions.

5.5 Design & Validation of the Spatial Ability Training Protocol

5.5.1 *Design of the Spatial Ability Training Protocol*

The objective of the Spatial Ability (SA) training protocol is to specifically improve this skill, and particularly the "Spatial Relation" aspect, by performing different kinds of mental rotation exercises. Based on the recommendations from instructional design (Lotte et

Figure 13 – One item per exercise included in the Spatial Ability training: the shape on top is the target, and the participant must identify the two shapes that are identical to the target among the four below. From the left to the right are displayed the *shapes, matrices, cubes, arms* exercises.

al., 2013), which have shown that variability in training tasks leads to better learning, we propose different kinds of exercises, 4 in total (see Figure 13), theoretically associated with a different degree of difficulty. Indeed, two exercises comprised 2D rotations while the other two were associated with 3D rotations.

We wanted the SA training sessions to be comparable to standard MI-BCI training sessions in terms of training duration and structure. During each training session, participants had to perform 5 runs, each of them lasting 7 minutes. At each run a different exercise was presented, but the instructions were always the same: a target figure was displayed at the top of the screen, followed by a further four figures below ; among these four figures, two corresponded to the target figure that had been rotated and two were mirror images of the target figure. The participant had to select the two correct proposals, i.e. the two rotated figures. A time limit of 7 minutes was set, during which participants had to answer as many questions as possible. From the second run onwards, participants were able to click on a “check” button in order to receive feedback (i.e., to know whether they had answered correctly or not).

The SA training was implemented with the aim of testing its efficiency in terms of MI-BCI performance improvement. Thus, we compared this Spatial Ability (SA) training protocol (1) with a standard MI-BCI training protocol and (2) with a similarly structured Verbal Comprehension (VC) training protocol. We chose to train verbal comprehension because it would appear that, to our knowledge, this skill is independent from SA skills. In this way, the verbal comprehension training should not have had any impact on users’ SA, but enabled us to control that any improvement in MI-BCI performance was due to the SA training, and not just to a different cognitive training.

Therefore, in order for VC and SA training to be comparable, we proposed 4 different kinds of exercises. The first and second exercises consisted in finding synonyms and antonyms, respectively. The third consisted in completing sentences with analogies and the last one consisted in determining the meaning of a proverb. The structure of the sessions was the same as for the SA training protocol: during each session, participants performed 5 runs, each lasting 7 minutes. At each run a different exercise was presented, but the instructions were always the same: a target word/sentence was presented at the top of the screen, followed by four options ; among these four options, the participants had to select the two correct ones. For example, an exercise on synonyms might provide the user with the word "Big", followed by four options : "Huge", "Edible", "Large" and "Fruitful". The goal of the participant is to select the two correct answers. A 7 minute time limit was set for participants to complete as many items as possible. From the second run onwards, participants were able to click on a "check" button in order to receive feedback (i.e., to know whether they had answered correctly or not).

5.5.2 *Validation - Step # 1 : Determining the Degree of Difficulty of SA and VC Training Exercises*

The aim of this first step was to determine the degree of difficulty, both objective (i.e. performance) and subjective (i.e. perceived difficulty), of the exercises proposed in the SA and VC training protocols. This analysis enabled us to check experimentally if the different exercises were indeed associated with increasing degrees of difficulty, as recommended by instructional design literature (Lotte et al., 2013). Also, it enabled us to assess whether the SA and VC training protocols require participants to mobilise the same level of cognitive resources.

5.5.2.1 *Materials and Methods*

Each participant (N=31, 9 women) performed 8 exercises (4 SA and 4 VC exercises). Half (N=16, 4 females) of the participants started with 4 SA questionnaires and finished with the 4 VC questionnaires, while the other half (N=15, 5 females) started with 4 VC questionnaires and then completed 4 SA questionnaires. The SA and VC exercises were performed in a counterbalanced order across the participants. This study was conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki, and was approved by the Ethics Committee of Inria Bordeaux Sud-Ouest (the COERLE; approval number: 2016/02-00). All the participants signed an informed consent form at the beginning of the experiments.

As stated earlier, each participant performed 8 on-line exercises (4 SA and 4 VC). Each exercise comprised 8 items. At the end of each exercise, they completed a Likert-scale in order to rate their perceived effort from 0 to 10. The statistical analysis enabled us to detect any significant differences between the exercises (and thus between the training protocols), both in terms of performance ("objective" difficulty - called "score" in the analyses) and perceived effort ("subjective" difficulty - called "effort" in the analyses).

5.5.2.2 *Results*

We performed four ANOVAs to assess the differences between the exercises of each training protocol, i.e., SA and VC, both in terms of difficulty ("score") and perceived effort required to complete the task ("effort"). Concerning the SA training, the results showed a main effect of the exercise both in terms of score ($D(30)=102.900$, $p \leqslant 0.001$, $\eta^2=0.774$) and in terms of effort ($D(30)=118.637$, $p \leqslant 0.001$, $\eta^2=0.798$). Post-hoc analyses indicated that the "shapes" exercise was associated with significantly better scores and lower effort than the "matrices" exercise, itself being easier and requiring less effort than the "arms" exercise, itself being rated easier and requiring less effort than the "cubes" exercise. On the other hand, concerning the VC training, the ANOVA revealed a main effect of the exercise in terms of score ($D(30)=22.942$, $p \leqslant 0.001$, $\eta^2=0.433$) but not in terms of effort ($D(30)=2.098$, $p=0.158$, $\eta^2=0.065$). Post-hoc analyses revealed that the "synonyms" and "analogies" exercises were associated with similar scores while the "antonyms" exercise was significantly more difficult, and the "proverbs" exercise even more difficult still. Finally, we performed a two 2-way ANOVA for repeated measures in order to compare the two training protocols in terms of performance and required effort. The first ANOVA revealed no difference in terms of scores between the SA and VC trainings ($p=0.902$) while the second revealed a main effect of the training type on the perceived effort required to complete the task ($p \leqslant 0.001$): post-hoc analyses showed that the SA and VC exercises were equivalent except from the *cube* exercise that was perceived as much more difficult.

5.5.2.3 *Discussion*

This first study enabled us to to verify that both SA and VC training included exercises with different levels of difficulty, and thus followed the recommendations from instructional design (Lotte et al., 2013). Participants rated VC and SA exercises as demanding (subjective effort), except from the *cube* exercise that appeared to be much more demanding (which could be due to the fact that difficult VC exercises require previous knowledge while difficult SA exercises can be solved by thinking about it). Their scores (objective effort) were also equivalent for both training types, suggesting a comparable degree of difficulty. Since the exercises from the VC and SA training protocols proved to have an equivalent complexity, we were able to use VC training as a control. The next step was to verify the effectiveness of the SA training protocol for improving spatial abilities.

5.5.3 *Validation - Step # 2 : Validating the SA and VC Training Protocols*

A second pre-study was carried out in order to evaluate the effectiveness of our SA and VC training protocols. Indeed, although we designed the questionnaire exercises with theoretical considerations in mind, we still had to verify whether our SA training protocol actually led to an improvement of the user's spatial abilities. Conversely, we also had to ensure that the VC training protocol did not improve SA, in order for the control group to be able to use it without affecting the outcome. Accordingly, we enrolled two groups of participants who completed the entire SA or VC training protocols. Their spatial abilities were evaluated before and after training in order to assess the impact of each training protocol on SA.

5.5.3.1 *Materials and Methods*

The participants (N=19, 10 women) first took part in a session during which their SA and other cognitive abilities were measured. They were then divided into two homogeneous groups in terms of gender and mental rotation scores obtained during this first session. The first group (N=9, 5 women) completed the SA training protocol, i.e., they performed each of the three SA training sessions over several days. The second group (N=10, 5 women) completed the VC training protocol, with sessions being similarly spread out over different days. This study was conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki, and was approved by the Ethics Committee of Inria Bordeaux Sud-Ouest (the COERLE; approval number: 2016/02-00). All the participants signed an informed consent form at the beginning of the experiments.

During the first session, participants performed the mental rotation test (Vandenberg and Kuse, 1978) which assesses spatial visualisation abilities, i.e., SA. Their training was then performed online and at home, with a maximum of one session per day. They then performed the same psychometric test again in the final session.

5.5.3.2 *Results*

In order to assess the effectiveness of the SA training protocol, we performed a two way ANOVA for repeated measures. In this manner, we were able to detect any significant differences between pre- and post-training mental rotation scores (that were computed by dividing the raw score, out of 40, by the time spent to complete the test in seconds, with a maximum of 360s), as a function of both the group (SA vs. VC) and gender (as SA are known to be associated with an important gender effect). Before performing the ANOVA, we checked that the participants from both groups had similar SA at the beginning of the experiment, i.e., before training. Results re-

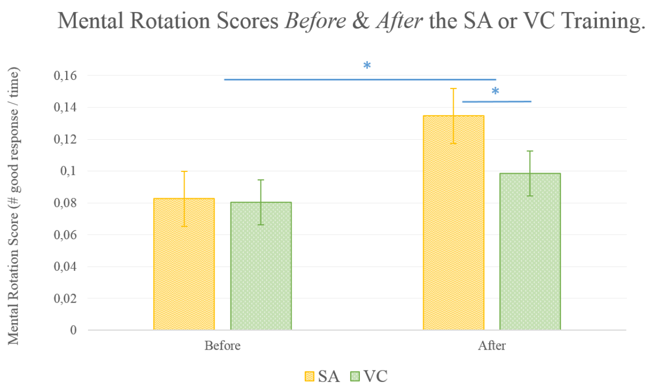


Figure 14 – Scores obtained at the Mental Rotation Test ("number of good responses" / "time needed to complete the questionnaire") for the two groups, SA and VC, before and after their training.

vealed that the variances were equal between the groups (F(19)=0.011, p=0.917), as well as the mean rotation scores (t(19)=0.402, p=0.692). Then, the ANOVA revealed, as stated in the literature, a main effect of the gender ($D(1,17)=5.056$, $p \leqslant 0.05$, $\eta^2=0.229$). Second, it revealed a rotationScore * gender interaction effect (($D(1,17)=7.388$, $p \leqslant 0.05$, $\eta^2=0.303$): participants in the SA group made significantly greater improvements compared to those in the VC group (see Figure 14).

5.5.3.3 *Discussion*

This second pre-study allowed us to confirm that participants performing the SA training protocol tend to improve their spatial abilities significantly better than participants in the VC training group. Although participants in the VC group did improve their SA, improvements were only minor and were more likely due to the fact that they had completed each questionnaire twice, and consequently were more familiar with the questionnaire the second time. Nonetheless, the marked improvement in SA abilities in the SA training group does confirm that the training exercises that we designed do indeed lead to improved spatial abilities. It was then possible to integrate this training approach in an MI-BCI training protocol with a view to assessing its impact on BCI performances.

5.6 TEST OF THE EFFICIENCY OF THE SPATIAL ABILITY TRAINING

In order to test the efficiency of our Spatial Ability training, we asked participants to train to control an MI-BCI using 3 different training paradigms, all lasting 6 sessions. As depicted in Figure 15 all the participants performed MI-BCI during sessions 1, 5 and 6. Sessions

2 to 4 were dedicated to the specific training paradigms. Thus, the control group #1 also performed MI-BCI during sessions 2 to 4 while the control group #2 followed a VC training procedure and the experimental group an SA training procedure. As explained in the previous Sections, SA and VC training protocols consisted in different SA and VC exercises, respectively, performed during 7-minute long runs so that all the groups had similar training durations.

Figure 15 – Training paradigm (over the 6 training sessions) as a function of the group participants were allocated to.

5.6.1 *Materials & Methods*

5.6.1.1 *Participants*

Each of the 27 participants was assigned to one condition: either one of the two control conditions (standard BCI training and VC training) or the experimental condition (SA training). The participants in the first control condition (N=9 - 5 women and 4 men; aged 21.5 ± 1.2 year-old) took part in 6 standard MI-BCI training sessions (MI condition). The participants of this first control group were selected from the participants of a previous study (Jeunet, 2015 - introduced in Section 5.2) for matching the characteristics of the participants from both the other groups in terms of mental rotation scores, MI-BCI performance and gender. The participants in the second control condition (N=9 - 5 women and 4 men; aged 21.7 ± 3.5 year-old) took part in 3 standard MI-BCI training sessions and 3 VC training sessions (VC condition). Finally, the participant in the experimental condition (N=9 - 5 women and 4 men; aged 23.8 ± 5.0 year-old) took part in 3 standard MI-BCI training sessions and 3 SA training sessions (SA condition). One participant of the experimental group abandoned the study after the third session. Therefore, her data were not considered. All the participants were right handed and healthy, i.e. they did not suffer from any neurological or psychiatric disorder that could impact their EEG signals or prevent them from focusing on a 2-hour long task.

5.6.1.2 *Variables and Factors*

In a first instance, the efficiency of the SA training to improve SA was assessed in terms of improvement of (1) mental rotation scores (difference after vs. before the SA training) and (2) the SA/VC exercises scores along the training (difference scores session 4 vs. session 2). In a second instance,ANCOVAs have been performed in order to assess the impact of the Run (4 modalities: run 1, run 2, run 3, run 4), of the Session (3 modalities: session 1, session 5, session 6) and of the group (3 modalities: MI, SA, VC) on MI-BCI performance, with the improvement of spatial abilities (measured in terms of difference of mental rotation scores before vs. after) as a covariable. MI-BCI performance was measured through classification accuracy. On the one hand, we considered the mean and peak classification accuracy obtained online during the experiment (based on a training of the classifier on the first run of the first session, as depicted in the experimental protocol). On the other hand, as we hypothesised that the SA training could modify significantly users' brain patterns, we retrained the classifier, offline, on the first run of each session, and assessed the offline performances of this session using this retrained classifier.

5.6.1.3 *Experimental Paradigm*

Please refer to Figure 16.

5.6.1.4 *Analyses*

Concerning the evaluation of the SA training efficiency, t-tests were performed to assess on the one hand mental rotation scores improvement after vs. before the SA training, and on the other hand SA exercises scores improvement between the first and the last SA training sessions (i.e. session 2 and session 4). Then, concerning the measure of improvement of MI-BCI performance, ANCOVAs were performed to assess the impact of the run (runs 2 to 5) the session (sessions 1, 5, 6) and of the group (MI vs. VC vs. SA) on MI-BCI performance, with SA improvement as a covariable.

5.6.2 *Results*

The results of this experiment will be introduced following three steps: (1) validation of the SA training's efficiency to improve users' SA, (2) evaluation of users' MI-BCI performance improvement as a function of their group (SA, VC, MI) and (3) neurophysiological anal-

EXPERIMENTAL PARADIGM

The 27 participants were spread over 3 groups: "standard MI-BCI – First control group" (MI-BCI) ; "Verbal Comprehension – Second control group" (VC) and "Spatial Ability – experimental group" (SA). The experiment was composed of 6 sessions of 2.00 hours each. All the participants were doing an MI-BCI training during sessions 1, 5 and 6. Sessions 2 to 4 were dedicated to the specific training: SA, VC or MI-BCI. This pipeline is summarised in Figure 15. SA and VC training sessions are described in the next paragraphs. This table aims at describing the MI-BCI sessions, which were divided into 5 runs, with 45 trials per run.

EVALUATIONS

PSYCHOMETRIC EVALUATIONS	*Personality assessment* ▼ Learning Style Inventory ▼ 16 Personality Factors-5 *Cognitive profile assessment* ▼ Corsi block task ▼ Bruininks-Oseretsky Test of Motor Proficiency ▼ Revised Visual Retention Test ▼ Mental Rotation test
NEUROPHYSIOLOGICAL EVALUATIONS	▼ Blankertz's SMR predictor: μ amplitude at rest, over the sensori-motor areas

BCI EXPERIMENTS – TRAINING PROTOCOL

TRAINING TASKS	▼ Left-Hand Motor Imagery ▼ Mental Subtraction ▼ Mental Rotation
FEEDBACK	▼ *Modality:* Visual [standard Graz blue bar feedback] ▼ *Update Frequency:* 16Hz ▼ *Content:* Only positive
TRAINING ENVIRONMENT	▼ Standard Graz Training Environment, adapted for 3 classes

BCI EXPERIMENTS – BRAIN SIGNAL RECORDINGS & PROCESSING

HARDWARE & EEG SET-UP	▼ g.USBamp amplifier (g.tec, Graz, Austria) ▼ See the list in the Materiels & Methods Chapter ▼ Referenced to the left ear, grounded to Afz ▼ Sampling of the EEG data: 256Hz
SIGNAL PROCESSING PIPELINE	▼ Band-pass filtering of the EEG data: 8-30Hz *Session 1: the classifier & CSP are trained on the run 1* ▼ 3 CSP «one class vs. the others» → 12 band-power features ▼ Combination of 3 sLDA in a one-versus-the-rest scheme ▼ Use of the resulting classifier to discriminate between the 3 tasks for the runs 2 to 5 *Sessions 2 to 6 (MI group) or Sessions 5 & 6 (other groups)* ▼ Run 1 with the classifier trained during Session 1 ▼ Re-computation of the sLDA's bias ▼ Use of the resulting classifier to discriminate between the 3 tasks for the runs 2 to 5

Figure 16 – Materials & Methods of the Study testing the efficiency of the spatial ability training, Section 5.6

yses of users' brain patterns evolution along the training as a function of their group and of the MI task.

5.6.2.1 *Validating the Efficiency of the SA Training to Improve Uers' SA*

A Wilcoxon test was performed in order to evaluate the difference of mental rotation score before vs. after the SA/VC training. It revealed a significant increase of mental rotation scores after the training [Z(15)=3.299, $p \leqslant 0.001$]: $\bar{X}_{before}$=21.93±6.67, $\bar{X}_{after}$=29.40±8.70. Nonetheless, this improvement surprisingly seems to be effective in both SA and VC groups [SA: Z(7)=2.201, $p \leqslant 0.05$; VC: Z(8)=2.527, $p \leqslant 0.05$]. This unexpected result led us to investigate the factors correlating with the improvement of mental rotation scores in each of the groups.

On the one hand, SA exercise scores significantly increased between the first SA training session (session 2) and the last SA training session (session 4) [Z(15)=2.371, $p \leqslant 0.05$]: $\bar{X}_{firstSAsession}$=26.71±11.08, $\bar{X}_{lastSAsession}$=33.54±12.71. Moreover, it appeared that the improvement of mental rotation scores (before vs. after the SA training) was positively correlated with this progression during the SA training (difference of scores between the first and last training session) [r=0.803, $p \leqslant 0.05$]. Both these results suggest that our SA training has a significant impact on participants' spatial abilities and thus reaches its goal.

On the other hand, concerning the VC group, no improvement of VC scores was noticed during the training [Z(15)=0.560, p=0.575]. Also, in this group, users' improvement in term of mental rotation scores do not correlate with their progression during the VC training but with their *spatial memory* score (assessed based on the Corsi test) [r=0.863, $p \leqslant 0.01$] and *coordination of upper limbs* score (which is one dimension of the BOT test) [r=0.814, $p \leqslant 0.05$]. Yet, both these scores also reflect spatial abilities and interestingly enough, coordination of the upper limbs abilities have already been shown to correlate with MI-BCI performance in Hammer et al., 2014.

These results suggest that SA training enables the participants to improve their SA. Nonetheless, it has to be noted that participants of the VC group who have good SA skills (based on the Corsi and BOT scales) also manage to improve their mental rotation scores during the test-retest process.

5.6.2.2 *Evaluating the Improvement of MI-BCI Performance as a Function of SA Improvement*

First, we checked that there was no difference in terms of MI-BCI performance between the groups in session 1. The one-factor ANOVA confirmed that the 3 groups had equivalent performance [F(2,23)=0.074, p=0.929]: $\bar{X}_{SA}$=57.54±8.97, $\bar{X}_{VC}$=58.06±11.99, $\bar{X}_{MI}$= 56.38±6.16. Another ANCOVA has been performed to evaluate the evolution of MI-BCI performance as a function of the Session (S_3: session1 vs. session5 vs. session6 - repeated measures), the Group

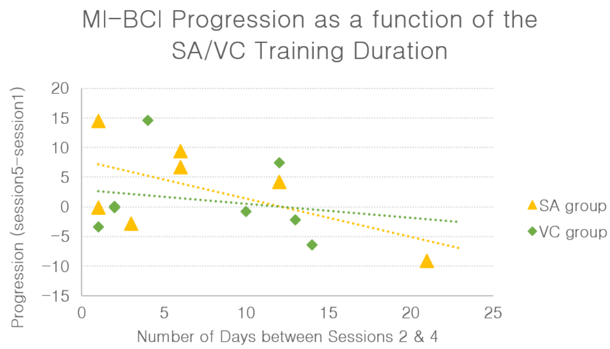
(G_3: SA vs. VC vs. MI - independent measures) and the Gender (D_2: men vs. women - independent measures), with the mental rotation score as a covariable. This analysis revealed neither significant effects of the factors nor any interaction. First, it could be due to the small sample (7 to 9 participants per group). It could also potentially result from the way the classifier was trained. Indeed, the classifier was trained on the data of the first run of the first session and was then rebiased after the first runs of the other sessions. Yet, the SA training is expected to help the users improve their mental imagery abilities, which could result in much different brain patterns in sessions 5 and 6 (i.e., the 2 last MI-BCI sessions). Thus, in a second instance we re-trained the classifier offline after the first run of each session. Considering the resulting MI-BCI performance the ANCOVA showed a strong tendency towards a main effect of mental rotation scores ($D(1,17)=3.843$, $p=0.067$, $\eta^2=0.433$) strengthening once more the impact of SA on MI-BCI performance.

In the following analyses, we focused on MI-BCI performance obtained offline after retraining the classifier on the first run of each session.

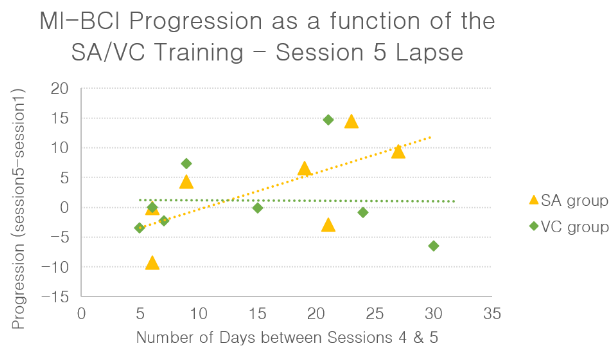
We investigated, for each group (SA, VC and MI) the correlations between MI-BCI performance progression and the training duration (i.e., the time lapses between the sessions). On the one hand, Pearson correlation analyses on the data of the SA group suggest a strong tendency towards a negative correlation between the duration of the SA training (i.e., time lapse between session 2 and session 4) and MI-BCI performance progression (between session 1 and session 5) ($r=-0.733$, $p=0.061$) (see Figure 17 (a)); and a positive correlation between this MI-BCI performance progression (between session 1 and session 5) and the time lapse between the end of the SA training (session 4) and session 5 ($r=0.940$,$p\leqslant0.005$) (see Figure 17 (b)). In other words, based on our data these results suggest that the most efficient planning would be to do a short SA training (less than 12 days) followed by an incubation phase (more than 10 days) before performing another MI-BCI session (here the second MI-BCI session, session 5). For the VC group however, no correlation was found between the training duration and MI-BCI performance or progression. The correlations between le duration of the training and MI-BCI progress for the SA group, as well as the absence of correlation in the VC group, reinforce the hypothesis of an impact of the SA training on MI-BCI control abilities (despite the fact there is no linear correlation between SA progress and MI-BCI performance). Finally, for the MI group (the participants of which performed 6 MI-BCI sessions), MI-BCI progression (between session1 and session5/session6) negativel correlates with inter-session time lapses (between session1 and session5/session6, respectively) ($r=-0.737$, $p\leqslant0.05$ / $r=-0.769$, $p\leqslant0.05$, respectively). It suggests that a short inter-session period would enable a better progress when performing only MI-BCI sessions.

5.6.2.3 *Neurophysiological Analyses*

The object of this SA training was to enable MI-BCI users to improve their ability to perform MI tasks. This improvement may take the form of modifications of their brain activity patterns. In other words, it is likely that the patterns associated to each MI task are different before vs. after the SA training. The classifier being only trained on the first session, such a modification of brain activity patterns may not result in better MI-BCI performances in our experimental paradigm. Therefore, we decided to perform analyses in order to describe and quantify the neurophysiological differences between ses-



(a)



(b)

Figure 17 – MI-BCI progression, in terms of classification accuracy, as a function of participants' group: SA (yellow triangles) or VC (green diamond) and (a) as a function of the SA/VC training duration or (b) as a function of the time lapse separating the end of the SA/VC training from the subsequent MI-BCI session (i.e., session 5). For the SA group, the progression is negatively correlated to the duration of the SA training, and positively correlated to the time lapse between the end of the SA training and session 5.

sion1, session5 and session6 for each participant, with respect to their group (SA, VC, MI).

In order to do so, we performed an analysis in two steps. First, we computed the signal band-power for each participant/task/electrode/trial/run/session, in [8;30] Hz, i.e., the frequency band used for feature extraction and classification, on 2 time windows: (1) in pre-trial, i.e., from 2500ms to 500ms before the instruction cue and (2) during the feedback period, i.e., from 500 to 3500ms after the cue. We then performed t-tests to assess the difference in band-power between pretrial and feedback over each electrode for each MI-task, session and participant. This difference should reflect the involved brain areas during each MI task. In the second step of the analyses, we selected only the electrode associated with the smallest p-value for each task/session/participant. We transformed this p-value into an activation coefficient c = -log(p-value) (Lotte et al., 2015) so that the better the electrode is to discriminate between pre-trial and trial, the higher its coefficient. In the second step, the signal band-power was computed again for each task/session/participant, but only for the selected electrode (with the highest coefficient) and on 4 frequency bands: low alpha [8;10]Hz, high alpha [10;12]Hz, low beta[12;24]Hz, high beta[24;30]Hz. We created 4 tables gathering the topographies corresponding to this second step results. Each one of the tables corresponds to 1 frequency band; each head corresponds to one task, one session and one group; on each head are displayed one point by participant: the location of the point represents the selected electrode while the size of the point represents the value of the coefficient for this task/session/frequency-band. We only provide here, in Figure 18, the table corresponding to the low beta frequency band as it is the one associated with the highest coefficients. The 3 other tables can be found in Appendix B.

Despite the low spatial resolution of EEG and the fact we cannot conclude on the source of the signal only based on the location of the most relevant electrode, it is interesting to note clusters of activation for each task. First, concerning the left-hand motor-imagery task, C4 is the most often selected channel (in 17% of the cases) ; yet, C4 is above the right sensori-motor cortex, which is the zone theoretically activated when performing left-hand motor-imagery (Pfurtscheller and Klimesch, 1992). Second, FT8 seems to be the most solicited channel during mental-rotation tasks (in 36% of the cases). Yet, mental rotation tasks, and more generally tasks related to spatial orientation/-navigation have been shown to be underlain by the activation of the right temporo-parietal cortex (Ratcliff, 1979; Roberts and Bell, 2000). Finally, two main patterns emerge when observing the region related to the mental subtraction task: either the more relevant channel was F3 (in 11% of the cases) or around Pz/PO8/PO7 (Pz was selected in 28% of the cases). It suggests that both the left-frontal lobe and

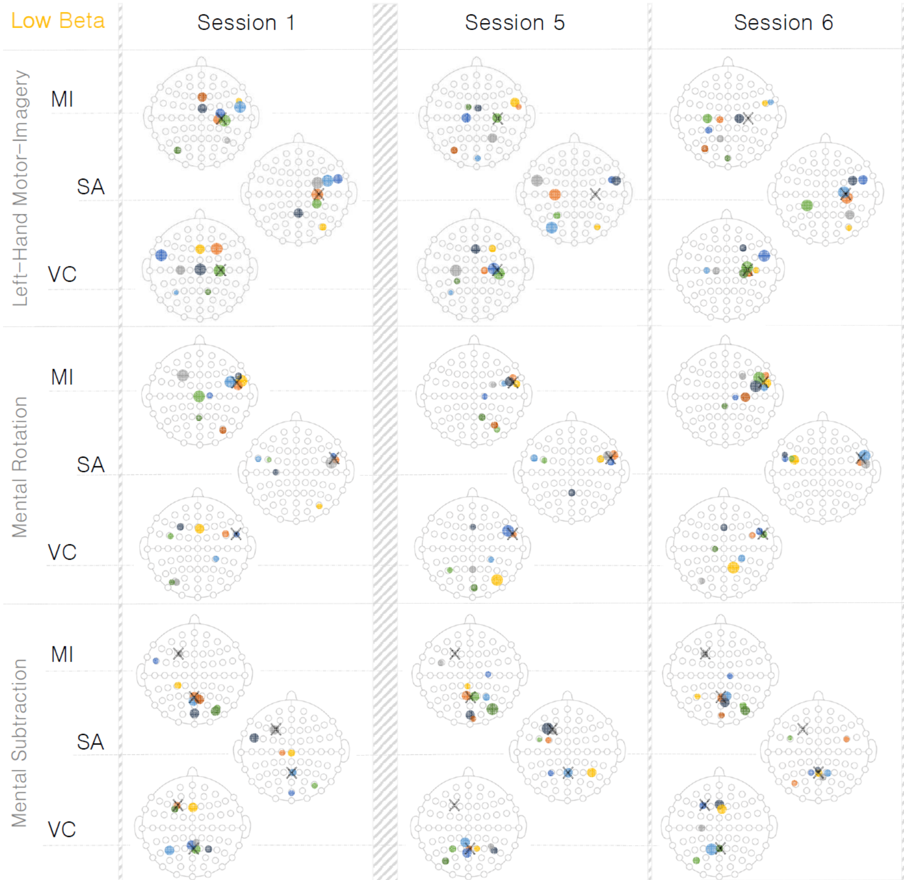


Figure 18 – Table representing the selected electrode as well as its associated activation coefficient for each participant-group/task/session in the low beta band, i.e., [12;24]Hz; each head corresponds to one task, on session and one group; on each head are displayed one point by participant: the location of the point represents the selected electrode while the size of the point represents the value of the activation coefficient for this task/session. The black crosses represent the "theoretical electrode", i.e., the one which is theoretically the closest to the brain region triggered for each of the MI tasks: C4 for the left-hand motor-imagery, FT8 for the mental rotation, F3/Pz for the mental subtraction.

parietal regions would be involved in the mental subtraction process. Yet, Burbaud et al., 1999, performed an fMRI study to investigate the process of mental subtraction. Their results revealed that when participants were performing the calculation, several areas were solicited: frontal areas (the left dorso-lateral pre-frontal cortex, the pre-motor cortex, Broca area) as well as the posterior parietal lobe. Interestingly enough, despite the fact, once more, that with our 32-channel EEG we do not have the precision of an fMRI, our results in terms of solicited electrodes seem to match Burbaud et al., 1999, results. The observation of the tables seems to indicate a low variability of the selected electrodes over the different sessions for the MI group, for the mental rotation and subtraction tasks. Most participants' selected electrodes are gathered around the "theoretical" electrode for both these tasks. Nonetheless, for the mental-rotation task, while it was clear there was a cluster around C4 during Session 1, it is not the case any-more at the end of the training. Concerning the VC group, results reveal a high variability in terms of selected electrodes, and consequently no important cluster except maybe for the motor-imagery task. Also, the coefficients associated to these electrodes seem to be lower than for the other groups, especially for the mental rotation and subtraction tasks. It suggests that the selected electrodes do not enable a strong discrimination between pre-trial and in-trial band-powers. Finally, participants of the SA group show an important cluster around C4 for the motor-imagery task at the end of the training. Furthermore, it is interesting to see that for all the participants of the SA group, either FT7 or FT8 was selected as the most relevant electrode for the mental rotation task. It is the only group for which there is no right lateralisation for this task. Nonetheless, given the fact that during session 1 for some participants of this group left-temporal electrodes had been selected, we cannot conclude on the fact it is due to the training or not. Finally, participants of the SA group also show an important cluster for the mental subtraction task, around Pz, by the end of the training (while it was not the case at the beginning). In the future, further statistical analyses would be necessary to quantify the evolution of the selected electrodes and of their relevance to discriminate a specific task from rest.

Finally, we performed ANOVAs aiming at investigating the electrodes solicited (in comparison to the ones that should theoretically be solicited) as a function of the Task, of the Session (session1, session5 and session6) and of the Group (MI, SA, VC). Thus, for each participant/session/task, we computed the distance between the standard 3D coordinates of the selected electrode and of the electrode that should be selected theoretically. For the motor-imagery of the left-hand and the mental rotation tasks, C4 and FT8 were designated as the electrodes theoretically solicited. For the subtraction task, we chose to consider 2 theoretical electrodes: F3 and Pz. Thus, for this last task, two distances were computed for each participant/session (one for F3 and one for Pz). The results are summarised in the following lines:

Motor-Imagery of the Left-Hand task – ANOVA with the distance to C4 as dependent variable.

— Main effect of the Group - *no* ($D(2,21)=0.074$, $p=0.929$, $\eta^2=0.007$)
— Main effect of the Session - *no* ($D(1,21)=0.097$, $p=0.758$, $\eta^2=0.005$)
— Group*Session Interaction effect - *yes* ($D(2,21)=5.611$, $p\leqslant0.05$, $\eta^2=0.348$), see Figure 19 (a)

Mental Rotation task – ANOVA with the distance to FT8 as dependent variable.

— Main effect of the Group - *no* ($D(2,21)=1.491$, $p=0.248$, $\eta^2=0.124$)
— Main effect of the Session - *no* ($D(1,21)=1.315$, $p=0.264$, $\eta^2=0.059$)
— Group*Session Interaction effect - *no* ($D(2,21)=0.807$, $p=0.459$, $\eta^2=0.071$)

Mental Subtraction task 1/3 – ANOVA with the distance to F3 as dependent variable.

— Main effect of the Group - *no* ($D(2,21)=1.367$, $p=0.277$, $\eta^2=0.115$)
— Main effect of the Session - *no* ($D(1,21)=0.171$, $p=0.683$, $\eta^2=0.008$)
— Group*Session Interaction effect - *no* ($D(2,21)=0.333$, $p=0.720$, $\eta^2=0.031$)

Mental Subtraction task 2/3 – ANOVA with the distance to Pz as dependent variable.

— Main effect of the Group - *no* ($D(2,21)=0.349$, $p=0.709$, $\eta^2=0.032$)
— Main effect of the Session - *no* ($D(1,21)=0.497$, $p=0.488$, $\eta^2=0.023$)
— Group*Session Interaction effect - *no* ($D(2,21)=1.263$, $p=0.304$, $\eta^2=0.107$)

For the mental subtraction task, the ANOVAs did not reveal any significant result. It is potentially due to the fact that the distances to F3 and Pz should be considered together rather than separately. This is why we combined them in a unique measure that corresponded to the minimum between the distance of the selected electrode to F3 or Pz. Here are the results:

Mental Subtraction task 3/3 – ANOVA with the minimum distance to Pz/F3 as dependent variable.

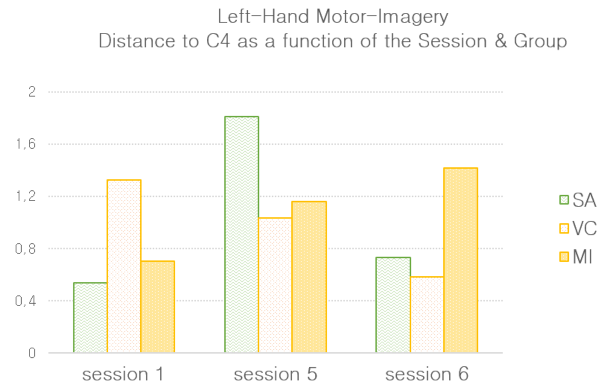
— Main effect of the Group - *no* ($D(2,21)=0.065$, $p=0.801$, $\eta^2=0.003$)
— Main effect of the Session - *no* ($D(1,21)=0.497$, $p=0.488$, $\eta^2=0.023$)
— Group*Session Interaction effect - *trend* ($D(2,21)=2.881$, $p=0.078$, $\eta^2=0.215$), see Figure 19 (b)

Furthermore, no significant correlation was found between MI-BCI performance and these distance measures.

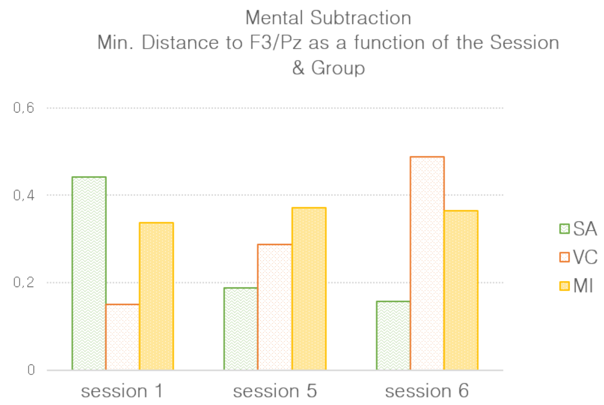
To summarise, no effect was revealed for the mental rotation task. However, the Session*Group interaction was shown for the left-hand motor-imagery task: it seems that by the end of the training, the distance between the selected electrode of participants of the SA and VC groups and C4 is lower than for the MI group. Also, there is a trend towards a Session*Group interaction for the mental subtraction task (when the minimal distance to F3 or Pz is used as dependent variable). Here, participants of the SA group are the only ones for whom the distance between the selected electrode and either F3 or Pz decreases. Both these effects are depicted in Figure 19.

5.6.3 *Discussion*

First, let us summarise the different results:



(a)



(b)

Figure 19 – Representation of the average distance of the selected electrode to C4 (a) or to closest electrode between F3 and Pz (b) as a function of the Group (SA, VC, MI) and the group.

-1- This experiment enabled us to validate the SA training protocol: (1) participants' mental rotation scores were increased after the training process, (2) participants improved their SA exercise scores along the training process, (2) mental rotation scores improvement correlates with SA exercise scores improvement.
-2- The analysis of the improvement of MI-BCI performance as a function of participants' group, session, gender and mental rotation scores did not reveal any significant result. It could be de to the fact that participants' manner to perform the different MI-tasks evolves along the sessions, which results in an obsolete classifier. This hypothesis was tested thanks to the neurophysiological analyses summarised hereafter. To finish with this point: the duration of the SA training had a significant impact on participants' progression.
-3- The representation of the most solicited electrode fore each participant/task/session revealed an important inter-session variablity. Nonetheless, some clusters were revealed: C4 was much solicited for

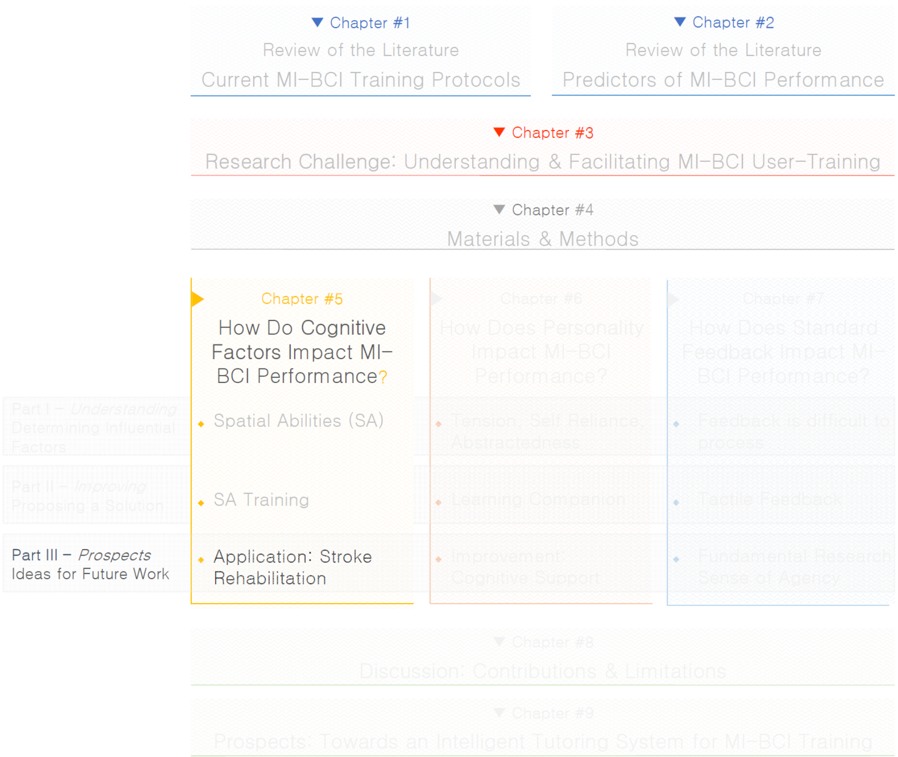
the left-hand motor-imagery task, FT8 for the mental rotation task and finally F3/Pz were the most solicited channels for the mental-subtraction task. The selection of these electrodes is in line with the literature. Statistical analyses results suggest that for the left-hand motor-imagery, participants of SA and VC groups solicit electrodes close to C4 at the end of the training process ; for the mental subtraction task, only the participants of the SA group diminish the distance of their most solicited electrode to F3 or Pz during the training.

Before going into further details, it should be reminded that these results were obtained on small samples (7 to 9 participants per group) and should therefore be considered with caution.

Nonetheless, it is interesting to note that despite the absence of a linear correlation between SA progression and MI-BCI performance, the duration of the SA training has an impact of MI-BCI performance. A further investigation of the appropriate duration of an SA training that would enable a skill transfer to MI-BCI is required. Also, as a future work, the brain regions solicited during an SA training should be investigated. I would also be interesting to evaluate the evolution of the brain patterns along the training process. Furthermore, given the high variability in terms of solicited electrodes over the sessions, it seems important to use different classification methods and performance measures in the future. Also, if metrics allowed to link specific brain-patterns (e.g., the solicitation of specific electrodes) to MI-BCI performance, we would be able to provide users with some kind of cognitive feedback. Let us take the example of the mental subtraction task. Burbaud et al., 1999, explain in their paper that when the subtraction is performed with calculation, frontal and parietal areas are triggered; while when it is performed without calculation, mainly frontal areas (and especially Broca) are triggered. If it appears (this is only an example) that a parietal activation correlates to MI-BCI performance, then we can hypothesise that performing a calculation is more efficient than not performing a calculation. As a consequence, users could be guided to this process and provided with more difficult subtractions (that would force them performing a classification, potentially improving their MI-BCI performance). More details about the possibility of providing users with a cognitive feedback are provided in Section 6.6.

PART III - PROSPECTS: TOWARDS THE INCLUSION OF A SPATIAL ABILITY TRAINING IN MI-BCI BASED STROKE REHABILITATION PROCEDURES.

ROADMAP -



QUICK SUMMARY -

In this section, we argue that SA training could benefit MI-BCI based stroke rehabilitation. Therefore, we first explain the rationale of MI-BCI based stroke rehabilitation and we consequently elaborate on the fact that training SA could potentially help patients feel better during the rehabilitation process.

COLLABORATORS -

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Dr. Bertrand Glize (Ph.D-M.D) & Pr. Pierre-Alain Joseph (Ph.D-M.D)
Eric Sorita (Ph.D, Ergotherapist)

5.7 A SHORT REVIEW OF STROKE REHABILITATION: FOCUS ON MI-BCI BASED STROKE REHABILITATION PROCEDURES

A stroke is caused by the blood supply to specific regions of the brain being cut off, which in turn induces an inflammatory reaction in the surrounding areas, and consequently a deterioration of the functions related to those areas (i.e., cognitive, motor and emotional functions). A stroke can be classified as either haemorrhagic (if it is due to the rupture of an artery) or ischemic (if it is due to the occlusion of an artery), the latter being the most frequent (around 85% of all strokes are ischemic - Deb, Sharma, and Hassan, 2010). Stroke rehabilitation represents a major challenge: strokes are the third cause of disability world-wide (Feigin et al., 2014) and more than half of stroke patients subsequently become dependent for daily-life activities (based on the *Intercollegiate Stroke Working Party* report, 2012). Indeed, as stated earlier, stroke often reults in cognitive and motor deficits. Diverse cognitive deficit types can be observed (Rode, Jacquin-Courtois, and Yelnik, 2008): lesions located in the left hemisphere are likely to result in aphasia or apraxia while right-hemisphere lesions are often associated with hemineglect; moreover, bilateral lesions can result in attention and memory deficits. On the other hand, concerning motor after-effects, patients can suffer from various degrees of hemiparesis of the side of their body opposite the lesion; also, the upper limbs (arms and hands) are often affected.

Several procedures can be used for upper limb rehabilitation. First, *Physical Practice* has been shown to be beneficial for the clinical improvement of patients in a chronic phase (Gaggioli et al., 2006; Johnson-Frey, 2004; Liu et al., 2004; Page et al., 2001; Stevens and Stoykov, 2003). A specific type of physical practice is the *Task Repetition Technique* which consists in repeatedly performing the same sequence of movements so that its execution is improved (O'Dell, Lin, and Harrison, 2009. However, in the context of upper-limb motor recovery, no formal proof of the efficiency of this technique for patients in sub-acute or chronic phases exists. On the contrary, *Constraint-Induced Movement Therapy* (CIMT) has been scientifically validated in a study including 222 patients (Wolf et al., 2006): patients who followed CIMT showed significant clinical improvement of their symptoms. This method consists in immobilising the *healthy* limb almost all day-long and practising rehabilitation tasks such as prehension movements, distal thumb-index pinch and precise target-reaching for at least 6 hours a day in order to solicit the impaired limb as much as possible.

Over the last few years, the exponential development of robotics and artificial intelligence has enabled the emergence of new paradigms for stroke rehabilitation, such as Robot-Assisted Therapy which consists in the patient performing movements (i.e., doing physical practice) constrained by an electro-mechanical system. The use of robots aims to provide patients with a proprioceptive feedback (which should favour brain plasticity processes).

All the techniques introduced here-above require the patient to perform movements. Yet, many patients do not present any residual movements at all. For these patients, MI-BCI based rehabilitation could be useful. Indeed, MI-BCI enable attempted movements to be detected in the patient's brain-activity, which could not be otherwise detected by the therapist. Then, the patient can be provided with appropriate feedback, synchronised with their attempted movement. Until now, two modalities have been proposed for this feedback: visual (in the shape or bar/cursor, like in standard MI-BCI paradigms, or as a virtual representation of an arm) and proprioceptive (most of the time using a brace or a robotic arm).

A review of the literature of MI-BCI based stroke rehabilitation is proposed in Ang and Guan, 2015. To summarise, experimental results tend to support the efficiency of MI-BCI to improve stroke rehabilitation. More precisely, it seems that the feedback provided by such technologies, which is consistent and synchronised with the performed motor (or motor-imagery) tasks, enables a better recovery of motor functions than MI alone. In the following section, we argue that incorporating SA training in the MI-BCI based rehabilitation process may enable to improve the rehabilitation procedure by taking the patient's well-being into account.

5.8 HOW TRAINING SPATIAL ABILITIES COULD ENABLE MI-BCI BASED STROKE REHABILITATION PROCEDURES TO BE IMPROVED.

In this Chapter, we demonstrated that having high spatial abilities enables users to perform better at MI-BCI, supposedly because it facilitates the production and manipulation of mental images. It has also been shown, as stated in the literature, that training spatial abilities triggers the motor-cortex (Windischberger et al., 2003).

On the other hand, MI-BCI based stroke rehabilitation has been shown to be related to valuable advantages, but also some drawbacks. The advantage of this procedure is that it allows therapists to visualise, in real time, representations of the patient's brain activity, but also provides the patient with sensorimotor feedback in real-time (while he is performing the task) in order to *close the sensorimotor loop*. This feedback is supposed to favour brain plasticity processes which in turn lead to motor recovery. Along this procedure, as is the case in more standard rehabilitation procedures, the patient is asked to perform (or attempt to perform) movements with their disabled arm. In a personal communication, Reinhold Scherer explained that this process, while having been proved efficient for motor recovery, does not take into account the well-being of patients. Indeed, these patients are often fragile, and often suffer from depression after their stroke.

Reminding them, repeatedly, during the training process of the fact that they have lost the ability to move their limb is likely to enhance their depressive state.

Therefore, it would seem most appropriate to offer a different kind of task, non-motor tasks, that could trigger the motor cortex without risking a negative impact on the patient's well-being. Spatial ability tasks such as the ones introduced in this chapter could be used as they are underlain by an activation of the motor-cortex and do not require the patient to be asked to move their limbs. Thus, a rehabilitation procedure in which reduced motor tasks are alternated with spatial ability tasks may be effective, especially at the beginning of the process (when patients do not have any residual movements).

Of course, this training process should be adapted to each patient. Indeed, some personality profiles prefer a direct rehabilitation process: they want to recover mobility of their arm so they try to move their arm and are not interested by other exercises they do not understand the point of. On the contrary, some patients are prone to depression and do not want to be constantly reminded that they cannot move their limb. For them, indirect rehabilitation procedures leading to motor recovery might be more adapted.

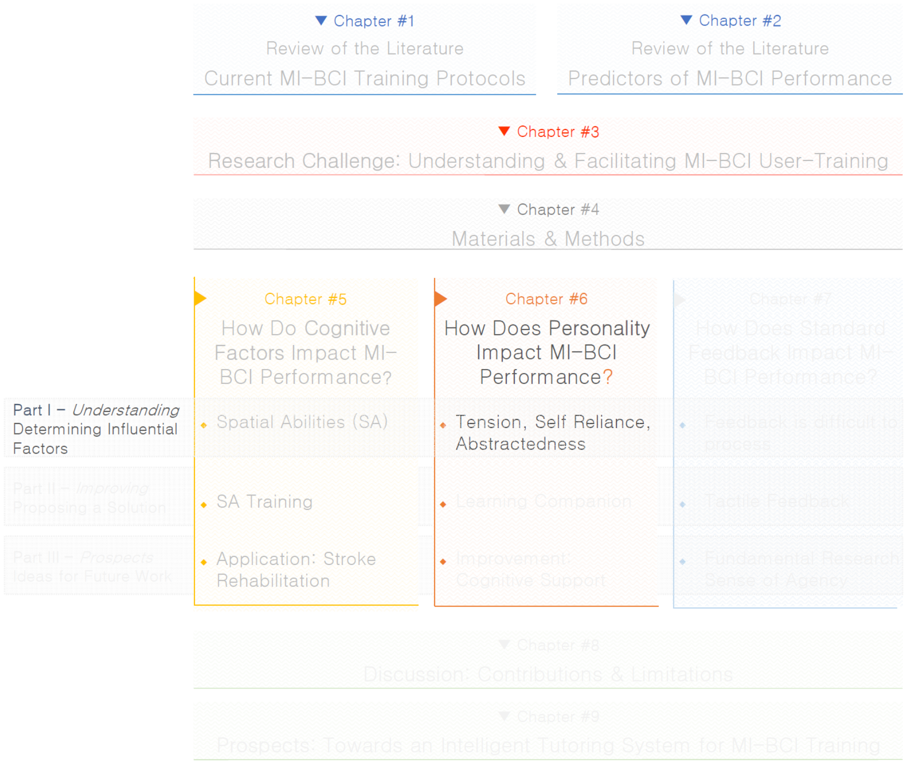
6 CONSIDERING PERSONALITY TO UNDERSTAND & IMPROVE MI-BCI USER-TRAINING.

6.1 RESEARCH QUESTION

As stated in Chapter 5, one of the main objectives of this project was to investigate potential predictors of MI-BCI performance with the view of improving MI-BCI user-training based on these predictors. The previous Chapter revealed that Spatial Abilities are one such predictor related to the user's cognitive profile. In addition to their cognitive profile, users' personality was investigated in our study, along with the relationship between personality and MI-BCI control abilities (Jeunet, 2015). Indeed, personality has repeatedly been shown to impact both people's ability to acquire knowledge and the manner in which they acquire it (Cattell and Cattell, 1995). It thus seems necessary to understand which personality factors impact users' control abilities so that we are able to adapt the training process accordingly.

PART I - WHICH PERSONALITY FACTORS INFLUENCE MI-BCI USER TRAINING?

ROADMAP -



QUICK SUMMARY -

We performed a study on 18 participants following a 6 session-long MI-BCI training. They trained for 3 MI-tasks: mental rotation, mental subtraction, left-hand motor-imagery. They were also asked to complete psychometric questionnaires. Using a linear regression, we determined a predictive model of MI-BCI performance (R^2_{adj}=0.809, p⩽0.001) including 4 personality traits: tension, self-reliance, abstractedness and the learning style (active vs. reflective).These dimensions are described and the model is discussed.

COLLABORATOR -

Morgane Sueur (Master Student).

RELATED PAPERS -

-1- Jeunet, C., N'Kaoua, B., Subramanian, S., Hachet, M., and Lotte, F. (2015). 'Predicting Mental Imagery-Based BCI Performance from Personality, Cognitive Profile and Neurophysiological Patterns.' In: *PLOS ONE* 10.12, e0143962.
[please refer to Chapter 5 for other aspects, related to cognitive factors]
-2- Jeunet, C., N'Kaoua, B., Hachet, M., and Lotte, F. (2015). 'Predicting Mental-Imagery Based Brain-Computer Interface Performance from Psychometric Questionnaires.' In: *womENcourage'15*.

6.2 STUDY 1 - HOW DOES PERSONALITY IMPACT MI-BCI CONTROL ABILITIES?

The study introduced below is the same one as the study introduced in Chapter 5, Section 5.2 (Jeunet et al., 2015b). This study aimed at understanding the impact of the user profile, notably personality and cognitive profile, on MI-BCI performance. The Chapter 5 focused on the cognitive profile and more specifically on spatial abilities. In this section, the focus is on personality factors and on their complementarity with spatial abilities to explain MI-BCI performance. Also, both Section 5.2 and this section relating the results resulting from the same study, some redundancies with former Section will appear: the reader will be notified of these redundancies at the beginning of the paragraphs.

6.2.1 *Materials & Methods*

6.2.1.1 *Participants*

As introduced in 5.2.1, 18 BCI-naive participants (9 females; aged 21.5 $\pm$ 1.2) took part in this study, which was conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki. This study was also approved by the legal authorities of Inria Bordeaux Sud-Ouest (the COERLE, approval number: 2015-004) as it satisfied the ethical rules and principles of the institute. All the participants signed an informed consent form at the beginning of the experiment and received a compensation of 100 euros at the end. Furthermore, in the aim of avoiding confounding factors, age [21.5 $\pm$ 1.2 year old] and educational level [14.5 $\pm$ 1.8 years of education] were controlled, which means that the ranges of these variables were low: participants were in the [20;25] year old interval and were studying at the University, for a Bachelor or Master degree. All of the participants were healthy and right handed (Harris lateralisation test - Harris, 1958).

6.2.1.2 *Experimental Paradigm*

Please refer to Figure 20.

6.2.1.3 *Variables and Factors*

The aim of this study was to evaluate the impact of personality factors on MI-BCI performance in healthy participants in order to propose a model that could predict MI-BCI performances. Thus, the effect of the scores obtained at different neuropsychological questionnaires on the variable “MI-BCI classification performance" was evaluated.

EXPERIMENTAL PARADIGM	
This experiment was composed of 6 mental-imagery based BCI sessions of 2.00 hours each. Each session was divided into 5 runs, with 45 trials per run.	
EVALUATIONS	
PSYCHOMETRIC EVALUATIONS	*Personality assessment* ▼ Learning Style Inventory ▼ 16 Personality Factors-5 ▼ Internal, Powerful others and Chance scale *Cognitive profile assessment & Cognitive State measure* ▼ Several others tests had been performed. They are depicted in Section 5.2.1, but are not relevant for this Section.
NEUROPHYSIOLOGICAL EVALUATIONS	▼ Several neurophysiological tests had been performed. They are depicted in Section 5.2.1, but are not relevant for this Section.
BCI EXPERIMENTS – TRAINING PROTOCOL	
TRAINING TASKS	▼ Left-Hand Motor Imagery ▼ Mental Subtraction ▼ Mental Rotation
FEEDBACK	▼ *Modality:* Visual [standard Graz blue bar feedback] ▼ *Update Frequency:* 16Hz ▼ *Content:* Only positive
TRAINING ENVIRONMENT	▼ Standard Graz Training Environment, adapted for 3 classes
BCI EXPERIMENTS – BRAIN SIGNAL RECORDINGS & PROCESSING	
HARDWARE & EEG SET-UP	▼ g.USBamp amplifier (g.tec, Graz, Austria) ▼ See the list in the Materiels & Methods Chapter ▼ Referenced to the left ear, grounded to Afz ▼ Sampling of the EEG data: 256Hz
SIGNAL PROCESSING PIPELINE	▼ Band-pass filtering of the EEG data: 8-30Hz *Session 1: the classifier & CSP are trained on the run 1* ▼ 3 CSP «one class vs. the others» → 12 band-power features ▼ Combination of 3 sLDA in a one-versus-the-rest scheme ▼ Use of the resulting classifier to discriminate between the 3 tasks for the runs 2 to 5 *Sessions 2 to 6* ▼ Run 1 with the classifier trained during Session 1 ▼ Re-computation of the sLDA's bias ▼ Use of the resulting classifier to discriminate between the 3 tasks for the runs 2 to 5

Figure 20 – Materials & Methods of the Study 1 of Section 6.2

6.2.1.4 *Analyses*

During each of the 6 sessions, participants performed 5 runs. However, as the classifier was updated after the first run of each session, we only used the 4 last runs (of each session) for the analyses. Thus, we considered 360 trials (15 trials x 4 runs x 6 sessions) per mental task, i.e. 1080 trials (360 x 3 MI-tasks) for each of the 18 participants. The psychometric-test results were analysed using SPSS (http://www-01.ibm.com/software/analytics/spss/) in order to find a relevant model of MI-BCI performance predictors. In particular, correlation analyses and (step-wise) linear regressions were computed as descriptive analyses. Then, leave-one-subject-out cross-validation tests were performed in order to evaluate the predictive power and the stability of the models.

6.2.2 *Results*

6.2.2.1 *Mental-Imagery Task Performance*

As a reminder (all the results in this paragraph having been reported in Section 5.2), eighteen participants took part in this experiment. The data of one outlier participant were rejected since, with a mean performance of 67.21%, he outperformed (by more than two SDs) the group's mean performance over the six sessions ($\bar{X}_{group}$ = 52.50%; *SD* = 5.62). Thus, the following analyses were based on the data of 17 subjects.

Over the six sessions, participants achieved a mean performance of $\bar{X}$ = 51.63% (*SD* = 4.39; *range*: [43.04, 60.14]). All the participants obtained performances higher than chance level, this chance level being estimated to be 37.7% of correct classification accuracy for three classes and more than 160 trials per class and α=5% (Müller-Putz et al., 2008). For more details about the performance per session, please report to Section 5.2.2. No gender effect [t_{15} = -1.733, p = 0.104] was noticed.

6.2.2.2 *Correlations between Performance and Psychometric Tests*

Bivariate Pearson correlation analyses revealed correlations between MI-BCI performance and (1) Mental Rotation scores [r = 0.696, $p <$ 0.005] (as stated in Chapter 5), (2) Tension [r = -0.569, $p <$ 0.05], (3) Abstractedness ability [r = 0.526, $p <$ 0.05] and (4) Self-Reliance [r = 0.514, $p <$ 0.05] (see Fig. 21). Tension, abstractedness and self-reliance were assessed by the 16 PF-5. High tension scores reflect highly tense, impatient and frustrated personalities. The Self-Reliant trait, also called self-sufficiency, reflects the learners' ability to learn by themselves, i.e., in an autonomous way. Finally, abstractedness refers to creativity and imagination abilities. Among these four factors, only the Mental Rotation score reached significance after the Positive False Discovery Rate correction for multiple comparisons [$p <$ 0.05] (Noble, 2009).

6.2.2.3 *First Predictive Model of MI-BCI Performance:* MODEL ♯1

A Step-Wise Linear Regression was used in order to determine a predictive model of each user's average MI-BCI performance obtained across the different training sessions. To reduce the dimensionality of the problem (and thus avoid the Curse-of-Dimensionality - Friedman, 1997), while all the psychometric test scores were used (43), only the neurophysiological predictors introduced in Section

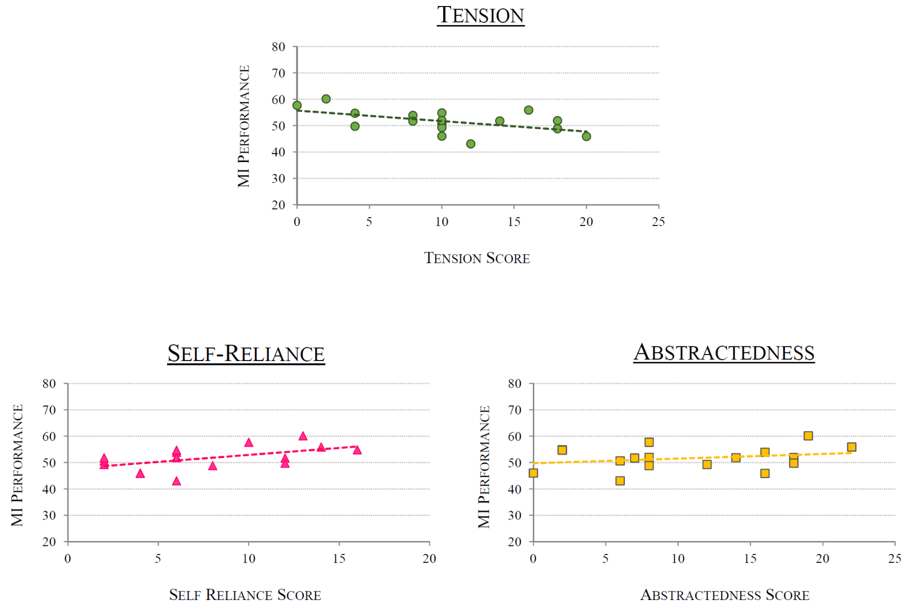


Figure 21 – MI-BCI Performance as a function of personality profile - Graphs representing the participants' MI-BCI performances as a function of (1) Tension -top-, r=-0.569; (2) Self-Reliance -bottom left-, r=0.514; (3) Abstractedness -bottom right-, r=0.526.

5.2.2 (and summarised in Figure 9) which were correlated with MI-BCI performance before the pFDR (20 out of ±280 neurophysiological patterns) were used as potential explanative variables in the regression. This regression resulted in a first model, called Model ♯1, including six factors [$R^2_{adj} = 0.962$, $p < 0.001$] (see Fig. 22): Mental Rotation score, Self-Reliance, Memory Span, Tension, Apprehension and the "Visual/Verbal" subscale of Learning Style . Model ♯1 explains more than 96% of the performance variance of the dataset.

In order to evaluate (1) the stability and (2) reliability of Model ♯1, step-wise linear regressions were then performed using a leave-one-subject-out cross validation process. During the *first step*, 17 models were generated, each of them based on the data of all the participants except one (i.e., the training dataset). This *first step* allowed to assess the *stability* of the model by comparing the factors included in each of the models to the ones included in Model ♯1. During the *second step*, each of these models was tested on the only participant not included in the respective training datasets (i.e., the testing dataset). This *second step* aimed at determining the *reliability* of the models. Each model generated from the training dataset enabled to determine a predicted performance as well as a confidence interval for the corresponding testing dataset. This testing dataset used the participant's scores obtained at the psychometric tests that were included as factors in the respective training model. The model was considered reliable when the real preformance fell within the predicted confidence interval.

Model #1

R	R²	R² adjusted	Standard Error
0.988	0.976	**0.962**	0.859

	Non Stand. coefficients		Stand. Coefficients	T	Sign.
	A	*Standard Error*	*B*		
(Constant)	34.089	3.772		9.037	.000
Mental Rotation	.468	.036	.858	13.064	.000
Self-Reliance	1.749	.171	.677	10.202	.000
Memory Span	-1.042	.232	-.272	-4.487	.001
Tension	-.430	.111	-.239	-3.889	.003
Apprehension	.836	.155	.452	5.411	.000
LSI visual verbal	.260	.086	.206	3.040	.012

Figure 22 – Characteristics of Model #1 - This model included 6 factors: Mental Rotation, Self-Reliance, Memory Span, Tension, Apprehension and the "Visual/Verbal" dimension of the Learning Style. It enabled to explain 96.2% participants MI-BCI performance variance [R^2_{adj} = 0.962, $p < 0.001$]

The first step of the leave-one-subject-out cross validation process revealed the instability of Model ♯1. Indeed, only 5 out of 17 models included the same factors as Model ♯1. In 11 out of 17 models, 2 or more factors were different from Model ♯1. More specifically, the cross validation resulted in 13 different models for the 17 training datasets, with 27 different factors included in the different models. Among these 27 factors, 17 were present in only 1 or 2 models out of the 17.

The second step consisted in testing these 17 models on their respective testing datasets, i.e., on the only participant not included in each training dataset. Results revealed that the real performance of 9 out of 17 participants fell within the predicted confidence interval, with an absolute mean error ($Perf_{predicted}$ - $Perf_{real}$) of 2.68 points (*SD* = 2.37, *range*: [0.38, 8.98]).

6.2.2.4 *Second Predictive Model of MI-BCI Performance:* Model ♯2

In Model ♯1, the mental rotation factor was selected first in the regression and highly correlated with performance (r=0.696), which demonstrates its strong influence on the model. While being consistent with the nature of the tasks performed by the participants, this strong influence was likely to hide the effect of other important factors (Derksen and Keselman, 1992; Whittingham et al., 2006). Consequently, a second regression analysis was performed without the mental rotation variable. It resulted in a model, called Model ♯2 [R^2_{adj}=0.809, $p < 0.001$], described in Fig. 23 and including 4 parame-

Model #2

R	R²	R² ADJUSTED	STANDARD ERROR
0.925	0.857	**0.809**	1.919

	NON STAND. COEFFICIENTS		STAND. COEFFICIENTS	T	SIGN.
	A	*STANDARD ERROR*	*B*		
(CONSTANT)	46.783	2.472		18.928	.000
TENSION	-1.320	.227	-.733	-5.816	.000
ABSTRACTEDNESS	.863	.227	.458	3.806	.003
ILS ACTIVE/REFLECTIVE	.723	.175	.527	4.172	.001
SELF-RELIANCE	.853	.340	.330	2.250	.027

Figure 23 – Characteristics of MODEL #2. This model included 4 factors: Tension, Abstractedness, the "Visual/Verbal" dimension of the Learning Style and Self-Reliance. Abstractedness, the "Visual/Verbal" dimension of the Learning Style and Self-Reliance had positive weights. Tension was the only factor to have a negative weight. This model enabled to explain 80.9% of MI-BCI performance variance [R^2_{adj}=0.809, $p < 0.001$].

ters: Tension, Abstractedness, the Learning Style "Active/Reflective" subscale and Self-Reliance. Tension, Abstractedness and Self Reliance were assessed by the 16 PF-5, whereas the "Active/Reflective" dimension is a subscale of the Learning Style Inventory.

As was done for MODEL #1, the stability and reliability of MODEL #2 were assessed using a leave-one-subject-out cross validation process. Results are detailed in Fig. 24 which presents each training dataset, *all\XX* meaning that the training dataset was composed of all the participants except XX. The factors included in the model as a function of the dataset considered, as well as the R^2_{adj} value of each model are also shown.

The first step allowed to evaluate the stability of MODEL ♯2. The same process as the one introduced in the previous section was used: 17 models were generated from the 17 training datasets, each of them including the data of all the participants except one. Results revealed that among these 17 models, 10 included exactly the same factors as the ones included in MODEL ♯2: Tension, Abstractedness, the "Active/Reflective" Learning Style subscale and Self-Reliance. In 5 out of the 7 remaining models, only one factor, Self-Reliance, was missing. Finally, one training dataset (all\23) induced a model including all the parameters present in MODEL ♯2 plus the Power dimension of the Locus of Control and the Matrix subscale of the WAIS-IV, while in another dataset (all\28), Tension, Abstractedness and the Digit Span subscale of the WAIS-IV were included.

Training DataSet	Step-Wise Linear Regression Model								$R^2_{adjusted}$
	Constant	Tension	Abstractness	LSI active / reflective	Self-Reliance	IPC Power	WAIS-IV Matrix	WAIS-IV Digit Span	
all \ 12	44.656	- 1.364	+ 1.220	+ 0.731	+ 0.787				0.813
all \ 13	46.085	- 1.298	+ 0.875	+ 0.711	+ 0.931				0.812
all \ 14	47.445	- 1.206	+ 0.748	+ 0.629	+ 0.854				0.841
all \ 15	47.183	- 1.366	+ 0.823	+ 0.719	+ 0.864				0.814
all \ 16	50.951	- 1.445	+ 1.069	+ 0.597					0.735
all \ 17	51.049	- 1.579	+ 1.141	+ 0.644					0.754
all \ 18	51.102	- 1.482	+ 1.103	+ 0.663					0.781
all \ 19	46.931	- 1.354	+ 0.888	+ 0.748	+ 0.832				0.807
all \ 21	51.857	- 1.494	+ 0.981	+ 0.570					0.745
all \ 22	46.553	- 1.321	+ 0.878	+ 0.724	+ 0.860				0.814
all \ 23	45.000	- 1.588	+ 0.620	+ 1.055	+ 1.697	+ 0.251	- 0.307		0.953
all \ 24	46.756	- 1.306	+ 0.868	+ 0.717	+ 0.844				0.779
all \ 25	46.342	- 1.282	+ 0.825	+ 0.740	+ 0.915				0.807
all \ 26	46.421	- 1.269	+ 0.872	+ 0.725	+ 0.842				0.778
all \ 27	50.703	- 1.461	+ 1.128	+ 0.665					0.745
all \ 28	60.170	- 1.461	+ 1.300					- 1.248	0.805
all \ 29	46.818	- 1.246	+ 0.821	+ 0.689	+ 0.817				0.755

Figure 24 – The 17 models generated from leave-one-subject-out cross validation process. The coefficients for each factor that was included in the model generated from the training datasets (*all**XX* meaning that the training dataset was composed of all the participants except XX) are detailed in each row.

The second step allowed to determine the reliability of Model ♯2. It consisted in testing each model on the corresponding testing dataset, i.e., on the only participant whose data were not included in the training dataset. The results of this second step are detailed in Fig. 25. This figure shows, for each participant (i.e., each testing dataset), (1) real mean MI-BCI performance across the 6 sessions, (2) predicted performance, with its associated confidence interval and (3) the error of the model, i.e., $\mathtt{Perf}_{\mathtt{predicted}}$ - $\mathtt{Perf}_{\mathtt{real}}$. The average size of the confidence interval was 9.89% and the mean value of the absolute model error was 2.87%. The real performance of 14 out of 17 participants fell within the confidence interval, while the real performance of the 3 remaining participants, S14, S23 and S28, was lower than predicted.

In order to ensure that the successful prediction of BCI performance using the personality and cognitive profiles of the users was not due to chance, a permutation test was performed. The aim of this test was to estimate the true chance level in mean absolute error given our data. To do so, the first step consisted in randomly permuting the mean BCI performances of the training subjects (still using a leave-one-subject-out cross validation). The second step consisted in using the step-wise linear regression to obtain a model predicting the (random) performances of these training subjects from their

	Training DataSet	Testing DataSet	Real Performance	Predicted Performance	Confidence Interval	Error (Predicted - Real)	Mental Rotation Test Score
WOMEN	all \ 12	12	46.02	41.81	[35.16 ; 48.47]	-4.21	19
	all \ 13	13	50.61	49.02	[44.18 ; 53.87]	-1.59	22
	all \ 14	14	43.04	47.64	[43.87 ; 51.41]	4.60	5
	all \ 15	15	51.87	50.22	[45.41 ; 55.03]	-1.65	21
	all \ 16	16	54.79	52.62	[47.44 ; 57.80]	-2.17	19
	all \ 17	17	48.83	45.61	[40.22 ; 51.01]	-3.22	21
	all \ 18	18	49.27	53.25	[48.44 ; 58.06]	3.98	27
	all \ 19	19	53.87	55.16	[50.45 ; 59.87]	1.30	19
MEN	all \ 21	21	55.86	52.57	[47.13 ; 58.01]	-3.29	31
	all \ 22	22	51.94	50.37	[45.91 ; 54.82]	-1.58	34
	all \ 23	23	51.69	58.74	[55.54 ; 61.64]	7.05	18
	all \ 24	24	45.87	46.16	[40.84 ; 51.48]	0.29	25
	all \ 25	25	54.70	53.41	[48.64 ; 58.18]	-1.29	34
	all \ 26	26	57.70	56.82	[50.95 ; 62.69]	-0.88	35
	all \ 27	27	51.78	54.16	[48.65 ; 59.66]	2.38	29
	all \ 28	28	49.76	57.29	[52.58 ; 62.01]	7.54	20
	all \ 29	29	60.14	58.26	[53.31 ; 63.20]	-1.88	35

Figure 25 – Results of the test of the 17 models generated from the training datasets on their respective testing datasets. The table shows training and testing datasets, the real performance of the testing dataset, the predicted performance of the testing dataset with the corresponding confidence interval, as well as the error of the model. Finally, in the last column the mental rotation score of the participant is outlined.

(real) personality and cognitive profile, in order to simulate a random predictive model. During the third step, this model was used to predict the real BCI performance of the left-out subject. This step was repeated using each subject as the test subject, and the obtained mean absolute error over all subjects was stored. This process was repeated 1000 times, each time with a different random permutation of the subjects' BCI performances, to estimate the performances obtained by 1000 predictive models with chance level accuracy. The obtained mean absolute errors were then sorted over the 1000 permutations in descending order, and the 99-percentile and 95-percentile were assessed to identify the chance level for $p = 0.01$ and $p = 0.05$, respectively. The results indicated that the mean absolute error of 2.87 that we obtained was better than chance with $p < 0.01$. This means our model can indeed generalise to new subjects and predict their MI-BCI performances from their personality and cognitive profile.

6.2.2.5 *Relationship between* Model #2 *and Mental Rotation Scores*

Figure 26 outlines women's results on top and men's results on the bottom at both the MI-tasks (left) and mental rotation test (right). First, graphs on the left represent each participant's real (left) and predicted (right) performance for each participant, with the corre-

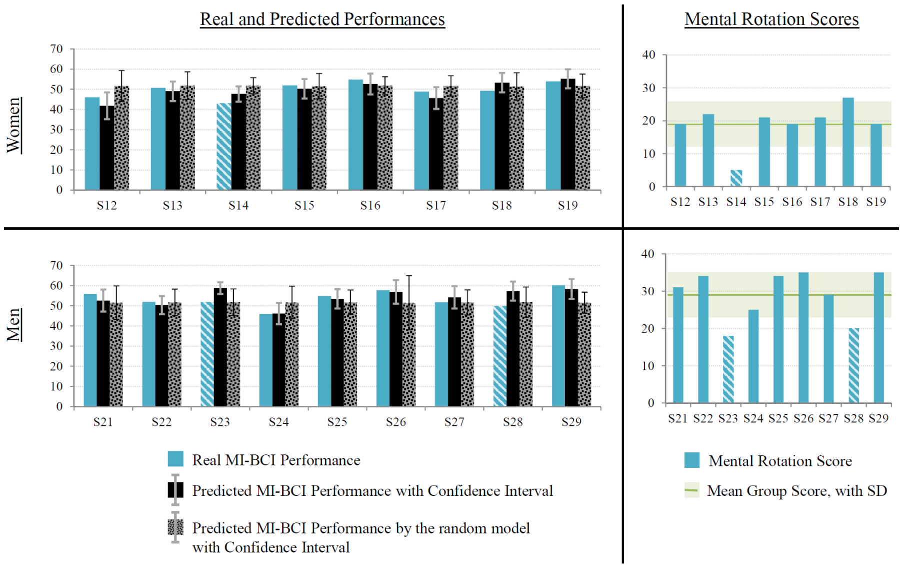


Figure 26 – Real and predicted BCI performance as well as Mental Rotation scores according to the gender. Women's results are shown at the top, men's results on bottom. On the left, the graphical representation of the real (left) and predicted (right) BCI-performance of each participant, with the corresponding confidence intervals. On the right, the mental rotation scores of each participant with the horizontal line representing the mean score of the group. The three participants for whom the model overrated the performance are those with the lowest mental rotation scores (striped participants).

sponding confidence intervals. These graphs show that the real performance value of 14 out of 17 participants fell within the predicted confidence interval, while it was lower for only 3 participants: S14, S23 and S28. Second, graphs on the right represent the Mental Rotation scores for all the participants. Women and men were separated due to the important gender effect associated with this test (Vandenberg and Kuse, 1978). Women's mean score is 19.13/40 (*SD*: 6.29, *range*: [5, 27]). Men's mean score is 29/40 (*SD*: 6.56, *range*: [18, 35]). Women's and men's mean scores are represented as a horizontal line on the graphs on the right of Fig. 26. The rectangle surrounding this line represents the mean $\pm$ 1SD interval. Only 3 participants, one woman and two men, are below this interval: S14, S23 and S28.

It is noticeable that the same participants, i.e. S14, S23 and S28, (1) had lower real MI-BCI performance than the one predicted by the model and (2) had lower mental rotation scores than the average.

6.2.3 *Discussion*

In addition to the strong correlation between Spatial Abilities and MI-BCI performance, this study revealed interesting performance predictors. Indeed, the Model #1 explained more than 96% of the variance of participants' MI-BCI performance. This model was composed of six factors: mental rotation, self-reliance, visuo-spatial memory span, tension, apprehension and the "visual/verbal" dimension of the learning style. The main flaw of Model #1 was its instability, revealed by the cross validation process. This instability could be due to the important role of the mental rotation factor in the MI-BCI performance prediction. Indeed, its strong correlation with MI-BCI performance could prevent other important factors from being expressed in the regression. Thus, we proposed the Model #2, from which the mental rotation factor was excluded. Model #2 explained more than 80% of MI-BCI performance variance and was composed of four factors: tension, abstractedness, self-reliance and the "active/reflective" dimension of the learning style. This model appeared to be both stable and reliable to predict MI-BCI performance. Finally, the last very interesting result is the complementarity between Model #2 and mental rotation scores. Indeed, the only participants for whom Model #2 failed, by overestimating their performances, were the participants with a very low mental rotation score. These results are discussed in the following paragraphs.

Two personality factors were correlated with MI-BCI performance and are included in both models: *tension* and *self-reliance*. The *tension* dimension reflects highly tense, impatient and frustrated personalities while the *self-reliance* dimension, also called self-sufficiency, reflects the learner's ability to learn by themselves, i.e., in an autonomous way. Both were assessed using the 16 PF-5 questionnaire. MI-BCI performance appeared to be negatively correlated with the *tension* dimension and positively correlated with the *self-reliance* dimension. These factors have been shown to be related to the nature of MI-BCI training which is a *distant learning*, i.e., a learning occurring in a context free of social interaction (the learner interacts with a computer, there are no teachers or students). Indeed, on the one hand, Hara, 2001 showed that learners easily feel confusion, frustration and anxiety when confronted to distant education due to the lack of feedback from an instructor, compared to classic classroom education situations. Therefore, it seems relevant that learners with highly tense personalities encounter difficulties in learning tasks based on distant education such as the one presented in this study. On the other hand, in Moore, 1972, autonomy is presented as being of utmost importance in independent learning, and thus in distant learning. During MI-BCI training, users have to lead important metacognitive processing to identify knowledge and strategies allowing them to optimise their performances. As a consequence, users with low *Self-Reliance* scores may have difficulty when confronted with MI-BCI training protocols, because they need more guidance about strategies and key steps to carry out during a training session. To summarise, it seems users with high “Tension" and low “Self-Reliance" traits may need a social presence and emotional feedback to improve their control performance.

The *abstractedness* dimension of the 16 PF-5 was also correlated with MI-BCI performance and included in MODEL #2. Abstractedness refers to creativity and imagination abilities. It has been reported that creative people frequently use mental imagery for scientific and artistic productions (LeBoutillier and Marks, 2003) which could explain why participants with high abstractedness abilities are better at performing mental imagery.

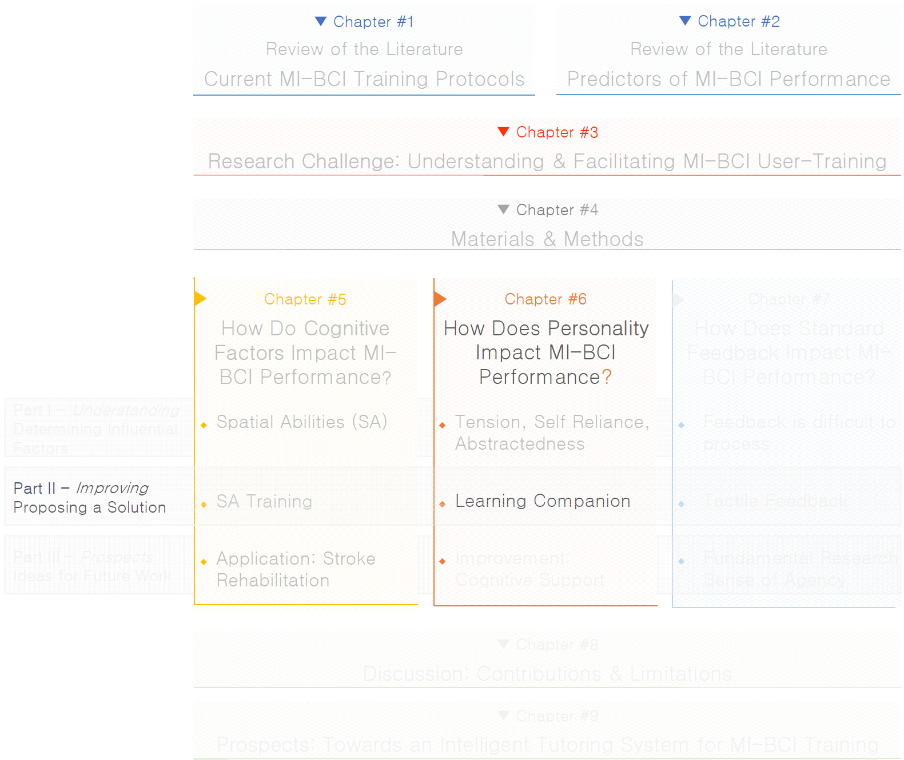
The other factors included in MODEL #1 and MODEL #2 were not (linearly) correlated with MI-BCI performance. First, in MODEL #1, three additional factors were included: memory span (assessed by the Corsi block task), which had a negative impact on performance, apprehension (dimension of the 16 PF-5) and the “Visual/Verbal" subscale of the Learning Style Inventory, both of them having had a positive impact on participants' MI-BCI performance. The instability of MODEL #1 made the inclusion of these factors anecdotal. However, concerning MODEL #2, the last factor, i.e., the “Active/Reflective" dimension of the Learning Style Inventory does not seem to be anecdotal as it was also included in 16 out of the 17 models generated during the cross validation process. This “Active/Reflective" dimension seems to be an important factor even if it is not linearly correlated to MI-BCI performance. Thus, active learners appear to be more efficient in learning to control an MI-BCI. The “Active/Reflective" dimension considers the complex mental process that allows converting perceived information into knowledge. This process can be of two categories: active experimentation or reflective observation (Felder and Silverman, 1988). While active learners like testing and discussing the information, reflective learners need more time to think and examine it introspectively. As stated by Felder and Silverman, 1988, reflective learners need the opportunity and time to think about the information being presented to achieve a good level of performance. Yet, in current standard protocols like the one used in the present study, participants only have four seconds to perform each MI-task proposed. Another characteristic of active learners is the fact they are more effective when they “learn by doing". Yet, Neuper et al., 2005 showed that motor-imagery performances are higher when the subjects use active kinaesthetic movement imagination strategies. It could also explain the positive impact of the “Active" trait on MI-BCI performance.

The final result is of utmost interest and concerns the complementarity of MODEL #2 with the mental rotation score. Indeed, results show that 14 out of 17 participants achieved a real MI-BCI performance that fell within the predicted confidence interval generated from the step-wise linear regression using a cross-validation process. For the 3 other participants, the real performance was below this confidence interval. Yet, these three participants were also the ones with the lowest mental rotation scores. This means that the only times the model failed by overestimating a participant's performance, was when this participant's spatial abilities were significantly lower than average. This result suggests that the factors included in MODEL #2, i.e., tension, abstractedness abilities, the "active/reflective" dimension and self-reliance are highly reliable to predict MI-BCI performance while the user has *normal* to *good* spatial abilities. However, if the user's spatial abilities are too low, this factor's weight being the most influential, it has the upper hand and decreases MI-BCI performance. In this case, the model's overestimation of MI-BCI performance can be anticipated. Considering both MODEL #2 and spatial abilities together has the advantage of taking into account *all* the parameters that seem to impact MI-BCI performance (according to our results).

This model should now be tested on larger and more heterogeneous populations (for instance to have a wider range of performance) in order to confirm (or refute) its validity, and adjust the value of the coefficients associated with each factor. Nonetheless, this model offers promising perspectives for improving MI-BCI training protocols.

PART II - HOW COULD MI-BCI USER-TRAINING BE IMPROVED BASED ON THESE FACTORS?

ROADMAP -



QUICK SUMMARY -

Highly tense and poorly autonomous users struggle when learning to use an MI-BCI. We hypothesised that this could be due, at least in part, to the fact that no emotional support or social presence are provided during MI-BCI user-training. This is why we designed and implemented a learning companion to provide this support, that could be adapted to users' performance and progression. We called it PEANUT, for "Personalised Emotional Agent for Neurotechnology User-Training". We tested PEANUT's efficiency to improve MI-BCI user training, both in terms of performance and user-experience. Results (N=31) showed that participants who were accompanied by PEANUT found the MI-BCI system more usable; also, PEANUT was more appreciated when its behaviour was adapted to users' performance and progression than when it was generic.

COLLABORATORS -

Léa Pillette (Engineering Student) & Boris Mansencal (Engineer).

RELATED PAPER -

-1- Pillette, L., Jeunet, C., Mansencal, B., N'Kambou, R., N'Kaoua, B., and Lotte, F. 'PEANUT: Personalised Emotional Agent for Neurotechnology User-Training.' In: *Submitted*.

6.3 THEORY - WHY TO PROPOSE A LEARNING COMPANION TO FACILITATE MI-BCI USER-TRAINING?

Among the four factors included in the previously-mentioned model, we chose to focus on the Tension and Self-Reliance parameters. As a reminder, we have shown that highly tense and non-autonomous MI-BCI users were struggling using MI-BCI. Such a result could be explained by the fact the MI-BCI training process does lack one aspect of utmost importance for learning: social presence and emotional support (Johnson and Johnson, 2009; Salancik and Pfeffer, 1978). In other HCI fields, and especially in "Distance Learning" applications (i.e., learning without a teacher or classmates, using a computer for instance - Sherry, 1996), the absence of social presence and emotional support has been shown to be efficiently compensated by the use of Learning Companions (Nkambou, Bourdeau, and Mizoguchi, 2010). Learning Companions are virtual or physical characters that can speak and have facial/bodily expressions. They provide the learner with different kinds of interventions in order to overcome the lack of social interactions and induce positive emotions. Indeed, emotions have a significant impact on learning (Meyer and Turner, 2002). Among others, positive emotions, induced by emotional support, can result in increased creativity and flexibility during a problem solving task (Isen, Daubman, and Nowicki, 1987). Despite its potential to improve MI-BCI user-training both in terms of performance and user-experience, the use of a social presence and an emotional support as provided by a Learning Companion has never been explored in this context. Besides, the supportive dimension, which is of utmost importance to favour the learning process according to Shute, 2008, has never been formally investigated in the context of MI-BCI user-training. To our knowledge, only two studies used smiley faces as feedback to maintain motivation along the MI-BCI training (Kübler et al., 2001a; Leeb et al., 2007). More precisely, Leeb et al., 2007 used a cursor with a grey smiley that moves towards the left or the right depending on the task recognised. After each trial, the smiley was becoming green and happy if the trial was successful, sad and red if not. While associated with good results in terms of performance and user-experience, neither of these studies offered a formal comparison with the standard feedback to prove their efficiency.

In this section, we introduce the design, implementation and validation of a learning companion to improve MI-BCI user-training. We called this companion **PEANUT** for *Personalised Emotional Agent for Neurotechnology User-Training*.

We chose to use a learning companion because they can be seen as social actors which are just as capable of influencing users than any other social actor (Nass et al., 1993; Reeves and Nass, 1996). Several research studies have already shown learning companions' positive effect on motivation (Lester et al., 1997), interest towards the task and efficiency while performing the task (Kim, Baylor, and Group, 2006). Also, they have been shown to induce emotions favouring learning (Arroyo et al., 2009). Learning companions can be allocated to different roles, e.g., the learner's associate or a competitor (Chou, Chan, and Lin, 2003). Nonetheless, they should always be on an equal footing with the learner and never have an authoritative attitude (Chou, Chan, and Lin, 2003).

However, while being potentially beneficial when well conceived, inappropriately designed companions can also have a decremental impact on performance and user-experience (Kennedy, Baxter, and Belpaeme, 2015). For instance, discrepancies between users' expectations towards the companion and the latter's real possibilities would lead to a bad perception of the companion (Norman, 1994). Such a situation is likely to happen when the companion's design is realistic while its functionalities are basic (and do not allow it to interact with the learner for instance). As a consequence, the design process of such a companion must be very cautious. Several challenges have to be addressed. On the one hand, the time, frequency, content and style of the interventions (i.e., speech and displayed emotions) should be determined. On the other hand, the appearance of the companion and the consistency of the character (body style and size, face style) with respect to its abilities should be investigated. The whole design process of PEANUT is described in the following sections.

6.4 DESIGN & IMPLEMENTATION OF PEANUT - PERSONALISED EMOTIONAL AGENT FOR NEUROTECHNOLOGY USER-TRAINING.

In the following paragraphs, we will introduce the design process as well as the implementation of PEANUT. The design process was divided into two steps: we first designed PEANUT's behaviour and then its appearance. All the decisions were thoroughly considered based either on a review of the literature, on the analysis of data from previous experiments or on user-studies. The whole process that led to PEANUT is described below.

6.4.1 *Designing the Behaviour of PEANUT*

In order to design a relevant behaviour for PEANUT, different aspects had to be considered:

- Support content - What kind of intervention (sentence & facial expression) should the participant be provided with according to the context (performance & progression)?
- Intervention style - How should the intervention be expressed with respect to the context? In other words, should it be exclam-

atory or declarative; personal (second person) or non-personal (third person)?
- Performance and progression thresholds - What performance should be considered as poor/average/good? What progression should be considered negative/neutral/positive? The relevance of the interventions depends on these thresholds.

6.4.1.1 *Support Content*

The companion's behaviour can be determined based on different elements such as the user's emotional, motivational or cognitive states. Nevertheless, physiological sensor-based emotion and motivation detection being still far from perfect, we chose not to use them for inferring users' state and selecting PEANUT behaviour. As a consequence, the interventions of the companion were solely selected with respect to objective measures: their MI-BCI performance and progression. Hereafter is provided a list of the possible intervention categories Arroyo et al., 2009; Dweck, 2002, the context for which they were selected and their goal. An intervention corresponds to the association of a sentence and a facial expression (see also Figure 27 for an exhaustive description of the intervention selection rules).
- Temporal interventions are related to the temporal progress of the experiment. They are divided into 2 categories, *Temporal-Start* and *Temporal-End*, the goal of which is to greet and say goodbye to the users, e.g., "I am happy to meet you". Both these intervention types were associated with a facial expression of *Joy* for PEANUT.
- Effort-related intervention categories i.e., *General Effort* and *Support Effort*, contain sentences like "Your efforts will be rewarded". Indeed, it seems important to value the efforts that are made by the participant throughout training Dweck, 2002. These sentences focus on the fact that learning is the goal, and are intended to minimise the importance of current performance while promoting long-term learning Woolf et al., 2010. More specifically, General-Effort interventions are more adapted to negative or neutral progression while Support-Effort interventions are appropriate for positive progression. Therefore, General-Effort interventions were associated with *Trust* while Support-Effort interventions were associated with *Joy*.
- The category expressing empathy, i.e. *General-Empathy*, aims at letting users know that their companion understands that they are facing a difficult training process, through the use of sentences such as "Don't let difficulties discourage you" or "I believe in you". Indeed, learning has been suggested to correlate with the amount of empathy and support received Graham and Weiner, 1996. This type of intervention was preferably provided for negative or neutral progression, especially when

combined with bad performance. These interventions were associated with animations ranging from *Sadness* to *Trust*.

— Categories associated with performance/results and progression, i.e. *Results-Good*, *Results-VeryGood* and *Progress-Good*, only target positive performance and progression, e.g., "You are doing a good job!". Sentences in this category were designed to motivate users by focusing on the abilities they had already acquired Jaques et al., 2004. Also, Results-Good and Results-VeryGood were associated to *Joy* and *Admiration*, respectively, while Progress-Good was associated to an animation going from *Surprise* to *Trust*.

— The last category consisted in strategy-related interventions, i.e., *Strategy-Change* and *Strategy-Keep*, with sentences such as "You seem to have found an efficient strategy". These interventions aimed at encouraging people to keep the same strategy when progression was positive or to change strategy when it was negative/neutral. Strategy-Keep was associated with *Joy* while Strategy-Change was associated with an animation going from *Pensiveness* to *Joy*.

6.4.1.2 *Style of the Interventions*

Each intervention could have been provided in different styles, e.g., as an exclamatory or declarative sentence; in a personal (second person) or non-personal (third person) mode. We hypothesised that depending on the context, the users' perception of these different styles could be different. Therefore, we led a user-study to determine the style in which the intervention should be provided, depending on the context. This user-study consisted in an online questionnaire simulating an MI-BCI user-training process.

<u>Materials & Methods</u>
We created 3 questionnaires, each of them simulating an MI-BCI training process in a different context: negative progression, neutral progression, positive progression. Each questionnaire included 8 situations, with two possible interventions for each situation (which resulted in 16 intervention sentences per questionnaire). Each situation corresponded to an MI-BCI task that the participant was asked to perform (left-hand motor imagery, mental subtraction or mental rotation - as explained in Figure 29), followed by feedback indicating the success of the task. After the situation was introduced, two different sentences were displayed on screen. Participants had to rate each of them (on a Likert scale ranging from 1 to 5) based on five criteria: appropriate, clear, evaluative, funny, motivating. The object of this questionnaire was to determine the impact of the *Context* (negative, neutral or positive progression), of the *Type* (exclamatory or declarative) and of the *Mode* (personal or non-personal) on the five dimensions introduced above. Thus, four kinds of sentences were presented in each

context: exclamatory/personal, exclamatory/non-personal, declarative/personal, declarative/non-personal. One hundred and four people answered the online questionnaires. Each of them was randomly allocated to one questionnaire, which makes around 34 participants per *Context*. We led five 3-way ANOVAs for repeated measures, one per dimension, to assess the impact of the *Context* (C_3 - independent measures), *Type* (T_2 - repeated measures) and *Mode* (M_2 - repeated measures) on each dimension.

Results
For the 5 dimensions, the ANOVAs showed *Context*Type*Mode* interactions: appropriate [$F(2,101)=5.861$; $p \leqslant 0.005$, $\eta^2=0.104$], clear [$F(2,101)=21.596$; $p \leqslant 0.001$, $\eta^2=0.300$], evaluative [$F(2,101)=11.461$; $p \leqslant 0.001$, $\eta^2=0.185$], funny [$F(2,101)=4.114$; $p \leqslant 0.05$, $\eta^2=0.075$], motivating [$D(2,101)= 7.854$; $p \leqslant 0.001$, $\eta^2=0.135$]. These results seem to confirm that the *Type* and *Mode* of each intervention should be adapted to the *Context*:

— *Negative progression* - In this context, people definitely prefer declarative and personal sentences that they find more appropriate, clear, funny, motivating and less evaluative.
— *Neutral progression* - Here, people prefer personal sentences, but appreciate as much the declarative and exclamatory sentences for all the dimensions.
— *Positive progression* - In this context, declarative and non-personal sentences are perceived as more clear, appropriate and less evaluative while exclamatory and personal sentences are perceived as more funny and motivating.

Discussion
Based on these results, we chose to provide users facing a negative progression only with declarative personal interventions and those facing a neutral progression with either declarative or exclamatory personal interventions. Finally, depending on the intervention goal, we chose to provide participants showing a positive progression with declarative non-personal sentences (when the goal was to give clear information about the task) or exclamatory personal sentences (when the goal was to increase motivation) (see Figure 27). One should add that when an exclamatory sentence was used for the intervention, the emotion displayed through PEANUT's facial expressions was made more intense than for an equivalent declarative sentence.

These results are rather general and thus may prove useful and relevant beyond this MI-BCI application, for any other training application involving a learning companion, or more generally involving support during a training process. Indeed, exclamatory sentences for instance can be perceived as more aggressive than declarative sentences, and should therefore be avoided in situations of failure. Also, in case of failure, emotional support is very important. Thus, personal sentences should be favoured to make the user feel the companion is really taking care of them. On the contrary, good performers do not consider they really require this support and thus prefer general, non-personal interventions.

6.4.1.3 *Performance and Progression Thresholds*

As previously mentioned, we aimed for PEANUT to provide interventions based on the user's performances and progression. Therefore, we had to determine thresholds of performance/progression delimiting intervals within which specific interventions should be provided. We decided to define 2 performance thresholds delimiting 3 intervals: bad, average and good performance. These thresholds were labelled the "low performance threshold" and the "high performance threshold". Similarly, we determined a "negative progression threshold" and a "positive progression threshold", separating negative from neutral, and neutral from positive progression, respectively. Finally, we had to decide which data to use in order to estimate those thresholds and to ensure that these estimations could reliably predict performance and progression thresholds in subsequent uses of the BCI by the user. To do so, we re-analysed the data from 17 participants Jeunet et al., 2015b who had learned to perform the same three mental tasks as in the present study, over the course of 6 sessions, using the same training protocol (without the companion) as in the present paper (see Section *Experimental Protocol*). A session comprised 5 sequences called runs. A run was divided into trials, the participant being asked to perform a specific mental task during each of these trials. Run 1 of session 1 was used to calibrate the system, i.e., the data collected was used to optimise the BCI. We used classification accuracy as the performance metric for each trial , i.e., the percentage of EEG time windows that were correctly classified as the required mental task for this trial (see Section *EEG Recordings & Signal Processing* for details). In order to estimate the different thresholds, the data was analysed offline with Matlab using the same algorithms as the ones used online (see Section *EEG Recordings & Signal Processing*).

Estimating the Performance Thresholds

To estimate performance thresholds, we constructed the distribution of performance values over trials, and defined the bad and good performance thresholds as the 25^{th} and the 75^{th} percentiles of that distribution, respectively. Thus, the bottom 25% were considered bad performances, the top 25%good performances, and the remaining performances in-between were considered neutral. The question was to assess the feasibility of predicting future performance (and thus thresholds) based on the data collected at the beginning of the training (first run of the first session). Indeed, the sooner we are able to determine the performance thresholds, the sooner we provided the users with interventions adapted to their performance, thus maximising the relevance of these interventions. First, we checked whether we could estimate those thresholds on the first run with BCI use, i.e., on run 2 of session 1 (run 1 being the calibration run). We thus estimated the performance thresholds independently on run 2, and on runs 3, 4 and 5 of session 1 together. We then computed their correlations over participants, to find whether thresholds estimated on run 2 could be used to predict thresholds estimated on run 3, 4, 5. We obtained significant correlations of $r = 0.6422$ ($p < 0.01$) for bad performance thresholds, and of $r = 0.5482$ ($p < 0.05$) for good performance thresholds. The ratio between the thresholds estimated on run 2 and the thresholds estimated with runs 3, 4 and 5 was 1.1525 ± 0.35 and 1.1249 ± 0.22 for bad and good performances, respectively. Thus, in order to select the appropriate behaviour for PEANUT, we used as thresholds for runs 3, 4 and 5 of session 1 the thresholds estimated on run 2 divided by 1.1525 and by 1.1249, for bad and good performance thresholds, respectively. However, thresholds estimated on the data from a single run are bound to be less reliable than thresholds based on several runs. We thus studied whether thresholds estimated on runs 2 to 5 together, could be used to predict the thresholds of the runs of subsequent sessions. They appear to be correlated with $r = 0.6628$ ($p < 0.01$) and 0.4438 ($p = 0.07$ - not significant but a strong trend), and a ratio of 1.2166 ± 0.33 and 0.9971 ± 0.13, for bad and good performance thresholds respectively. Thus, to determine PEANUT's behaviour for subsequent sessions, we estimated the thresholds on runs 2 to 5 of session 1, and divided them by 1.2166 and 0.9971, for bad or good performance thresholds, respectively.

Estimating the Progression Thresholds

To estimate progression thresholds, we used the performances from N successive trials, and computed the slope of a linear regression relating time (here trial indexes) with performance. A positive/negative slope indicated a positive/negative progression, respectively. We then constructed the distribution of these regression slopes over trials, and determined the negative progression threshold as the 25^{th} percentile of this distribution, and the positive progression threshold as the 75^{th} percentile of this distribution. Similarly as for the performance thresholds, we studied whether we could predict the future progression thresholds from their estimation on the first runs. Nonetheless, progression estimation requires more trials than performance estimation (N versus 1). As such there are fewer progression measures in a single run, which in practice made it impossible to reliably predict the progression thresholds of runs 3, 4 and 5 by using run 2 alone for threshold-estimation. However, it appeared to be possible to predict progression thresholds for all the runs of sessions 2 to 6, from the threshold-estimated based on runs 2 to 5 of session 1. In particular, the positive progression threshold appeared to be significantly correlated with both the positive ($r = 0.4843$, $p < 0.05$) and negative ($r = -0.5476$, $p < 0.05$) progression thresholds from the

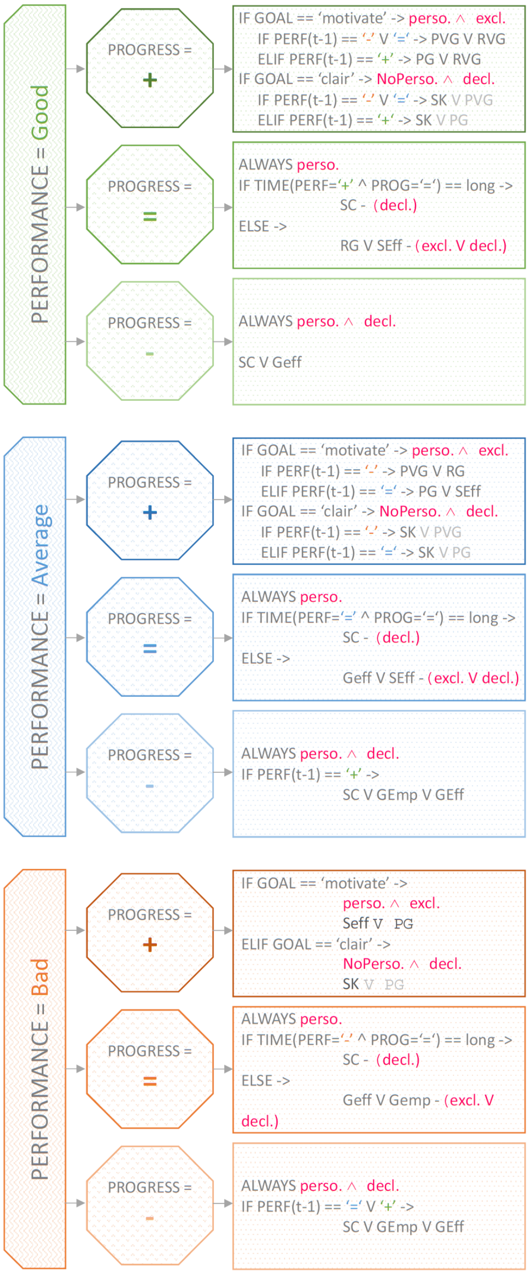


Figure 27 – PEANUT's rule tree. Depending on the performance and progression ("-"=negative, "="=neutral", "+"=positive), a set of rules is determined. Type of sentences: "perso." for personal, "NoPerso." for non-personal ; Mode of the sentence: "decl." for declarative, "excl." for exclamatory. Interventions: "GEff" for general effort, "SEff" for support effort, "GEmp" for general empathy, "SK" for strategy keep, "SC" for strategy change, "RG" for results good, "RVG" for results very good, "PG" for progress good, "PVG" for progress very good. Moreover, "∧" sign represents the logical "and" while "∨" sign represents the logical "or".

subsequent sessions. Their ratio was 0.9628 ± 0.21 and -0.8182 ± 0.17 respectively. Note that these correlations were obtained for $N = 6$. Indeed, we studied N between 2 and 10, and selected the best N as the one maximizing the correlations, to obtain the most reliable thresholds. Therefore, the progression thresholds were estimated by computing the positive progression threshold from runs 2 to 5 of session 1, and dividing it by 0.9628 and by -0.8182 to obtain the positive and negative progression thresholds for the remaining sessions. The companion thus provided progression related interventions only from session 2 onwards. These analyses also guided the selection PEANUT's intervention frequency. Since progression was measured over N=6 trials, we informally tested different intervention frequencies of about one every 6 trials. These informal tests with pilot testers revealed that interventions every 6 ± 2 trials seemed appropriate, as they were neither annoying nor too rare. PEANUT thus intervened at that frequency, the exact trial of intervention being randomly selected in the 6 ± 2 trials following the previous intervention.

6.4.2 *Summary*

Once all the parameters governing PEANUT's behaviour had been determined, we were able to build the rule tree that enables the system to select one specific rule (i.e., an intervention content - sentence & expression - and style) with respect to the context. Figure 27 is a schematic representation of this rule tree: based on a specific performance and progression, it will execute a set of rules to select the appropriate intervention.

6.4.3 *Physical Appearance of PEANUT*

The following paragraphs relate the design process of PEANUT's body and facial expressions. While the former relies on a review of the literature, the latter was based on a user-study.

6.4.3.1 *PEANUT's Body*

The literature guided our choice towards the use of a physical companion which would increase social presence in comparison to a virtual companion Hornecker, 2011; Schmitz, 2011. Also, it seems that the use of anthropomorphic features facilitates social interactions Duffy, 2003. Moreover, for the companion to be relevant, the combination of physical characteristics, personality/abilities, functionalities and learning function had to be consistent. For instance if a learner's expectations of the companion are too high, due to a very realistic design for instance, motivation and credibility can be impacted negativelyNorman, 1994. Therefore, we were inspired by TEEGI Frey et al., 2014b and TOBE Gervais et al., 2016, two avatars aiming at providing users with tools to explore their inner state (EEG and physiological data, among others). Since their functions are simple and they are unable to interact with the user, their designers chose to propose cartoon-like characters with anthropomorphic child-like shapes. The functionalities of our companion being basic as well (reaction to performance/progression through a simple intervention: a sentence associated with a facial expression), we also decided to design a cartoon-like companion rather than a realistic one. Thus, we used the voice of a child to record PEANUT's interventions (which also enabled us not to associate PEANUT with a gender). Furthermore, we had to take into account our own constraints deriving from the size of the smartphone we used to display PEANUT's face and the learning environment. Indeed, the smartphone we chose was very large (around 150*75 mm) so the head had to be quite large. This might not be a problem though, as children also have a bigger head and baby-like shapes can induce positive emotions through our design Um et al., 2012. Finally, concerning the size of the companion, since PEANUT was on the desk right next to the computer screen that the feedback was displayed on, its proportions had to be suitable: not too small so that the body was proportional to its face, and not too large so that it could always be within a user's field of view without concealing the screen. This process resulted in a 30 cm high companion, see Figure 29.

6.4.3.2 *Facial Expressions of PEANUT*

Based on the results of PEANUT's behaviour design, we wanted the companion to be able to express eight emotions: Trust, Joy, Surprise, Admiration, Boredom, Sadness, Anger and a Neutral expressions. We asked a designer to create three styles of faces (see Figure 28). We wanted the faces to be cartoon-like, so that they fit the body and complied with the recommendations from the literature. The object of the user-study introduced hereafter was to find the best style (among three) for PEANUT with respect to 5 dimensions: expressiveness, sympathy, appeal, childlikeness, coherence.

<u>Materials & Methods</u>
We created an online questionnaire which was divided into different items, with each item corresponding to one emotion. These items were presented in a random order. For each item, the three face styles were presented (in a counterbalanced order), side by side. Participants were asked to chose which of the three styles was the most expressive, sympathetic, appealing, infantile and coherent (referred to as the dimension hereafter). They were also asked to rate each style on a 5-point Likert scale. Ninety-seven participants answered the online questionnaire. We first led a 1-way ANOVA to determine if the rates associated with each style were different. Then, we led

a 3-way ANOVA for repeated measures, to assess the impact of the face style (F_3 - repeated measures), the type of emotion (E_8 - repeated measures) and the dimension (D_5 - repeated measures) on the allocated score.

Results
On a 5-point Likert scale, the face with eyebrows was rated 3.58 ± 1.26, the face with a nose 2.96 ± 1.37 and the simple face 3.86 ± 1.10. The 1-way ANOVA for repeated measures revealed a main effect of the style [$F(1,93)=8.442$; $p \leqslant 0.005$, $\eta^2=0.083$]: the simple face and the face with eyebrows were significantly better rated than the face with a nose. However, there was no difference of rating between the simple face and that with eyebrows. Thus, we then performed a 3-way ANOVA for repeated measures to evaluate the effect of the face, of the emotion and of the dimension on the rating. Results suggested a main effect of the style of face [$F(1,93)=17.543$; $p \leqslant 0.001$, $\eta^2=0.159$], of the emotion [$F(1,93)=11.307$; $p \leqslant 0.001$, $\eta^2=0.108$] and of the dimension [$F(1,93)=12.184$; $p \leqslant 0.001$, $\eta^2=0.116$]. Moreover, face*dimension [$F(1,93)=58.531$; $p \leqslant 0.001$, $\eta^2=0.386$], face*emotion [$F(1,93)=11.307$; $p \leqslant 0.001$, $\eta^2=0.108$] and dimension*emotion [$F(1,93)=17.543$; $p \leqslant 0.001$, $\eta^2=0.159$] interaction effects were revealed. The face with the eyebrows was significantly preferred to the others, which was strengthened by participants' comments indicating that eyebrows increased expressiveness. However, this face was not preferred for Joy and Admiration. An analysis of the comments helped us improve those expressions: in particular, several people felt like the shape of the eyes gave the impression the companion was about to cry and that it was squinting.

Discussion
For PEANUT, we selected the face with eyebrows (see Figure 28) which our results suggested was the most appropriate. We asked the designer to improve the expressions of Joy and Admiration with respect to participants' comments. In a second instance, the designer

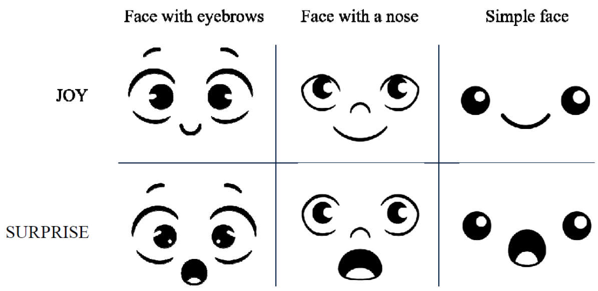


Figure 28 – Three face styles, with the example of 2 emotions: Joy and Surprise. Participants of the dedicated user-study selected the face with eyebrows for PEANUT.

animated each of the expressions. The animations enabled a transfer from a neutral expression to a high intensity of each of the emotions.

Figure 29 – Illustration of a participant taking part in a Mental-Imagery based Brain-Computer Interface (MI-BCI) training process during which he learns to perform different MI-tasks (here, imagining a left-hand movement) to control the system. Along the training, PEANUT provides the user with social presence and emotional support adapted to his performance and progression. This photo is an illustration ; the real experiments were performed in an experimental room, and PEANUT was providing interventions only between the trials - not during the trials so that it does not disturb the participant while the latter was performing the MI-tasks.

6.4.4 *System Architecture*

Implementing the whole BCI system as well as PEANUT required to design, assemble and connect multiple pieces of hardware and software. Users' EEG signals were first measured using EEG hardware (g.tec gUSBAmp, g.tec, Austria) and then collected and processed online using OpenViBE Renard et al., 2010. OpenViBE provided users with a visual feedback about the estimated mental task, and computed users' performances which were then transmitted to a homemade software, the "Rule Engine" using the Lab Streaming Layer (LSL) protocol (`https://github.com/sccn/labstreaminglayer`). The rule engine processed performance measures received from OpenViBE to compute progression measures and browsed the Rule Tree described in Figure 27 in order to select an appropriate intervention (sentence and facial expression) for PEANUT with respect to the context. The selected intervention was then transmitted to an Android smartphone application, using WebSocket, which enunciated the sentence and animated PEANUT's facial expression. This whole architecture is summarised in Figure 30. These modules are described hereafter.

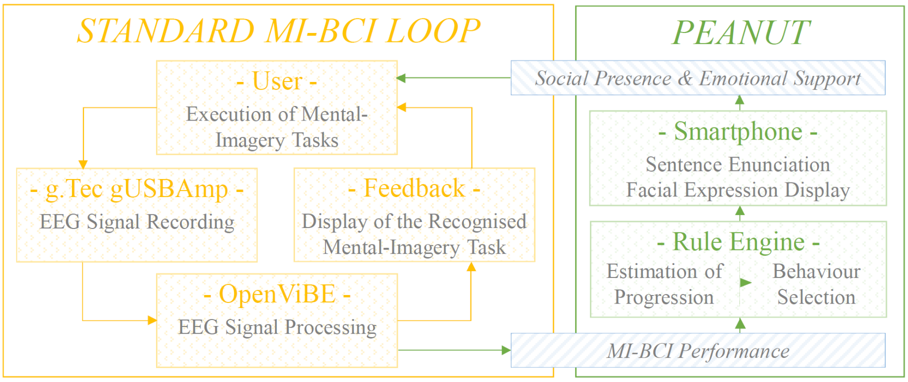


Figure 30 – Schematic representation of a standard MI-BCI functioning loop to which we added PEANUT. PEANUT takes as an input the user's MI-BCI performance. Based on this performance, it will compute user's progression and consequently select a specific intervention (sentence & facial expression) displayed using a smartphone (placed as PEANUT's face). The aim of this intervention is to provide the user with emotional support and social presence.

6.4.4.1 *Rule Engine*

The Rule Engine software receives from OpenViBE the markers indicating the start and end of trials, runs and sessions, as well as performance measures at the end of each trial. It first computes a progression measure (see Section *Estimating the progression thresholds*) and then browses the rule tree in order to select the intervention type to be triggered. Each intervention type contained between 1 and 17 sentences. One of them was selected randomly, taking care not to take a sentence that had already been chosen in the same run (thanks to a small cache of already triggered sentences kept for each category) in order to avoid repetition. Finally, the Rule Engine sent intervention identifiers to the smartphone application.

6.4.4.2 *Smartphone - Sentence Enunciation, Facial Expression Animation*

To display the facial animations and enunciate the sentences, we chose to use an Alcatel OneTouch Idol 3 with 5.5" screen, running Android 5.0.2. Indeed, such a device integrates all the required hardware (CPU, screen and speaker) in a small form factor that can be embedded in the head of the companion to display its face.We designed an Android application that displays the face of the companion, plays animations and sounds when required. By default a neutral facial expression is shown, with eye-blinks occurring from time to time. When intervention identifiers were received from the Rule Engine, the application animated the facial expressions and enunciated the sentences. Each of the (126) sentences had been previously recorded (as explained in the *Physical appearance of PEANUT* section). We used Praat software (http://www.fon.hum.uva.nl/praat/) offline in order to realise phonetic alignment with the companion's mouth movements for each sentence. Thus, phonemes, that may be described as individual sounds that make up speech, were aligned on the speech signal. Furthermore, visemes correspond to the shape of the mouth when a phoneme is pronounced (several phonemes may correspond to a given viseme). The number of visemes depends on the language used and the desired fidelity. As our companion's style is cartoon-like, we did not aim for high fidelity: we used 35 phonemes and 8 visemes. Once the animations and sounds had been planned, the application combined visemes corresponding to phonemes in the chosen sound, and added them to the animation plan. Finally, the application scheduled animations and sounds for execution (for instance, to ensure that an animation did not start while the companion was blinking).

6.5 TEST OF THE EFFICIENCY OF PEANUT TO BETTER MI-BCI USER- TRAINING.

Once the companion's behaviour and appearance had been designed and implemented, the next step consisted in validating its efficiency to improve MI-BCI user-training both in terms of MI-BCI performance and user-experience. Below we present the study performed to test PEANUT's efficiency.

6.5.1 *Materials & Methods*

6.5.1.1 *Participants*

Thirty-two MI-BCI-naive participants (15 women; aged 23.16±2.50) took part in this study, which was conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki. This study was approved by the local ethical committee. All the participants signed an informed consent form at the beginning of the experiment and received a compensation of 50 euros. Each participant was allocated to one of 3 groups, which determined the support they would received throughout the MI-BCI training sessions: no learning companion (*control group* #1), learning companion not adapted to their MI-BCI performance & progression (*control group* #2), learning companion adapted to their MI-BCI performance & progression (*experimental group*). For the control group #1, data from a previous experiment Jeunet et al., 2015b were used: among the 18 participants, 11 were selected so that they matched, as far as possible, the characteristics of the participants from both the other groups in terms of gender, tension and self-reliance scores Cattell and Cattell, 1995.

6.5.1.2 *Experimental Protocol*

Please refer to Figure 31.

6.5.1.3 *Variables & Factors*

We studied the impact of the group (no companion, non-adapted companion, adapted companion) on participants' MI-BCI performance, with respect to the session and participant's profile (tension and self-reliance scores). We also evaluated the impact of the group on MI-BCI

EXPERIMENTAL PARADIGM

This experiment was composed of 3 mental-imagery based BCI sessions of 2.00 hours each. Each session was divided into 5 runs, with 45 trials per run. The 32 participants were divided into 3 groups: one with no companion, one with a companion showing a generic behaviour, one with a companion adapted to users' performance and progression.

EVALUATIONS

PSYCHOMETRIC EVALUATIONS	*Personality assessment* ▼ Learning Style Inventory ▼ 16 Personality Factors-5 *Cognitive profile assessment* ▼ Mental Rotation test

BCI EXPERIMENTS – TRAINING PROTOCOL

TRAINING TASKS	▼ Left-Hand Motor Imagery ▼ Mental Subtraction ▼ Mental Rotation
FEEDBACK	▼ *Modality:* Visual [standard Graz blue bar feedback] ▼ *Update Frequency:* 16Hz ▼ *Content:* Only positive + Learning Companion (PEANUT)
TRAINING ENVIRONMENT	▼ Standard Graz Training Environment, adapted for 3 classes

BCI EXPERIMENTS – BRAIN SIGNAL RECORDINGS & PROCESSING

HARDWARE & EEG SET-UP	▼ g.USBamp amplifier (g.tec, Graz, Austria) ▼ See the list in the Materiels & Methods Chapter ▼ Referenced to the left ear, grounded to Afz ▼ Sampling of the EEG data: 256Hz
SIGNAL PROCESSING PIPELINE	▼ Band-pass filtering of the EEG data: 8-30Hz *Session 1: the classifier & CSP are trained on the run 1* ▼ 3 CSP «one class vs. the others» → 12 band-power features ▼ Combination of 3 sLDA in a one-versus-the-rest scheme ▼ Use of the resulting classifier to discriminate between the 3 tasks for the runs 2 to 5 *Sessions 2 & 3* ▼ Run 1 with the classifier trained during Session 1 ▼ Re-computation of the sLDA's bias ▼ Use of the resulting classifier to discriminate between the 3 tasks for the runs 2 to 5

Figure 31 – Materials & Methods of the Study aiming at testing PEANUT's efficiency, Section 6.5

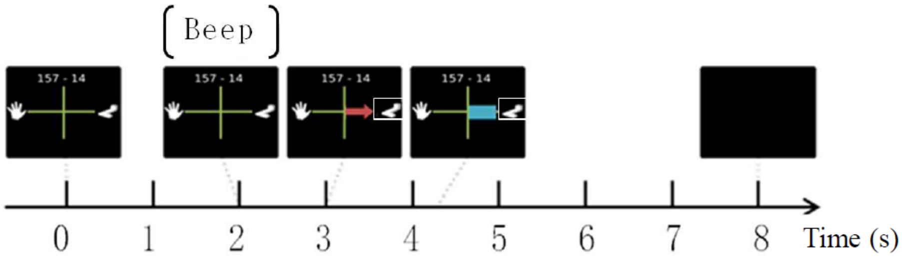


Figure 32 – Timing of a trial

usability and on the perception of the companion, with respect to MI-BCI performance. The corresponding questionnaires can be found in Appendix A & C, respectively.

6.5.2 *Results*

6.5.2.1 *MI-BCI Performance*

Due to technical issues, several participants of the groups accompanied by PEANUT were provided with a sub-optimal classifier which resulted in low peak classification accuracy (measured at the time window of the feedback period for which the classification accuracy over all trials is maximal). Indeed, the group with no companion (N=11) obtained 63.97% $\pm$ 5.18, the group with a non-adapted (N=11) companion obtained 52.48% $\pm$ 11.17 and the group with the adapted companion (N=10) obtained 48.25% $\pm$ 5.73 classification accuracy at the first session. One outlier participant of the group provided with a non-adapted companion was excluded (his performance, 78.74%, was superior to the mean of his group plus two standard deviations). Thus, the following analysis was performed on 31 participants. The one-way ANOVA for repeated measures indicated a significant effect of the group on peak performance of the first session [$F(2,30)=11.995$, $p \leqslant 0.001$]. A similar result was obtained for mean performance.

As a consequence, we were not able to compare the performance of the different groups for the other sessions. Nonetheless, we performed several other analyses to evaluate user-experience, by taking the performance as a covariable so that the usability scores are independent from the performance.

6.5.2.2 *Usability Questionnaires*

The following section is dedicated to the description of usability scores attributed to the MI-BCI system by each group. These scores appeared to be dependent of users' performance. Thus, we will present the analyses associated to mean and peak performance separately, most of the results being similar between both. We analysed the influence of the group on usability scores, and more specifically on 4 dimensions: learnability/memorability (LM), efficiency/effectiveness (EE), safety, satisfaction. We performed four 1-way ANCOVAs (one per dimension) with the Group as factor, the usability score for the target dimension as dependent variable and the mean/peak classification accuracy as covariable.

Mean Performance
The results of the ANCOVA revealed tendency towards a main effect of the group on the LM dimension [$D(2,30)=2.508$; $p=0.100$, $\eta^2=0.157$]: participants who were provided with a companion (adapted or not) considered the system's learnability/memorability as higher than those with no companion ; a main effect of the performance was also revealed [$D(1,30)=5.252$; $p\leqslant 0.005$, $\eta^2=0.163$]: thus, performance influences the perception of usability (the higher their performance, the better users rate LM). Concerning the EE dimension: a main effect of the Group was revealed [$D(2,30)=3.999$; $p\leqslant 0.05$, $\eta^2=0.228$]: participants who were provided with a companion (adapted or not) considered their efficiency/effectiveness as higher than those with no companion while interacting with the system ; similarly to the LM dimension, a main effect of the performance was revealed [$D(1,30)=10.780$; $p\leqslant 0.005$, $\eta^2=0.285$]. Nonetheless, for both safety and satisfaction, no effect of the group was revealed.

Peak Performance
Results revealed a main effect of the group on the LM dimension [$D(2,30)=4.901$; $p\leqslant 0.05$, $\eta^2=0.266$]: participants who were provided with a companion (adapted or not) considered the system's learnability/memorability as higher than those with no companion ; a main effect of the performance was also revealed [$D(1,30)=10.987$; $p\leqslant 0.005$, $\eta^2=0.289$]: thus, performance influences the perception of usability

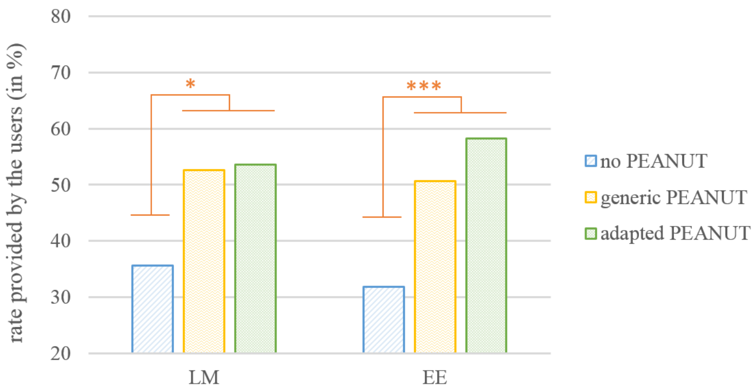


Figure 33 – LM and EE scores with respect to users' group, after the ANCOVA correction for the performance (estimated performance: 57,33% peak classification accuracy). Participants who were accompanied by PEANUT rated the MI-BCI system usability significantly better than the others.

(the higher their performance, the better users rate LM), see Figure 33. Similar results were found for the EE dimension: a main effect of the Group was revealed [D(2,30)=7.939; $p\leqslant 0.005$, η^2=0.370]: participants who were provided with a companion (adapted or not) considered their efficiency/effectiveness as higher than those with no companion while interacting with the system ; similarly to the LM dimension, a main effect of the performance was revealed [D(1,30)=21.952; $p\leqslant 0.001$, η^2=0.448], , see Figure 33. Nonetheless, for both safety and satisfaction, no effect of the group was revealed.

6.5.2.3 *Perception of the Companion*

On the other hand, we also explored the potential difference of perception of the companion with respect to the fact it was adapted to users' performance and progression or not. Despite the high variability of scores allocated to the adapted companion (71.43% $\pm$ 19.92) and to the non-adapted companion (52.96% $\pm$ 22.89), the 1-way ANOVA revealed a strong trend towards a main effect of the Group [F(1,19)= 3.746, p=0.069] suggesting that users provided with the adapted companion found it more appropriate and enjoyable.

6.5.2.4 *Impact of the Profile on Performance and Progression*

Finally, we performed two last analyses to assess the impact of the profile (self-reliance and tension levels) on performance, depending on the group and on the training session number. We re-trained offline the classifier at the beginning of each session so that so that users' performance were not dependent on their previous control abilities. Thus, two 2-way ANCOVAs with the *Group* and *Session Number* as factors and the *Performance* as dependent variable were performed. The first ANCOVA took users' self-reliance scores as covariable while the other one took their tension scores. No significant result was revealed concerning the self-reliance scores. However, a main effect of the Session was revealed for the ANCOVA using the tension level as covariable [F(1,27)=7.223 ; $p\leqslant 0.05$, η^2=0.211]. More importantly, this same analysis also revealed, a Session * Tension level interaction [F(1,27)=5.054 ; $p\leqslant 0.05$, η^2=0.158]. These results suggest that users progress along the sessions, but that their ability to improve depends on their tension level. Pearson correlation analyses revealed strong negative correlations between the Tension level and the Progression between sessions 1 & 3 [r=-0.334, p=0.066] and Progression between sessions 2 & 3 [r=-0.357, $p\leqslant 0.05$]. This result suggests that highly tense participants are the ones struggling the most to improve in performance. It confirms the importance of this personality trait for BCI training as was suggested in the first studyrelated in this Chapter.

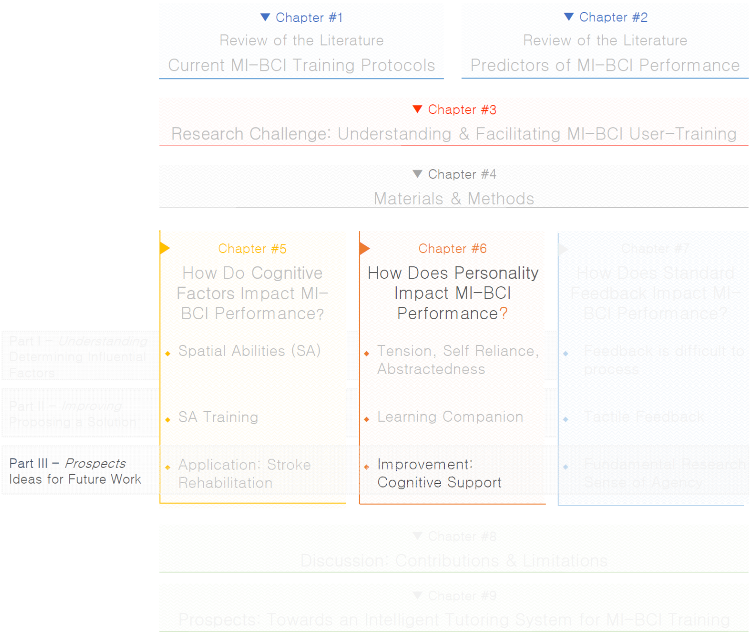
6.5.3 *Discussion*

Link to a video of PEANUT: here!

While this study did not allow us to draw conclusions about the impact of PEANUT on BCI performance (due to random initial differences between groups), it revealed several interesting points. In particular, using PEANUT improved the usability of the MI-BCI: participants in both groups using PEANUT gave significantly higher learning/memorability scores and efficiency/effectiveness scores than those given by the group with no companion. We therefore reached one of our objectives: to improve MI-BCI training user-experience (which is currently rather poor) thanks to the use of a learning companion providing emotional support and social presence. Our participants also seemed to prefer PEANUT with an adapted behaviour, as they graded the general perception of PEANUT higher in the adapted behaviour group (trend towards a significant effect: $p=0.069$). This is in line with the literature from educational psychology that we followed and that recommended providing adapted feedback Shute, 2008. Overall, this confirmed that carefully designing PEANUT based on the literature from educational psychology and user-centred design methods substantially benefited MI-BCI training user-experience. Another interesting result is the impact of users' tension on MI-BCI training: highly tense users struggle to improve their performance over MI-BCI training sessions; this confirms the results obtained in Jeunet et al., 2015b in which Tension was one of the variables that could be used to predict BCI performances.

PART III - PROSPECTS: TOWARDS A COGNITIVE & EMOTIONAL SUPPORT PROVIDED BY A LEARNING COMPANION TO IMPROVE MI-BCI USER-TRAINING

ROADMAP -



QUICK SUMMARY -

Using PEANUT seems to be a promising approach to improve MI-BCI user-training. In this section, we discuss how PEANUT could evolve. First, PEANUT's behaviour should not only be adapted to users' performance and progression, but also both to their personality and emotional state. On the other hand, beyond emotional support, PEANUT could be a promising tool to provide users with cognitive support to help them improve their performance. More specifically, we discuss how PEANUT and TEEGI (Frey et al., 2014b) could be combined to provide explanatory feedback.

COLLABORATORS -

Léa Pillette (Engineering Student - and new PhD student :)).
Renaud Gervais & Jérémy Frey (Post-Doc Fellows)

6.6 PROSPECTS - USING PEANUT TO PROVIDE USERS WITH COGNITIVE SUPPORT.

In this chapter, we first showed that personality had a significant impact on the ability of users to control an MI-BCI. More specifically, it seems that imaginative users as well as active learners perform better. On the other hand, highly tense and non-autonomous users struggle when learning to use an MI-BCI system.

Literature shows that highly tense and non-autonomous people require more emotional support and social presence throughout the learning process. Such support is not currently provided in standard training protocols: most of the time, MI-BCI users are alone in front of a computer. With the aim of providing emotional support and social presence, we introduced a learning companion dedicated to MI-BCI user-training: PEANUT. The strength of this companion is the way it was designed: by combining recommendations from the literature, the analysis of data from previous experiments and user-studies. What is more, these user-studies provided useful insights about the kind of intervention that users prefer depending on their progression, which could be useful beyond the field of MI-BCIs. PEANUT was validated in a large MI-BCI study (32 participants, 3 sessions per participant), with three conditions: no learning companion, a learning companion with a generic behaviour, and a learning companion whose behaviour was adapted to users' performance and progress. This study revealed that using PEANUT had a substantial impact on user-experience. First, participants who used PEANUT found it was easier to learn and memorise how to use the MI-BCI system and rated themselves more efficient and effective than participants who had no learning companion. Moreover, participants expressed a better general preference for the companion which provided interventions adapted to their performance/progression than for the non-adapted companion, which is in line with the literature (Shute, 2008).

To summarise, it seems that using PEANUT does benefit MI-BCI user-experience. In the future, a larger and more homogeneous population should be included in order to quantify any potential impact of PEANUT on MI-BCI performance. It would also be interesting to define more refined performance measures in order to provide more specific/adapted interventions, possibly further improving the support.

Furthermore, it would also be of utmost importance to consider the two other aspects of personality related to MI-BCI performance (based on our study - Jeunet et al., 2015b): namely, abstractedness (or imagination abilities) and the active/reflective dimension of the learning style. First, it would be interesting to make PEANUT able to help users develop their abstractedness abilities. One possible hypothesis is that more imaginative users present abilities to control MI-BCI because they are able to produce varied mental-images, and thus to modify their strategy by exploring new mental-images when necessary (this hypothesis of course requires further investigation). Therefore, a future experiment could consist in investigating the ability of PEANUT to guide users towards the exploration of different strategies potentially leading to improved MI-BCI user-training. In the same vein, active users, who "learn by doing", seem to perform better than reflective users, who "learn by thinking". This result agrees with results obtained by Neuper et al., 2005 which suggest that kinaesthetic motor-imagery leads to better MI-BCI performance than visual motor-imagery. While visual motor-imagery is reflective as it consists in visualising one's own hand (or the hand of a third party) moving, kinaesthetic motor-imagery can be categorised as active as it suggests the person is sending a motor command to their limb without moving it. It would be of utmost interest if PEANUT was able to determine the type of MI being performed in real time and to guide the user towards appropriate strategies with respect to their profile.

Both these types of support are classed as cognitive support. This kind of support is also known as explanatory feedback and is recommended by the educational psychology literature to ensure efficient training (Shute, 2008). Although promising, explanatory feedback cannot yet be provided in the context of BCIs. Indeed, it would require the definition of a cognitive model of MI-BCI tasks, i.e., theoretical knowledge about the skills to be acquired and how to acquire them, in order to provide users with appropriate advice leading them to the acquisition of MI-BCI related skills. The development of a cognitive model of MI-BCI tasks is elaborated in the Prospects of this manuscript, i.e., in Chapter 9.

Nonetheless, we hope that such theoretical knowledge will soon be developed so that we are able to provide better cognitive and emotional feedback to MI-BCI users thanks to the use of learning companions. One direction we are thinking of is to combine the use of PEANUT with the use of TEEGI (Frey et al., 2014b). TEEGI is a Tangible EEG Interface that was developed in our team, Potioc, by Jérémy Frey and Renaud Gervais. Originally, TEEGI was designed as an avatar to enable the general public to visualise their brain activity and the neurophysiological consequences of different tasks such as executing movements of their arms or closing their eyes, see Figure 34. This constructivist approach, through self-paced exploration, allowed participants to significantly improve their knowledge about the motor and visual cortex. In the context of MI-BCI user-training, once a cognitive model of the task has been established, combining PEANUT with TEEGI could enable PEANUT to propose strategies and provide cognitive support to users. Users could apply the advice provided by PEANUT and visualise how it impacts the neurophysiological patterns on their avatar, i.e., on TEEGI. Despite the fact that we do not yet have such a cognitive model of the task, we still know that theoretically, to optimise the efficiency of signal processing algorithms and thus the classification accuracy, users should produce stable and distinct brain activity pattern for each of the MI tasks. Thus, the first step of the user-training process could be the visualisation of their brain-activity while performing different MI-tasks on TEEGI. Helped by PEANUT, users could be trained to generate stable and distinct brain-activity patterns. The visual feedback could indeed overcome the lack of sensorimotor feedback while performing mental tasks, while the cognitive support could help users to be guided throughout the acquisition of these skills. Nonetheless, since brain activity is extremely complex with a high noise-signal ratio, it should not be provided in its raw state. Rather, the information on display should be carefully selected so that users' cognitive resources are not overloaded and they are still able to acquire skills.

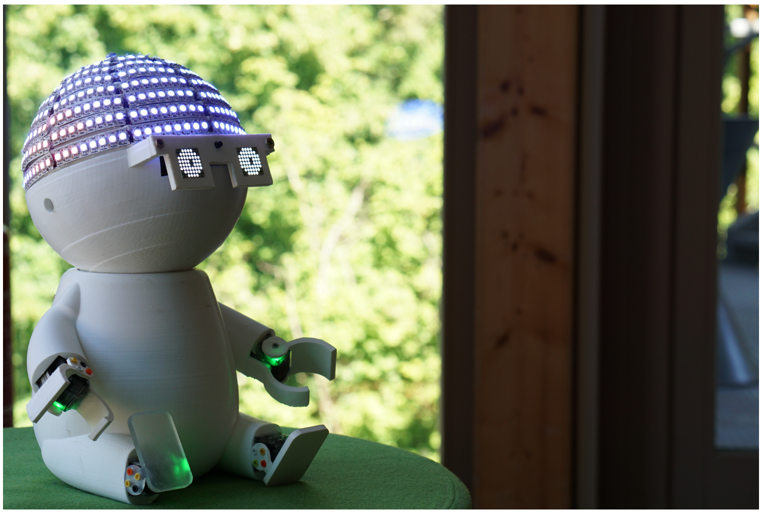


Figure 34 – Photo of TEEGI. TEEGI enables the visualisation of brain patterns associated to specific tasks such as the execution of motor movements.

Such a learning companion that is able to provide emotional and cognitive support could be very useful in different rehabilitation contexts. For instance, as depicted in the previous chapter, MI-BCIs are promising for stroke rehabilitation as they enable therapists both to visualise brain-activity in real time and to provide the user with a sensorimotor feedback accordingly. Also, as stated in the same chapter, stroke patients often suffer from depression and from various cognitive impairments (attention, memory, etc.). PEANUT could both help to cope with the depressive state of patients by providing them with emotional support and help to overcome their cognitive impairments through cognitive support which aims to maintain their attention towards the task and helps them to remember the tasks to be performed.

We hope that more effort will be provided to establish a cognitive model of the task so that such learning companions could become standard useful tools for MI-BCI user-training. We think this approach could push BCI performance and usability much further. In this view, we designed and implemented PEANUT for a low cost, using only open-source and free software.

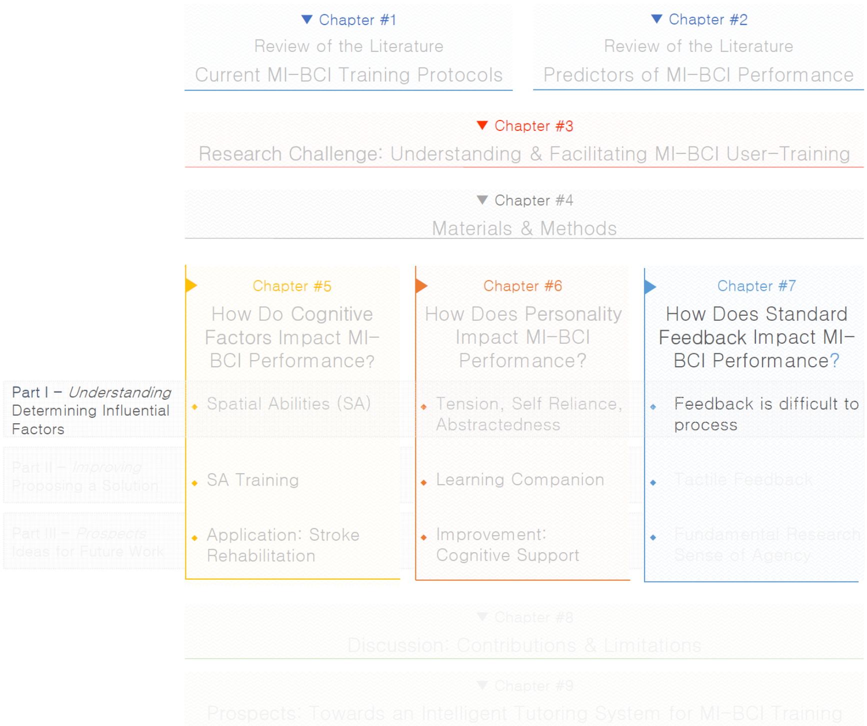
7 CONSIDERING THE FEEDBACK TO UNDERSTAND & IMPROVE MI-BCI USER-TRAINING.

7.1 RESEARCH QUESTION

The review of the literature dealing with current training protocols, introduced in Chapter 1, suggests that these protocols are, at least theoretically, inappropriate to acquire a skill and thus that they could be one of the factors responsible for inefficient MI-BCI user-training. In particular, participants are most of the time provided with uni-modal and evaluative feedback while literature recommends multi-modal, informative and supporting feedback (Lotte, Larrue, and Mühl, 2013). Although instructive, these insights (summarised in Lotte and Jeunet, 2015; Lotte et al., 2013) only provide theoretical considerations about the flaws associated with the feedback approaches used in MI-BCI. It is therefore necessary to *concretely* assess whether standard MI-BCI feedback is appropriate to train a skill, and to what extent the feedback impacts BCI performance and skill acquisition. Thus, the first object of Part I of this section was to evaluate the efficiency of a standard feedback, i.e., the Graz protocol feedback (Pfurtscheller and Neuper, 2001), for the acquisition of MI-BCI related skills. As described in Chapter 1, this feedback corresponds to the classifier output provided to the users as a blue bar (the direction and length of which informs the user about the task recognised by the system and its confidence in whether the task was recognised correctly, respectively). The following *Part I* determines the impact of the feedback on MI-BCI skill acquisition and investigates the aspects of the feedback that could be modified in order to improve MI-BCI user-training. In *Part II* we propose an alternative to the standard (visual) feedback: a vibrotactile feedback. We justify this choice and then depict the design, validation and testing of this feedback in an MI-BCI training context, before presenting prospective evaluations in *Part III* aiming at understanding the cognitive and neurophysiological mechanisms underlying the efficiency of different kinds of feedback.

PART I - HOW DOES THE FEEDBACK INFLUENCE MI-BCI USER TRAINING?

ROADMAP -



QUICK SUMMARY -

We have shown that the feedback MI-BCI users are provided with is theoretically inappropriate. In order to experimentally evaluate the extent to which such a feedback has an impact on their ability to acquire a skill, we used it to teach users to perform simple motor tasks. Results (N=53) revealed that with this feedback, 17% did not manage to learn the skill. A sub-group of participants (N=20) then took part in a motor-imagery based BCI experiment. Results showed that those who struggled during the first experiment improved in performance during the second, while the others did not. We hypothesise that these results are linked to the considerable cognitive resources required to process this feedback.

COLLABORATORS -

Alison Cellard (Engineer) & Emilie Jahanpour (Master Student).

RELATED PAPERS -

-1- Jeunet, C., Cellard, A., Subramanian, S., Hachet, M., N'Kaoua, B., and Lotte, F. (2014). 'How well can we learn with standard BCI training approaches? A pilot study.' In: *BCI Conference*, pp. 332–35.
-2- Jeunet, C., Jahanpour, E., and Lotte, F. (2016). 'Why standard brain-computer interface (BCI) training protocols should be changed: an experimental study.' In: *Journal of neural engineering* 13.3, p. 036024.

7.2 STUDY 1: INVESTIGATING THE RELEVANCE OF A STANDARD FEEDBACK TO ACQUIRE SKILLS.

The objective of this first study was to evaluate the impact of a standard feedback (from the Graz protocol, introduced in Chapter 1) on participants' ability to acquire a skill in an MI-BCI free context. It is necessary to perform this evaluation independently from MI-BCIs, to rule out possible biases due to BCI complexity, EEG non-stationarity and poor signal-to-noise ratio. Indeed, if a BCI training results in poor performances (i.e., the subject fails to obtain BCI control), this might not be due to the training protocol itself but simply to poor EEG signal processing, noisy or non-stationary signals, or to the fact that the relevant neural signals cannot be found in the EEG signals due to the orientation of the user's cortex, for instance. Therefore, to study the impact and usefulness of a given training protocol (and here more specifically a feedback approach), it is necessary to study it without the possible confounding factors originating from the BCI design.

Yet, studying the impact of this protocol in a BCI-free context led to a major challenge: finding tasks comparable to motor-imagery tasks. Or, in other words, tasks for which the standard feedback we will provide the participants with is as relevant as it is for MI-BCI tasks. It is not possible to provide users with a feedback about their performance at motor-imagery tasks without EEG or BCI. We thus looked for *equivalent* motor tasks. These motor tasks had to respect different constraints. First, as stated before they had to be relevant for the standard feedback. Also, their associated instruction had to be simple and the task precise, but while precise, the task also had to be vague enough to be associated to different possible strategies as the goal for the participants (as is the case for MI-BCI) was to find the right strategy so that the system recognises their actions. Finally, the task had to be possibly performed continuously during the feedback period.

We finally elected two motor tasks that participants were asked to learn to perform: drawing triangles and circles with a pen on a graphic tablet (see Figure 35), using the Graz protocol (Pfurtscheller and Neuper, 2001) (i.e., same instructions and feedback). As would have been the case in an MI-BCI training context, in which users have to learn a suitable movement imagination strategy, the participants here had to learn the strategy which allowed the system to correctly recognise their drawing, e.g. they had to identify the suitable shape size, angles and speed of drawing. The participants were divided into two groups: one used a "Standard" training approach (Pfurtscheller and Neuper, 2001) while the other one used a "Partially Self-Paced" BCI training approach, which provides the user with more autonomy. Indeed, with the standard approach, no autonomy is given to the user, who always has to perform the tasks required by the protocol. Yet, autonomy is known to increase motivation and learning efficiency in general (Lotte et al., 2013). Interestingly enough, the study described in Neuper et al., 2003 obtained promising results when providing more autonomy to a single BCI user.

7.2.1 *Materials & Methods*

7.2.1.1 *Participants*

54 BCI-naive and healthy participants (*20 females; aged 25.1 ± 4.6 year-old*) took part in this study, which was conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki. This study was also approved by the legal authorities of Inria Bordeaux Sud-Ouest (the COERLE, approval number: 2015-004) as it satisfied the ethical rules and principles of the institute. All the participants signed an informed consent form at the beginning of the experiment.

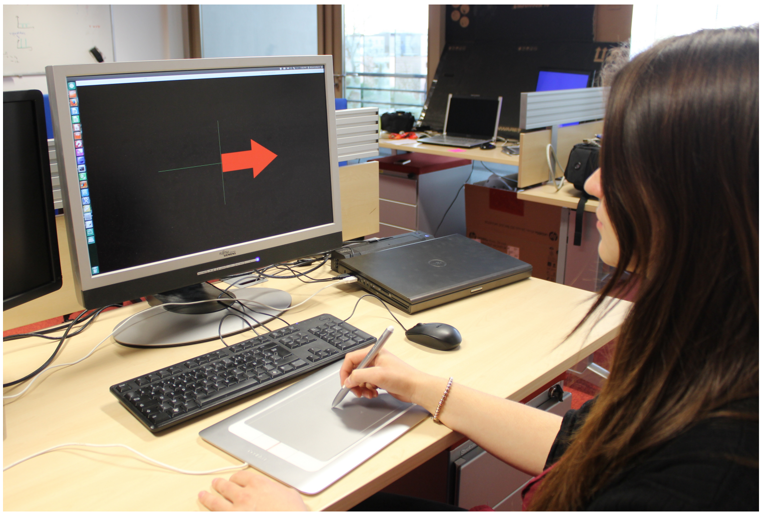


Figure 35 – Picture of a participant during the experiment. The instruction (red arrow pointing right) indicates that the participant has to draw triangles on the graphic tablet.

7.2.1.2 *Experimental Paradigm*

Each participant (N=54) had to learn to do 2 motor tasks, namely to draw circles and triangles on a graphic tablet so that they were recognised by the system. The training session was divided into runs which were either standard (s) or self-paced (sp). S-runs were composed of 20 trials per task. At the beginning of each trial a green cross was displayed. After 2s, an auditory cue (a beep) triggered the attention of the participant towards the red arrow, which was displayed at 3s for 1s, and indicated which task the participant had to perform, i.e., draw triangles or circles continuously upon appearance of a right or left arrow, respectively. The mapping between the task (drawing circles or triangles) and the instructions/feedback (arrow/bar extending to the left or right) being incongruent, we helped the participants to remember it by providing them with a picture representing the cross of the Graz protocol with a circle on its left and a triangle on its right side. This picture was visible at all times to ensure subjects could refer to it whenever needed. At 4.25s, a blue feedback bar appeared and was updated at 16Hz for 3.75s. Its direction indicated the shape recognised by the classifier (left: circle, right: triangle) and its length was proportional to the classifier output. During sp-runs, no instructions were given: the participants were asked to do the motor tasks in an autonomous way, i.e., they could do the task they wanted to, whenever they wanted to.

All participants were provided with the following instruction: "Your goal is to find the right strategy so that the system recognises as well as possible the shape you are drawing, which will concretely correspond to having the feedback bar as long as possible in the correct direction: left for circles and right for triangles".

Half the participants (N=27) were asked to learn using a Standard (S) training approach: they completed 4 seven-minute-long s-runs. The other half learned using the Partially Self-Paced (PSP) training approach: the 1^{st} and 4^{th} runs were s-runs, while the 2^{nd} run was replaced by a 3.5 minute long sp-run followed by a shortened s-run (10 trials per task, 3.5 minutes), and the 3rd run was replaced by a shortened s-run followed by a 3.5 minute long sp-run. Total training duration was the same in both conditions. We studied the impact of the condition, S vs. PSP, on the recognition accuracy of triangles and circles by the system and on subjective experience (measured by a usability questionnaire -UQ-).

7.2.1.3 *Variables & Factors*

The dependent variable was the Performance obtained by the participants at the motor-tasks (i.e., the accuracy with which the drawings were recognised by the system). The factors considered were the run number and the condition to which the participant had been allocated to (standard vs. partially self-paced). Also, at the end of the experiment, participants have been asked to complete a usability questionnaire measuring 4 dimensions: learnability/memorability (LM), efficiency/effectiveness (EE), safety and satisfaction. These four dimensions were studied as dependent variables potentially influenced by the Condition.

7.2.1.4 *Signal Processing*

In order to discriminate triangular from circular pen movements on the graphic tablet, we used a pattern recognition approach as in

BCIs. To this end, the 2D position of the pen on the tablet was acquired at a sampling frequency of 16 Hz. From the past 1s-long time window (in a sliding window scheme, with 1/16s step between consecutive time windows, with overlap) of the 2D pen position, a histogram of angles was computed. More precisely, the angles between each consecutive segment of the time window were first computed. Then the number of angles falling in the ranges 0-30°, 30-75°, 75-105°, 105-150° and 150-180° were counted, and these 5 count values were used as input features for a Linear Discriminant Analysis (LDA) classifier. The (subject-independent) LDA classifier was trained on 60 trials from each movement, from 2 persons (1 left-handed, 1 right-handed). The resulting classifier could discriminate triangles from circles with 73.8% classification accuracy (10-fold cross-validation on the training set), which is an accuracy equivalent to the average accuracy of an MI-BCI Blankertz et al., 2010a. The output of the LDA was mapped to the direction and length of the feedback bar, as in a typical MI-BCI.

Classically, subject-specific classifiers are used in BCI experiments. Nonetheless, here, the task being extremely simple, such a classifier would most likely have been perfect, i.e., with 100% classification accuracy, which is not the case in BCI experiments. We thus used a subject-independent classifier which enabled us to have a classification accuracy similar to that obtained for BCI. Furthermore, a subject-specific classifier would have added another bias to the training protocol evaluation as the obtained accuracy would also have depended on how well the two gestures were performed during the calibration run, and not only on the training protocol (instructions, tasks and feedback). Again, here we wished to isolate the training protocol in order to study it, hence the use of a subject-independent classifier (i.e., the same classifier for all), in order to obtain results that were independent from the classifier.

7.2.1.5 *Analyses*

To study how well subjects could learn the motor tasks, we measured their performance as the average classification accuracy obtained to discriminate triangular from circular pen movements, averaged over the whole feedback period, i.e., from t=4.25s to t=8s after the start of the trial. In order to analyse the interaction between the "Condition" (2 modalities: *S* and *PSP*; independent measures) and the performance obtained at each "Run" (4 modalities: *run1, run2, run3* and *run4*; repeated measures), we performed a 2-way ANOVA for repeated measures. Moreover, we asked the participants to complete a usability questionnaire which measured 4 dimensions: learnability/memorability (LM), efficiency/effectiveness (EE), safety and satisfaction. Thus, we did four one-way ANOVAs, each of them aiming at analysing the impact of the "Condition" on one "Evaluated

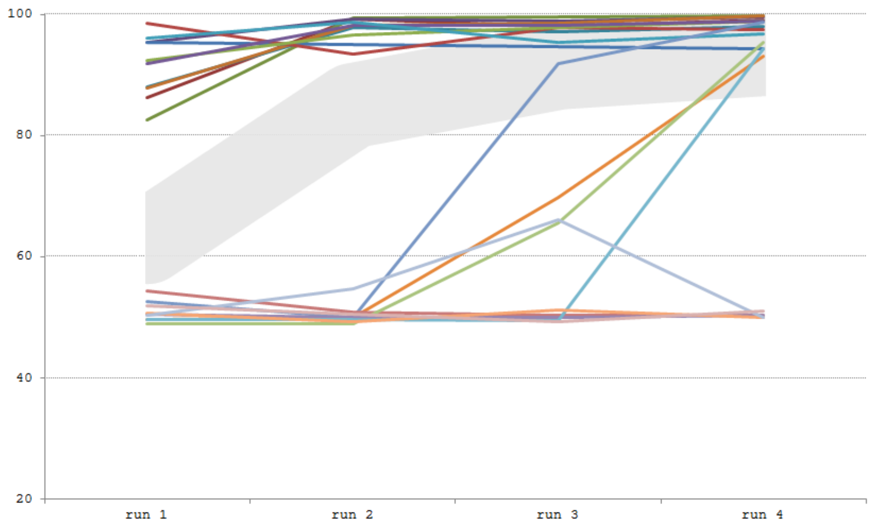


Figure 36 – Graphic representing the performance of the participants (mean classification accuracy) as a function of the run. For a better visibility, we chose to represent the 10 best and 10 worst performers. The average performance of the 34 other participants is represented by the large grey line.

Dimension" (4 modalities: *LM*, *EE*, *safety* and *satisfaction*; repeated measures).

7.2.2 *Results*

7.2.2.1 *Performance analyses*

Results (depicted in Figure 36) showed that 45 out of 54 participants managed to learn the task, i.e. obtained more than 70% average performance [1] -classification accuracy- (Müller-Putz et al., 2008) ($\bar{X}$ = 89.09%; *SD* = 6.35; *range* = [72.84, 98.26]) while 9 did not manage ($\bar{X}$ = 55.68%; *SD* = 6.35; *range* = [50.23, 65.64]). This rate of 16.67% of people who did not manage to learn allows one to hypothesise that BCI illiteracy could not only be due to the user, but also partly to the training protocol, and especially to the feedback. All the participants were cognitively and physically able to perform the simple motor tasks. The fact that such a proportion of them (around 17%) did not manage to reach good performance (when performing the motor tasks) suggests that, most likely, the feedback is not suitable to acquire skills (even if it is not a formal proof).

Furthermore, we performed a 2-way ANOVA for repeated measures to evaluate the impact of the *Condition* on motor performance ac-

1. This 70% accuracy is a threshold often used in the BCI community to distinguish subjects that achieved BCI control from those who did not achieve such a control Allison and Neuper, 2010

cording to the *Run* number. Checking the assumptions revealed that the normality [Skewness test - s_{Run1}=-0.203; s_{Run2}=-1.295; s_{Run3}=-1.709; s_{Run4}=-1.961] and equality of variance [Levene test - p_{Run1}= 0.044; p_{Run2}=0.024; p_{Run3}=0.160] were not totally respected. Nonetheless, given that the results were close to the threshold and the ANOVA being a robust analysis, we decided to use this analysis. The 2-way ANOVA revealed neither a main effet of the *Condition* [F(1,52)=1.997; p=0.164] nor a *Condition*Run* interaction [F(3,212)=1.301; p=0.259]. However, it revealed a main effect of the *Run* [F(3,50)=46.178; p$\leqslant$0.001]. Post-hoc analyses -Student t-test for paired samples- showed a significant increase in performance between the Runs ♯1 and ♯2 [$perf_{run1}$= 72.88%, $perf_{run2}$= 84.48%; p$\leqslant$ 0.001] and between Runs ♯2 and ♯3 [$perf_{run2}$= 84.48%, $perf_{run2}$= 87.62%; p$\leqslant$ 0.005] but not between Runs ♯3 and ♯4 [$perf_{run3}$= 87.62%, $perf_{run2}$= 89.11%; p= 0.277].

7.2.2.2 *Usability questionnaires*

Four one-way ANOVAs were performed to evaluate the impact of the Condition (S vs. PSP) on these dimensions. The prerequisites of the ANOVA were satisfied: all the dimensions had a normal distribution [Skewness test - s_{LM}= -0.072; s_{EE}= 0.046; s_{safety}= 0.098; $s_{satisfaction}$= 0.232] and the variances were equal [Levene test - p_{LM}= 0.938; p_{EE}= 0.415; p_{safety}= 0.861; $p_{satisfaction}$= 0.143]. However, results revealed no effect of the Condition: LM [F(1,53)= 2.257; p= 0.139], EE [F(1,53)= 0.089; p= 0.766], safety [F(1,53)= 0.166; p= 0.686] and satisfaction [F(1,53)= 0.895; p= 0.349].

7.2.3 *Discussion*

The aim of this study was to concretely assess whether the feedback used in BCI is appropriate to train a skill in general. Half the participants were asked to learn to perform simple motor tasks using a “Standard" (S) training approach while the other half used a “Partially Self-Paced" (PSP) one, in order to increase the feeling of autonomy. Results showed no differences between the conditions (S vs. PSP) in terms of performance or in terms of usability. This might be explained by the fact that most participants of the PSP group had found the right strategy, and thus had good performance, before the first sp-run. It might be that sp-runs could be useful for participants who still needed to explore strategies to find the right one. But once the right strategy found, sp-runs might not bring any further help to the particpants. In future experiments, it could be worth modifying the protocol so that the sp-runs come earlier in the training.

A very relevant result is the fact that while a learning effect was noted for the whole group on average over the 4 runs, around 17% of the participants (9 out of 54) seemed unable to learn to perform the motor tasks (their performances were below 70% on average over the 4 runs). While such an experiment provides no formal proof, it seems most likely that a substantial proportion of participants' modest performances are partly due to the feedback given the fact that all subjects were cognitively able to understand the instructions and had the motor abilities to perform the tasks. This result emphasises the fact that such a feedback should be improved to enable an efficient BCI training. In particular, numerous subjects reported verbally that the feedback was too poor as it did not indicate what they should do or change in order to succeed. It has to be noted that the poor performances of the participants might also be due to the difficulty of processing the mapping between the tasks and the protocol, i.e., drawing circles and triangles upon the appearance of a left- or right-facing arrow respectively. Indeed, the incongruence of this mapping could have led to a high workload and a low feeling of agency. In order to avoid such an effect, participants were provided with a picture representing this mapping which was available during the entirety of the experiment. Moreover, none of the participants reported difficulties in processing the mapping.

These results lead to two questions needing further investigations: (1) is the ability to learn using this kind of feedback correlated to some aspects of the user's personality, neurophysiological or cognitive profiles? and (2) are the performances obtained at these simple motor tasks predictive of MI-BCI performance?

Some aspects of these questions are investigated in the second study introduced below.

7.3 STUDY 2: EVALUATING THE IMPACT OF THE FEEDBACK ON MI-BCI RELATED SKILL ACQUISITION

If motor and MI-BCI performances are, at least partly, related to the user's ability to process the feedback, then one can hypothesise that users who reached good performances at the simple motor tasks should also be able to obtain good MI-BCI performances. This hypothesis has been tested in the experiment introduced below. Thus, this experiment enabled us to investigate the relationship between the ability to learn to perform simple motor tasks (as done in the first experiment) and the ability to learn to control an MI-BCI using a standard feedback (Pfurtscheller and Neuper, 2001). Indeed, based on our hypothesis, users who could learn motor tasks using this feedback would be likely to learn MI tasks using the same feedback as they already managed to learn a skill using this approach before. We also hypothesised that some aspects of the participants' profile would impact their MI-BCI performance. We focused on the two predictors which seemed to be the most reliable and adapted to our experiment context according to the literature and our previous experiments (see Chapter 5), namely the spatial abilities and the

Blankertz SMR-predictor. We thus selected the ten best and the ten worst performers from the first experiment (introduced in the previous Section), based on the averaged classification accuracy they obtained, and asked them to take part in an MI-BCI experiment during which they had to learn to perform motor-imagery tasks, i.e. imagination of left- and right-hand movements.

7.3.1 *Material & Methods*

7.3.1.1 *Participants*

20 BCI-naive participants (*10 females; aged 24.7* $\pm$ *4.0* year-old) took part in this second study, which was also conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki and approved by the legal authorities of Inria Bordeaux Sud-Ouest (the COERLE, approval number: 2015-004). Participants were selected from the first experiment and divided into two groups, the *good* and the *bad* performers. The 10 best performers of the first experiment [$\bar{X}$ = 96.00% of performance - classification accuracy; *SD* = 1.13] were in the *good* group while the 10 worst performers of the first experiment [$\bar{X}$ = 63.12% of performance - classification accuracy; *SD* = 11.54] were in the *bad* group. These two groups happened to be composed of 5 women and 5 men each. Moreover, in each group, 7 participants were in the Standard (S) and 3 were in the Partially Self-Paced (PSP) Conditions during the first study. Considering the results of the first experiment (showing no effect of the Condition on performance) as well as the distribution of the Conditions into the groups, we decided not to consider this variable (S vs. PSP) in this second experiment. In other words, the MI-BCI training only comprised standard runs.

7.3.1.2 *Experimental Paradigm*

Please refer to Figure 37.

7.3.1.3 *Variables & Factors*

In this study, we analysed the effect of 4 factors: the "Group" of the first experiment, the "Run", the "Mental Rotation Score" and the "Gender" on participants' MI-BCI performance, that is to say their classification accuracy (dependent variable).

7.3.1.4 *Analyses*

In this study, we analysed the effect of the "Group" of the first experiment (2 modalities: *good* vs. *bad*; independent measures), of the "Run" (4 modalities: *run1, run2, run3* and *run4*; repeated measures), of the "Mental Rotation Score" (continuous covariable) and of the "Gender" (2 modalities: *men* vs. *women*; independent measures) on participants' MI-BCI performance, that is to say their classification accuracy. We considered their "Gender" because of the important gender effect associated with the Mental Rotation test. Thus, we performed an ANCOVA with the "Mental Rotation scores" as the covariable and the "Group", the "Run" and the "Gender" as independent variables. We also studied the correlations between participants' MI-BCI performance and the Blankertz SMR-predictor.

7.3.2 *Results*

7.3.2.1 *MI-BCI Performance*

In our analysis aiming at evaluating the effect of the group (*bad* vs. *good* performers in the first experiment), gender (*men* vs. *women*) and run (*run1*, *run2*, *run3*, *run4*) on users' MI-BCI performance once the effect of the mental rotation had been controlled for, we considered two different measures of MI-BCI performance: (1) the **peak** classification accuracy (measured at the time window of the feedback period for which the classification accuracy over all trials is maximal), which

	EXPERIMENTAL PARADIGM
	This experiment was composed of 1 mental-imagery based BCI session of 2.00 hours. The session was divided into 5 runs, with 40 trials per run.
	EVALUATIONS
PSYCHOMETRIC EVALUATIONS	*Cognitive profile assessment* ▼ Mental Rotation test
NEUROPHYSIOLOGICAL EVALUATIONS	▼ Blankertz's SMR predictor: μ amplitude at rest, over the sensori-motor areas
	BCI EXPERIMENTS – TRAINING PROTOCOL
TRAINING TASKS	▼ Left-Hand Motor Imagery ▼ Right-Hand Motor Imagery
FEEDBACK	▼ *Modality:* Visual [standard Graz blue bar feedback] ▼ *Update Frequency:* 16Hz ▼ *Content:* Classifier output
TRAINING ENVIRONMENT	▼ Standard Graz Training Environment
	BCI EXPERIMENTS – BRAIN SIGNAL RECORDINGS & PROCESSING
HARDWARE & EEG SET-UP	▼ g.USBamp amplifier (g.tec, Graz, Austria) ▼ See the list in the Materiels & Methods Chapter ▼ Referenced to the left ear, grounded to Afz ▼ Sampling of the EEG data: 256Hz
SIGNAL PROCESSING PIPELINE	▼ Band-pass filtering of the EEG data: 8-30Hz *The classifier & CSP are trained on the run 1* ▼ CSP → 6 band-power features ▼ LDA (fed with the band-power features computed after CSP spatial filtering)

Figure 37 – Materials & Methods of the Study 2 of Section 7.3

is the typical performance measure used with the Graz protocol (see, e.g., Scherer et al., 2013) and (2) the **mean** classification accuracy over the whole feedback period of all trials. We thus performed two ANCOVAs. Note that the mean accuracy being the averaged accuracy over the whole feedback period, it is bound to be substantially lower than the usually reported peak accuracy, identified for the best time window. The mean accuracy is therefore a rather pessimistic performance estimate. We nonetheless believe it is useful as it reflects participant's ability to produce a long and stable BCI control signal.

PEAK PERFORMANCE

The average peak performance of the 20 participants was 66.95% (SD = 6.24; range = [57.09 ; 82.69]). Assumptions checking is depicted in Figure 38. It shows that the criteria for a normal distribution was satisfied for the mental rotation scores, for the peak performance of run1 and run4 but not for run2 and run3 (which was anecdotal, especially given the low number of subjects per group, and thus should not impact the analysis reliability). The homogeneity of the regression slopes and the equality of variance criteria were satisfied. However, it has to be noted that the linearity criteria was not: which could also be explained by the important inter-run variability due to the small sample size. Indeed, when considering the mean performance over the four runs, a linear relation with mental rotation scores is revealed. The ANCOVA with the **peak** MI-BCI performance as the dependent variable revealed a main effect of *Mental Rotation Scores* [$F(1,15) = 6.991$; $p \leqslant 0.05$; $\eta^2 = 0.318$] as well as a strong tendency towards a main effect of the *Run* [$F(1,15) = 3.638$; $p = 0.076$; $\eta^2 = 0.195$]. However, neither a main effect of the *Group* [$F(1,15) = 0.388$; $p = 0.789$; $\eta^2 = 0.050$] nor a main effect of the *Gender* [$F(1,15) = 0.719$; $p = 0.410$; $\eta^2 = 0.046$] were revealed. These results suggest a learning effect: participants' peak performance increased during the experiment. The ANCOVA also revealed significant interactions. First, a *Run * Mental Rotation Scores* interaction [$F(1,15) = 6.269$; $p \leqslant 0.05$; $\eta^2 = 0.295$] suggesting an impact of mental rotation on the ability to improve in terms of performance across the runs. Second, a *Run * Gender* interaction [$F(1,15) = 7.936$; $p \leqslant 0.05$; $\eta^2 = 0.346$] (see Figure 39) which suggests that, if we consider performance independently from participants' spatial abilities, while men's MI-BCI performances were stable accross the 4 runs, women's increased significantly. Furthermore, the *Run * Group* interaction [$F(1,15) = 4.907$; $p \leqslant 0.05$; $\eta^2 = 0.246$] revealed that, again if we consider performance independently from participants' spatial abilities, participants from the *good* group performed better than those of the *bad* group in the first run, but then they did not improve while participants from the *bad* group improved in terms of performance (see Figure 40). Finally, this ANCOVA revealed a strong tendency towards a *Run * Gender * Group* interaction

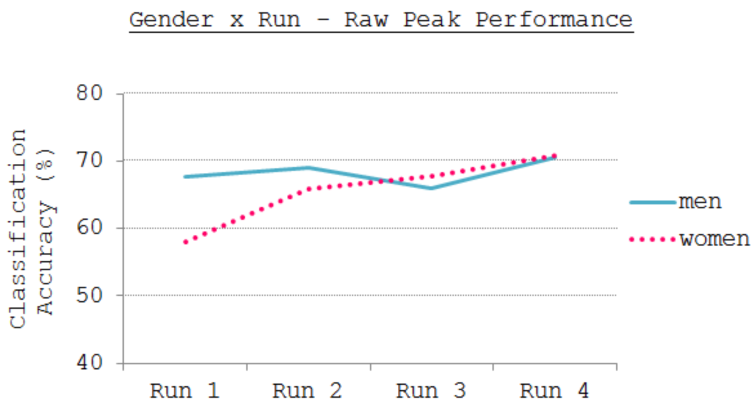
	NORMALITY	LINEARITY	HOMOGENEITY OF REGRESSION SLOTS	EQUALITY OF VARIANCES
MENTAL ROTATION SCORES	S = 0.049			
RUN 1	S = 0.676	P = 0.090	P = 0.155	P = 0.261
RUN 2	S = 1.259	P = 0.183		P = 0.410
RUN 3	S = 1.138	P = 0.508		P = 0.069
RUN 4	S = 0.421	P = 0.174		P = 0.203

Figure 38 – Table representing the assumptions checking for the ANCOVA on peak performance.

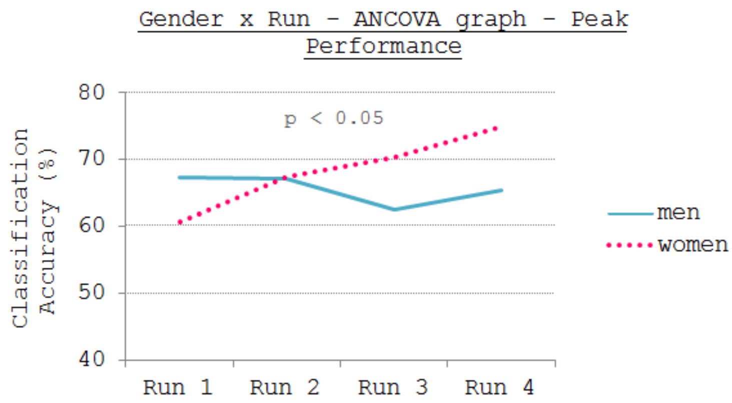
[$F(1,15)$ = 4.221; p = 0.058; η^2 = 0.220] (see Figure 41) but no *Gender * Group* interaction [$F(1,15)$ = 2.982; p = 0.105; η^2 = 0.166].

Mean Performance

The 20 participants obtained an average mean classification accuracy of 54.89% (SD = 6.56; range = [46.41 ; 68.12]). As expected, this measure leads to much lower and pessimistic performance estimates. The analysis of the assumptions satisfaction for the ANCOVA are represented in Figure 42. Mental rotation scores as well as mean performance of run1, run2 and run4 satisfied the criteria for a normal distribution, but run 3 did not. As stated in the previous paragraph, this can be explained by the low number of participants per group and should not impact the analysis reliability. Moreover, the homogeneity of the regression slopes as well as the equality of variance criteria were both satisfied. However, as was the case for the peak performance analysis, the criteria of linearity was violated which can be explained by the small sample size. The ANCOVA with the **mean** MI-BCI performance as the dependent variable was associated with quite similar results as for the peak performance. Indeed, it revealed a main effect of *Mental Rotation Scores* [$F(1,15)$ = 5.817; $p \leqslant 0.05$; η^2 = 0.279] as well as a strong tendency towards a main effect of the *Run* [$F(1,15)$ = 4.100; p = 0.061; η^2 = 0.215]. However, no main effect of the *Group* [$F(1,15)$ = 0.403; p = 0.535; η^2 = 0.026] or of the *Gender* [$F(1,15)$ = 2.965; p = 0.106; η^2 = 0.165] was revealed. Thus, these results suggest a learning effect, as it was the case in the peak performance analyses. This ANCOVA also revealed several significant interactions. First, there was a *Run * Mental Rotation Scores* interaction [$F(1,15)$ = 7.545; $p \leqslant 0.05$; η^2 = 0.335]. Second, the *Run * Gender* interaction [$F(1,15)$ = 7.381; $p \leqslant 0.05$; η^2 = 0.330] suggests that while men's MI-BCI performances (corrected so that they are independent from spatial ability scores) were stable accross the 4 runs, women's increased significantly (see Figure 43). Furthermore, the *Run * Group* interaction [$F(1,15)$ = 6.376; $p \leqslant 0.05$; η^2 = 0.298] revealed that, consid-



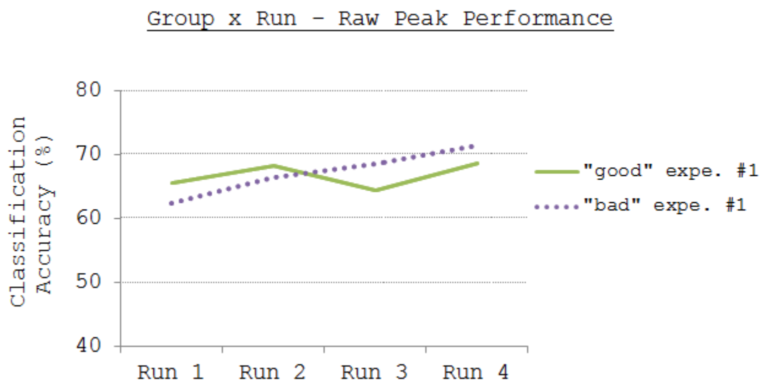
(a)



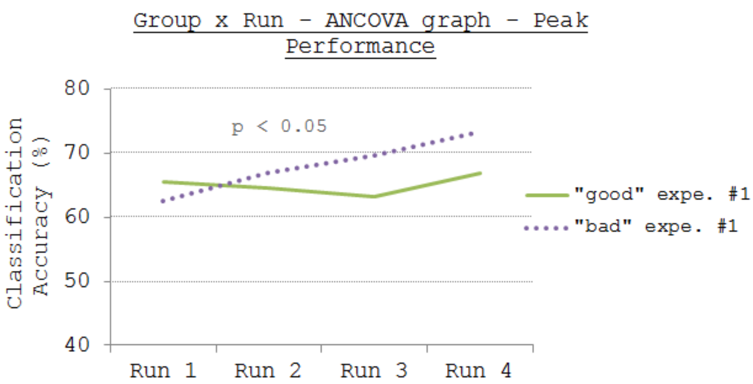
(b)

Figure 39 – (a) Graph representing participants' raw MI-BCI peak performance (i.e., without the ANCOVA correction) as a function of their gender and of the run; (b) Graph representing the ANCOVA results for the Gender*Run interaction ($p<0.05$), considering the Mental Rotation Scores as a covariable. When considering the performance independently from the mental rotation scores, women increase in performance accross the 4 runs while men do not.

ering performance independently from participants' spatial abilities, participants from the *good* group obtained a better performance than those of the *bad* group at the first run, but then they did not improve while participants from the *bad* group improved in terms of performance (see Figure 44), as was the case with the previous ANCOVA. Finally, contrary to what we observed with peak MI-BCI performance, it revealed a strong tendency towards a *Gender * Group* interaction [$F(1,15) = 3.833$; $p = 0.069$; $\eta^2 = 0.204$] (see Figure 45) but no *Run * Gender * Group* interaction [$F(1,15) = 2.319$; $p = 0.149$; $\eta^2 = 0.134$].



(a)

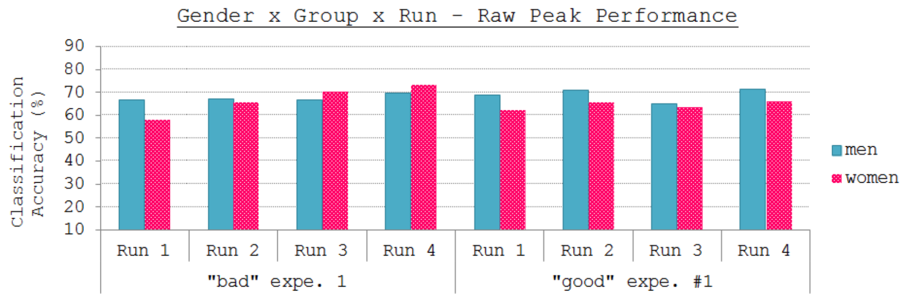


(b)

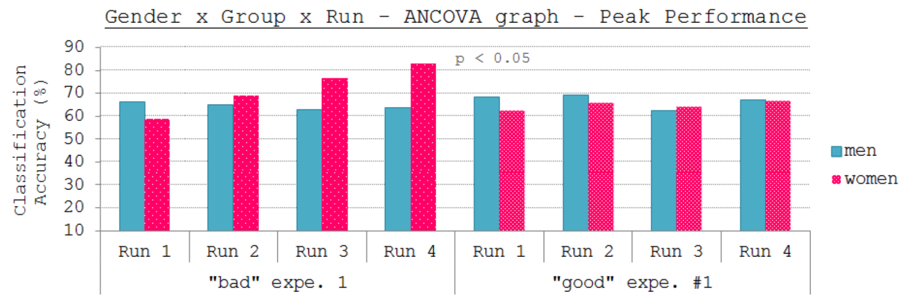
Figure 40 – (a) Graph representing participants' raw MI-BCI peak performance (i.e., without the ANCOVA correction) as a function of their group from experiment 1 and of the run; (b) Graph representing the ANCOVA results for the Group*Run interaction ($p<0.05$), considering the Mental Rotation Scores as a covariable. When considering the performance independently from the mental rotation scores, participants from the "good" group of the first experiment obtain stable performance across the four runs while participants from the "bad" group of the first experiment begin with lower performance but then improve and outperform the other group in the third and fourth runs.

7.3.2.2 *Usability Questionnaires*

We also evaluated the score associated with the four dimensions of the usability questionnaire [*learnability/memorability, efficiency/effectiveness, safety* and *satisfaction*] as a function of the participant's "Group" (*good* vs. *bad*), "Gender" (*men* vs. *women*) and of their "Mental Rotation Score". We thus performed four ANCOVAs. The prerequisite checking is depicted in Figure 46. The data satisfied the criteria for a normal distribution, homogeneity of the regression slopes and equality of variances. However, it has to be noticed that the linearity criteria was not satisfied.



(a)



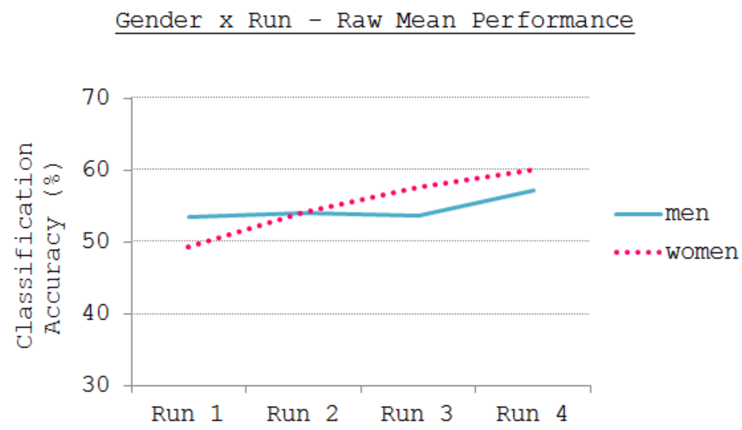
(b)

Figure 41 – (a) Graph representing participants' raw MI-BCI peak performance (i.e., without the ANCOVA correction) as a function of their gender, of their group and of the run; (b) Graph representing the ANCOVA results for the Gender*Group*Run interaction ($p<0.05$), considering the Mental Rotation Scores as a covariable. When considering the performance independently from the mental rotation scores, it can be noticed that women from the group "bad" [dark red on the left] improve in terms of performance across the runs while all the other participants do not.

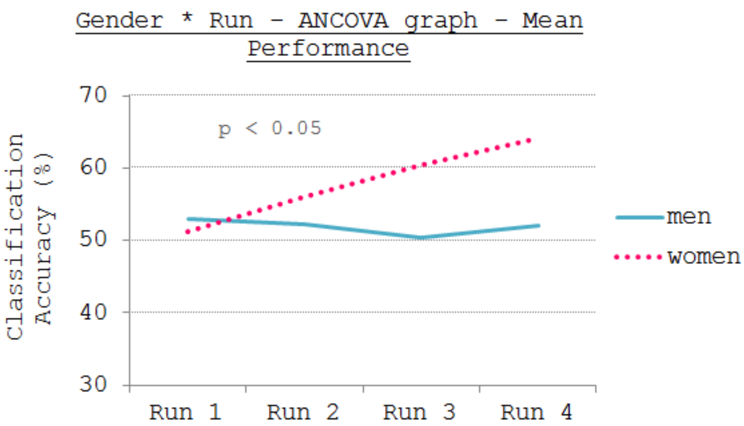
	Normality	Linearity	Homogeneity of Regression Slots	Equality of Variances
Mental Rotation Scores	s = 0.049		p = 0.450	
Run 1	s = 0.533	p = 0.159		p = 0.326
Run 2	s = 0.344	p = 0.600		p = 0.700
Run 3	s = 1.287	p = 0.684		p = 0.465
Run 4	s = 0.577	p = 0.280		p = 0.767

Figure 42 – Table representing the assumptions checking for the ANCOVA on mean performance.

No effect of the Group, of the Gender nor an interaction of both was revealed for the *Learnability/Memorability*, the *Safety* and the *Satisfaction* dimensions. For the *Efficiency/Effectiveness* dimension however, two strong tendencies were revealed: a tendency towards a main ef-



(a)

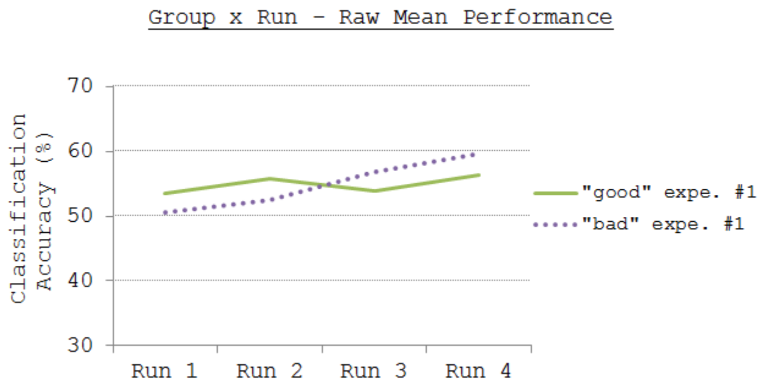


(b)

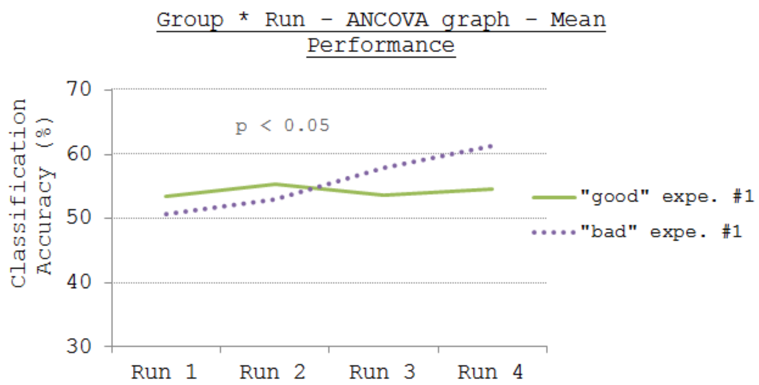
Figure 43 – (a) Graph representing participants' raw MI-BCI mean performance (i.e., without the ANCOVA correction) as a function of their gender and of the run; (b) Graph representing the ANCOVA results for the Gender*Run interaction (p<0.05), considering the Mental Rotation Scores as a covariable. When considering the performance independently from the mental rotation scores, women performances increase while men's do not.

fect of the group [$F(1,19) = 3.508$; $p = 0.081$; $\eta^2 = 0.190$] and towards a group*gender interaction [$F(1,19) = 3.439$; $p = 0.083$; $\eta^2 = 0.187$]. These interactions suggest that men evaluated the *Efficiency/Effectiveness* of the MI-BCI protocol the same whatever their performance at the first experiment, while women evaluated this dimension with lower scores when they had difficulties at the first experiment, and with higher scores when they managed at the first experiment.

Due to the low number of participants per group (N=20, i.e., only 5 per group*gender), all the results depicted have to be treated with caution.



(a)



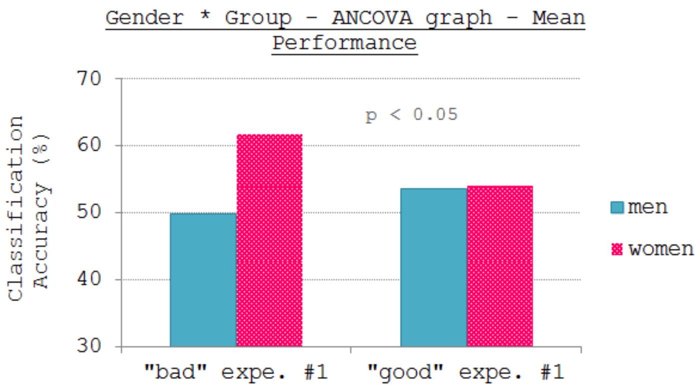
(b)

Figure 44 – (a) Graph representing participants' raw MI-BCI mean performance (i.e., without the ANCOVA correction) as a function of their group from experiment 1 and of the run; (b) Graph representing the ANCOVA results for the Group*Run interaction ($p<0.05$), considering the Mental Rotation Scores as a covariable. When considering the performance independently from the mental rotation scores, it can be noticed that participants from the group "good" of the first experiment obtain stable performance across the four runs while participants from the group "bad" of the first experiment begin with lower performance but then improve and outperform the other group from the third run.

7.3.3 *Discussion*

This second aimed at determining the impact of the feedback in the MI-BCI related skill acquisition process by comparing the profile of users' performance between the motor and MI-BCI tasks. Indeed, the hypothesis was that if motor and MI-BCI performances are, at least partly, related to the user's ability to process the feedback, then one can hypothesise that users who reached good performances at the simple motor tasks should also be able to obtain good MI-BCI performances.

(a)



(b)

Figure 45 – (a) Graph representing participants' raw MI-BCI mean performance (i.e., without the ANCOVA correction) as a function of their gender and of their group; (b) Graph representing the ANCOVA results for the Gender*Group interaction ($p<0.05$), considering the Mental Rotation Scores as a covariable. When considering the performance independently from the mental rotation scores, it can be noticed that men from both groups ("good" and "bad") keep the same ratio at the second experiment: participants from the "good" group outperform the ones from the "bad" group. It is not the case for women. Indeed, while women from the "good" group obtain similar performance to men of their group, women from the group "bad" outperforme all the other participants.

While this second experiment did not reveal any significant linear positive correlation between motor-task performance (first experiment) and MI-BCI performance, the ANCOVA results showed that whatever performance measure was used (peak or mean classification accuracy), there is a main effect of the Mental Rotation scores as well as significant Run*Mental-Rotation, Run*Gender and Run*Group interactions. First, the main effect of Mental Rotation scores confirms the important impact of spatial abilities on BCI performance that was

	Normality	Linearity	Homogeneity of Regression Slots	Equality of Variances
Mental Rotation Scores	s = 0.049			
Learnability / Memorability	s = -0.542	p = 0.543	p = 0.335	p = 0.103
Efficiency / Effectiveness	s = 0.191	p = 0.582	p = 0.230	p = 0.217
Safety	s = 0.344	p = 0.874	p = 0.564	p = 0.891
Satisfaction	s = -0.044	p = 0.366	p = 0.741	p = 0.213

Figure 46 – Table representing the assumptions checking for the ANCOVA. It has to be noticed that all the assumptions but the linearity were respected.

suggested in the previous Section for mental imagery based BCI (not purely motor ones). The important role of spatial abilities was also strengthened by the significant correlation between MI-BCI performance (peak classification accuracy) and Mental Rotation scores. Second, the interactions suggest that when the effect of the spatial abilities is controlled for, (1) *women* improved across the runs while *men* did not and (2) participants who were *bad* performers in the first experiment began with lower MI-BCI performance than *good* performers. However the former improved across the runs whereas the latter did not. There is in fact a strong tendency [p=0.058] towards a Run*Gender*Group interaction when assessing performance using peak classification accuracy. This last interaction indicates that men kept the same ratio between the first and the second experiment: men who were good at the first experiment remained better at the second experiment than the others (i.e., the bad performers of the first experiment) but none of them improved during the second experiment. Women who were good at the first experiment remained good at the second (at the same performance level as the men of their group), but they did not progress. However, women from the *bad* group began with low performances in the second experiment but their performances quickly improved and eventually surpassed the others. Thus, it would seem that participants who faced difficulty during the first experiment, especially women, improved more easily in terms of performance during the second experiment. This could be explained by the fact that facing difficulty in the context of a complex task (such as MI tasks, for which we are not trained and for which we do not have any proprioceptive feedback) requires substantial cognitive resources. Thus, these resources are not available to understand how to use the information provided by the feedback. By opposition, when users face difficulty to find the right strategy in a less complex context (such as performing motor tasks which they know they can do and for which they have proprioceptive feedback) their available resources allow them to pay attention to the feedback and to understand how the latter could be used to improve their performance. Once the process has already been executed, a re-exposition to this protocol would not require as many resources and so could be used efficiently in a more complex context.

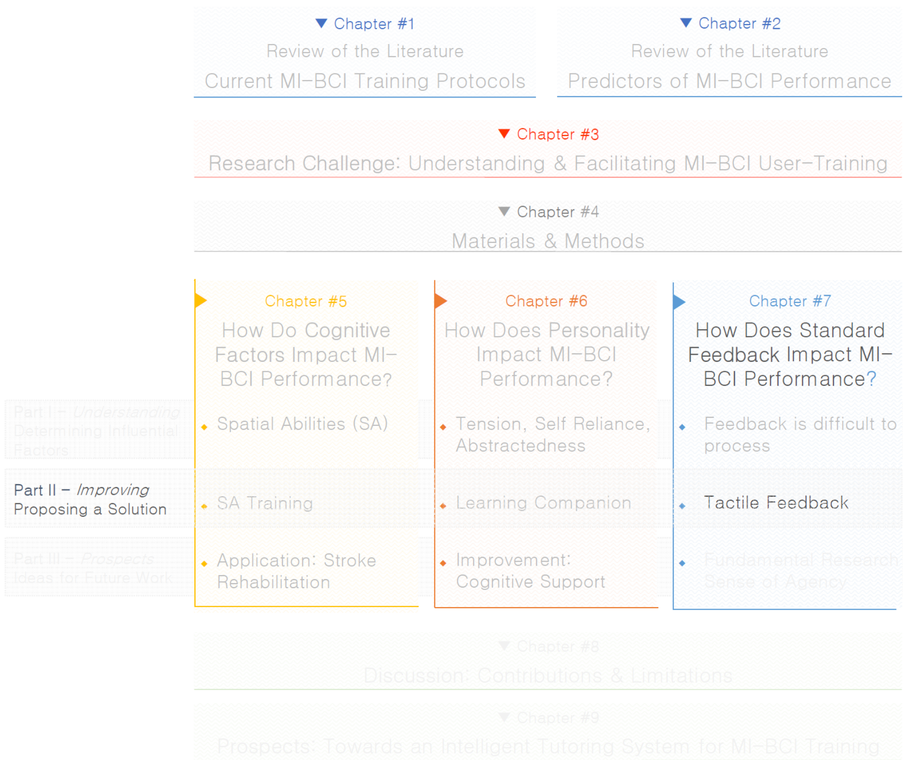
In our case, understanding the feedback would mean understanding what it means, when the user should maintain his strategy/when he should modify it. People who faced difficulty during the motor task learnt how and when to test and modify their strategies, which helped them when confronted with the MI-BCI experiment which was more complex. Of course, this hypothesis needs to be tested in a future experiment.

It is not entirely clear why gender plays a role in BCI performance and observed training effects. A possible interpretation could be that since women have lower spatial abilities than men on average (Linn and Petersen, 1985), and that spatial abilities are correlated to BCI performances, they have more room for improvement, which could explain why they improved over the runs while men did not. Indeed, Uttal et al., 2013 have shown that spatial abilities could improve, especially when the initial level was low. Another interpretation could be that women may rely on different cognitive mechanisms and strategies when faced with a difficult learning problem, although we are not aware of any literature on this topic. This should therefore be investigated further.

To summarise, this experiment revealed an effect of the motor training on MI-BCI performance. Contrariwise to our hypothesis, the participants who managed to reach the best MI-BCI performance were those who faced difficulty during the motor training ; while the good performers at the motor task did not manage to improve during the MI-BCI training. This result suggest that the standard feedback is difficult to process, that it requires much cognitive resources at least at the beginning. It would explain why participants who encountered difficulty while doing simple motor tasks, who had free cognitive resources, managed to learn how to use the feedback (and thus used it during the MI-BCI training) while the participants who were needing to use the feedback for the first time when confronted to a complex task (MI-BCI training) had no free resources to process it. The next Section relates theoretical cues that could be used to decrease the feedback-related cognitive resources. These cues are then tested and discussed.

PART II - HOW COULD MI-BCI USER-TRAINING BE IMPROVED THROUGH THE BETTERMENT OF THE FEEDBACK?

ROADMAP -



QUICK SUMMARY -

Our results suggest that the current standard feedback requires too many cognitive resources to be processed. Based on the Cognitive Load theory, we designed and implemented a tactile feedback, provided on the palms of the hands. We hypothesised that splitting the information -about the task and the feedback- into 2 channels -visual and tactile- would avoid cognitive resources being overloaded. First, we explain how the tactile feedback was designed. Then, we compare tactile and visual feedback. Results (N=18) show that participants who received tactile feedback performed better at the MI-BCI tasks as well as at a secondary attentional task than those who were provided with visual feedback.

COLLABORATOR -

Chi Tanh Vi & Daniel Spelmezan (Post-Doc Fellows).

RELATED PAPERS -

-1- Jeunet, C., Vi, C., Spelmezan, D., N'Kaoua, B., Lotte, F., and Subramanian, S. (2015). 'Continuous Tactile Feedback for Motor-Imagery based Brain-Computer Interaction in a Multitasking Context.' In: *Proceedings of Interact 2015*.

7.4 COGNITIVE LOAD THEORY - LESSONS FROM INSTRUCTIONAL DESIGN: REDUCING THE EXTRINSIC COGNITIVE LOAD ALLOCATED TO THE TRAINING PROTOCOL.

The two experiments we conducted provide a number of relevant insights regarding MI-BCI training with standard training protocols. The first experiment showed that using the Graz feedback, around 17% of the participants did not manage to find the right strategy to reach good performances at simple motor tasks. This result, added to the reports of the participants, suggests that the feedback is not clear and difficult to process and thus should be changed in order to enable all the participants to learn. Interestingly enough, this is also what is theoretically recommended for successful training in instructional design literature (Lotte et al., 2013). The results of the second experiment, that aimed at exploring the relationship between motor and MI-BCI performance obtained with the same Graz training protocol, suggested that participants who faced difficulty during the first experiment improved more easily in terms of performance during the second experiment. This could be explained by the fact that facing difficulty in the context of a complex task (such as MI tasks, for which we are not trained and for which we do not have any proprioceptive feedback) requires substantial cognitive resources. Thus, not much resources are available to understand how to use the information provided by the training protocol or by the feedback. By opposition, when users face difficulty to find the right strategy in a less complex context (such as performing motor tasks which they know they can do and for which they have proprioceptive feedback) they have more available resources to allow them to process the training protocol and feedback and to understand how the latter could be used to improve their performance. Once the process has already been executed, a re-exposition to this protocol would not require as many resources and so could be used efficiently in a more complex context. Based on this hypothesis, two solutions could be proposed: (1) to pre-expose all the users to a “simple" task (i.e., not requiring all their cognitive resources) and adapt the difficulty of this task so that they have to process the feedback before they are confronted to complex MI-BCI tasks or (2) to modify the feedback in order to decrease the amount of resources required to process it so that it can be processed while performing complex MI-BCI tasks.

These solutions can be modelled by the Cognitive Load Theory from Instructional Design (De Jong, 2010). This theory states that cognitive resources in working memory are limited and thus that if a task requires too much resources to be performed, learning will be hampered (De Jong, 2010). Therefore, the use of cognitive resources should be optimised to avoid overload. In the aim to do so, 3 types of cognitive load should be considered to design training protocols:

— Extrinsic Cognitive Load - is the load caused by superfluous information, itself due to design flaws in the training protocol.
— Intrinsic Cognitive Load - corresponds to the effort required to perform the task ; the task being the mean to reach the goal of acquiring knowledge
— Germane/Essential Cognitive Load - is the load corresponding to the construction of new knowledge.

Research in instructional design suggests that to improve learning, extrinsic cognitive load (and perhaps also intrinsic cognitive load, if possible) should be reduced so that more resources are allocated to the germane cognitive load.

To go back to MI-BCI user-training protocols, it seems that extrinsic cognitive load is important notably due to the feedback that is difficult to process. One solution to reduce this extrinsic cognitive load, and thus to enable BCI users to process the feedback at the same time they perform a complex cognitive task (namely the BCI control), would be to propose a feedback requiring less cognitive resources. In the next section, we explain why we chose a tactile feedback to reach this objective.

7.5 THEORY - A MORE INTUITIVE TACTILE FEEDBACK TO IMPROVE MI-BCI USER-TRAINING.

7.5.1 *Why Propose a Tactile Feedback?*

Research in instructional design put much effort in looking for solutions enabling to reduce extrinsic workload. Based on experimental results, researchers described the Modality Effect (Ginns, 2005): when performing a task requires the integration of different information sources, it is most of the time more efficient to provide the learners with these sources in different modalities. In other words, providing the participant with different pieces of information through different modalities would enable to reduce extrinsic cognitive load and thus to favour learning (as more resources are allocated to the germane cognitive load). One condition for the modality effect to occur is that the sources of information are complementary (and not redundant).

Most MI-BCI studies to date involved visual feedback to inform the user about the MI task recognised by the system. Yet, this visual feedback is difficult to assimilate when integrated with the visual layout of the primary interactive application that it supports (Gwak et al., 2014). Indeed, in interactive environments most of the information is communicated through the visual channel, the latter being often overtaxed (Leeb et al., 2013). Thus, integrating the visual feedback into the application is likely to induce an overload and thus a decrease in performance. Therefore, it seems that MI-BCI training protocols could benefit from multi-modality which is, interestingly enough, consistent with the cognitive load theory and the modality effect.

On the other hand, tactile feedback, although popular in other areas of HCI, has not received much attention for MI-BCI despite its advantages such as: (a) freeing the visual channel in order to reduce cognitive workload (Leeb et al., 2013), (b) maintaining a certain amount of privacy, as it is more difficult to be perceived by the surroundings than the visual or auditory ones, and (c) the possibility to be used in a wide range of interactive tasks, such as in gaming conditions. Using tactile feedback will separate the application channel (visual) from the MI-BCI feedback channel (tactile), thus potentially decreasing the extrinsic cognitive load. This should consequently increase the user's performance and system's efficiency.

The benefits of providing a tactile feedback to improve MI-BCI users' performance (i.e., their ability to do MI tasks correctly recognised by the system) have been explored in the study introduced below (Jeunet et al., 2015a). The efficiency of this feedback has been tested in an environment containing visual distracters. Indeed, BCIs are inherently developed to promote interaction. Yet, most MI-BCI studies test their feedback efficiency (1) in a laboratory context, i.e., with no distracters and (2) with no side task, while in real applications such as games users would have to perform multitasking. Thus, the efficiency of these feedbacks cannot be guaranteed in an interactive and multitasking context. This is why we study our tactile feedback's efficiency by comparing it to the equivalent visual feedback, similar to the Graz protocol (from which it differs only in terms of sensory modality), (1) in a context including visual distracters (to mimic an interaction environment) and (2) by adding a counting task (to evaluate the cognitive resources needed to process each kind of feedback) (for a description of the training environment, see Section 7.7.1). Our tactile system is in the form of a wearable glove that integrates five vibrotactile actuators for each hand to provide continuous tactile feedback to the user regarding the classifier output (for more information about the design of the tactile feedback, see Section 7.6). This feedback is expected to expand the user's feedback bandwidth while reducing the visual cognitive load.

7.5.2 *State of the Art of Tactile Feedback for BCI User-Training*

Tactile feedback for MI-BCIs has been mainly used in a medical context. Indeed, Wilson et al., 2012 explored lingual electro-tactile stimulation, as the tongue provides an excellent spatial resolution, and its sensitivity is preserved in the case of spinal cord injuries; while Gomez Rodriguez et al., 2011 and Ramos-Murguialday et al., 2012 focused on proprioceptive feedback (i.e., information about the limbs' position and about the strength developed while performing a movement) and showed that proprioceptive feedback allows increasing BCI performance, indicating that these alternative feedback are very promising for patients. However, these kinds of tactile feedback are quite cumbersome and expensive. Thus, they do not seem to be relevant for applications targeting the general public.

A few studies explored tactile feedback for general public applications. Most of these studies in which haptic feedback has been chosen to inform the user about the classifier output used vibrotactile feedback with either a variation of the vibration patterns (e.g., different motor activation rhythms according to the classifier output) (Chatterjee et al., 2007) or variations in spatial location (Cincotti et al., 2007; McCraedie, Coyle, and Prasad, 2014). Results show benefits when coupled with visual feedback, but only when the vibrotactile feedback maps the "stimulus" location (i.e., the MI task the participant has to perform). This relationship is known as “control-display mapping” (Thurlings et al., 2012). For example, when a right-hand MI is recognised, tactile feedback provided to the right part of the body will be more efficient (i.e., associated with better performance and user experience) than tactile feedback provided to the left side. Results also show similar performances between visual and tactile feedback, and the participants reported that tactile feedback was more natural than visual feedback, although negative feedback due to a misclassification of the mental task (e.g., vibrations on the left-hand because a left-hand motor-imagery was recognised while you were imagining a right-hand movement) can be annoying. Nevertheless, Cincotti et al., 2007 and Leeb et al., 2013 suggest that although it is disturbing, negative vibrotactile feedback (i.e., vibrations on the *wrong* hand) has no impact on classification (i.e., it does not affect the brain patterns used by the system to recognise the MI tasks). A few studies already attempted to use continuous vibrotactile feedback (Cincotti et al., 2007; Gwak et al., 2014; Leeb et al., 2013). For instance, Cincotti et al., 2007 propose a continuous tactile feedback in one of their studies. However, their set up is different from ours: feedback is provided on the neck (as opposed to the palm of the hand, see Section 7.6), only updated every 2 seconds (as opposed to every 0.250s, see Section 7.6) and more importantly, the feedback has not been tested in a BCI control context. In Gwak et al., 2014, a comparison between visual and tactile feedback was proposed, and the findings showed that they are associated with equivalent performances in a BCI context. In Leeb et al., 2013, visual and tactile feedback were compared in the context of a visual attention task performed using a BCI. In the latter study, tactile feedback was shown to be associated with better performances than the visual one. Unfortunately, these studies present some limitations. First, the samples are small: 6–7 subjects. Second, and most importantly, as they used within subject comparisons and that the conditions were not counterbalanced (the visual feedback was always tested before the tactile feedback), one cannot rule out that these results are due to an order effect. Finally, while the feedbacks were tested in presence of distracters (Leeb et al., 2013), it is not a multitasking context as the visual attention task and the MI-BCI control task have been performed sequentially. In our study, we propose to overcome these limitations with a larger sample (18 participants), a between-subject paradigm and an MI-BCI control task combined with a counting task requiring supplementary cognitive resources.

7.6 DESIGN & VALIDATION OF THE TACTILE FEEDBACK.

The main goal of our work is to compare the standard visual feedback with an equivalent tactile feedback in a context of multitasking and in an environment containing distracters in order to mimic possible interaction situations in which MI-BCIs could be used, e.g., a video game. Thus, in this section we first explain how we designed our vibrotactile and corresponding visual feedback. Then we describe the developed hardware prototype and the design of the glove for providing this tactile feedback at the hand, as well as the mapping between visual and tactile stimuli.

7.6.1 *Design of the Tactile Feedback*

7.6.1.1 *The Temporally Continuous Tactile Feedback*

As pointed out earlier, the MI-BCI classifier output, which is usually provided as feedback to the user, is the combination of the label of the recognised MI task and the confidence value of the classifier in the recognition of this task. The classifier output can be mapped to [-0.5, 0.5] (e.g., when a probabilistic SVM is used, see the Table in Section 7.7.2.2). Negative values correspond to a left hand MI recognition while positive values correspond to right hand MI recognition. The closer these values are to the end of the range, the higher the confidence level of the classifier (e.g., for right hand MI the value 0.42 represents a higher confidence level than 0.16). Our goal was to represent this output via the tactile channel as closely as possible to the standard visual feedback (in which the output is represented as a bar varying in length and direction). The MI-BCI system we will use in this study relies on left- and right-hand MI. Thus, we decided to give tactile feedback to the hands to maintain the control-display mapping (Thurlings et al., 2012) between the intended user actions (MI) and the sensory information perceived by the user (the tactile feedback). Indeed, control-display mapping has been shown to be necessary so that tactile feedback is efficient (Thurlings et al., 2012). The large surface of the palm (the average width is 74 mm for women, 84 mm for men) makes it possible to create a tactile display suitable

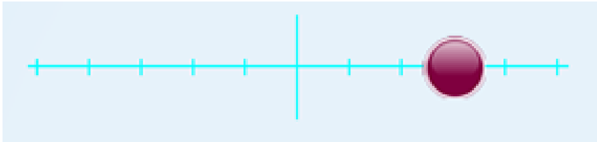


Figure 47 – Visual feedback with current feedback symbolising the recognition of a right hand MI, at level 3/5.

for representing the MI-BCI classifier output. Indeed, considering the two-point threshold of the palm (around 8 mm - Gescheider, Wright, and Verrillo, 2010), the width of the actuators, 8 mm, and the fact that we wanted our design to be suitable for most of the users (and thus narrower than the average palm width, 74 mm), we determined that we could put 5 motors maximum on each hand. Thus, we divided the classifier output range of [-0.5, 0.5] into 10 discrete levels, with 5 levels on the left and 5 levels on the right hand. Vibrations on the left-/right palm corresponded to the recognition of a left/right hand MI by the classifier, respectively. With the palms being facing upwards, vibrations near the thumbs corresponded to high confidence levels (close to |0.5|) while vibrations near the little finger corresponded to low confidence levels (close to 0). Standard MI-BCI update rates, i.e., 16Hz (62.5ms), can be difficult to achieve with tactile feedback as a stimulus should be provided for at least 200ms to be easily recognisable over the tactile channel (Gescheider, Wright, and Verrillo, 2010). Consequently, we chose an update rate of 4Hz (every 250ms), to ensure a perceivable tactile feedback.

7.6.1.2 *The Equivalent Visual Feedback*

Standard visual feedback corresponds to a continuous bar varying in length and direction. To make both the visual and tactile feedback as similar as possible, and because the tactile feedback has been spatially discretised (classifier output range of [-0.5, 0.5] divided into 10 discrete levels), we also discretised the standard bar in the same way. Thus, the feedback was displayed as a red cursor on a cross, with 5 ticks on the left and 5 ticks on the right side (see Figure 47). The cursor was on the left/right side of the cross when a left/right hand MI was recognised, respectively. Moreover, the cursor moving to the extremities of the cross represented high confidence values. Finally, we also reduced the standard update rate of 16Hz to 4Hz so that it fits the tactile feedback update rate.

7.6.1.3 *Hardware Design*

To provide the user with tactile feedback, we designed a glove for the left and the right hand in which 5 vibrotactile actuators were embedded (see Figure 48). The actuators were cylindrical vibration motors (model 307-100 by Precision Microdrives, Figure 48, left). Each

Figure 48 – Left: A vibration motor. Right: Our gloves with 10 embedded motors (5 per hand). In the tactile feedback condition, individual motors are activated to represent the classifier output.

motor is 8.0 mm wide and 25 mm long. The motors were connected to a custom-built motor shield and were controlled by pulse-width modulation using an Arduino Due. The ten motors were powered from an external supply (2V).

7.6.2 *Validation of the Tactile Feedback - Determining the Most Distinguishable Intensity and Pattern of Activation of the Motors.*

As stated earlier, some previous studies have explored continuously updated feedback for MI-BCIs (Cincotti et al., 2007; Gwak et al., 2014; Leeb et al., 2013), but not much work has been led in order to evaluate the optimal parameters for this feedback modality. For instance, should the vibration pattern be encoded as localised vibration from a single motor, or as simultaneous vibrations of multiple neighbouring motors to represent a specific classifier output? Another question concerns the tactile stimulus intensity. Indeed, the vibration should be strong enough to be perceived but not too intense, as it could distract the user and be uncomfortable. Below, we describe the user study conducted to investigate these questions.

7.6.2.1 *Participants*

Ten volunteers (*4 females; aged 28.8* $\pm$ *8.2* year-old) from the local university participated in this study. Some participants had previous experience with vibrotactile feedback but none of them had participated in this experiment before. This study has been approved by the Ethics Committee of the University of Bristol (July 31st, 2014). All the participants signed an informed consent form.

7.6.2.2 *Experimental Design*

We investigated two designs of vibration patterns for representing the classifier output. One design implemented localised vibration, i.e., only one of the vibration motors was active at a given time (e.g., the third motor of the right hand if a right-hand MI was recognised with a confidence value in [0.2, 0.3]). The other design implemented simultaneous vibration of neighbouring motors. The latter pattern entailed activating all motors of the hand corresponding to the recognised MI task whose index value was smaller or equal to the current classifier level (e.g., the first, second and third motors of the right hand, from left to right, if a right-hand MI was recognised with a confidence value in [0.2, 0.3]). The rationale between these two designs was to (1) maintain the spatial mapping between the visual and tactile feedback and (2) to indicate the relative change in the classifier's output. Our first informal test of the motors (2V) revealed a strong unpleasant tactile stimulus (the normalised vibration amplitude of the motor was 3G relative to a 100g mass). In order to design more subtle tactile stimuli, we adjusted the voltage used to control the motors (pulse-width modulation), which implicitly changed the motor's vibration frequency and vibration amplitude.

The experiment followed a 2x4 within-participant design with the factors:

- Pattern: localised vs. simultaneous vibration;
- Intensity: [0.1, 0.3, 0.5, 1] G with corresponding frequencies of [10, 40, 60, 85] Hz.

The participants were then asked to put on the gloves and to place their hands on the table in front of them in a supine position (palms facing upwards, as in Figure 48, right). We designed 8 vibration sequences which simulated vibrotactile feedback. As in a real scenario, these sequences were provided for 4s, during which 16 tactile stimuli appeared (4Hz update rate). We varied the factors Pattern and Intensity to compare:

- a. Localised to simultaneous vibrations with the same intensity level (4 possibilities);
- b. Localised vibration at 2 different intensity levels (6 possibilities);
- c. Simultaneous vibration at 2 different intensity levels (6 possibilities).

We considered both presentation orders for the patterns in (a), i.e., first localised then simultaneous and vice versa, and for the intensities in (b, c), i.e., first intensity 1 then intensity 2 and vice versa. Overall, we tested (4+6+6)*2=32 combinations. We randomly assigned one of the eight sequences at each of the combinations (so that they are not associated with the same combination for the different participants). For each combination, we asked the participants their favourite feedback (in terms of distinguishability and sensation), i.e., localised or simultaneous for (a) and intensity 1 or intensity 2 for (b, c). Thus, we evaluated the quality of the different patterns and intensities according to the number of times they were selected as the favourite one.

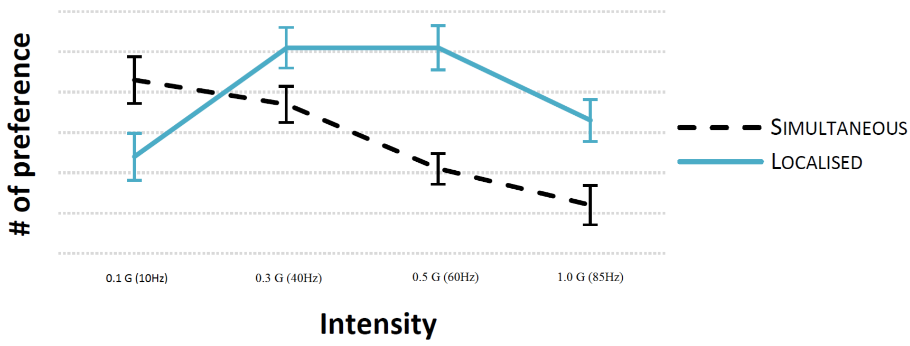


Figure 49 – Average number of times that a pattern was preferred as a function of its intensity.

This paradigm allowed us to find the best pattern*intensity association, which was the most often chosen as the favourite one.

7.6.2.3 *Variables & Factors*

The dependent variable studied here is the clearness/distinguishability of the feedback, as a function of 2 factors: the Intensity and Pattern of Activation of the motors.

7.6.2.4 *Results*

The 2-way ANOVA for repeated measures reveals a Pattern x Intensity interaction [$F(3,72) = 8.785$, $p \leqslant 0.001$, $\eta^2 = 0.268$], a main effect of the pattern [$F(1,72) = 10.184$, $p \leqslant 0.005$, $\eta^2 = 0.124$], and a main effect of the intensity [$F(3,72) = 6.071$, $p \leqslant 0.005$, $\eta^2 = 0.202$] (see Figure 49). Participants preferred the localised vibration over the simultaneous vibrations. Moreover, they preferred the lowest intensity in the case of simultaneous vibrations (the other ones being perceived as too strong). For the localised vibration, however, the lowest intensity (0.1G, 10Hz) was barely noticeable and did not allow the participants to clearly perceive the tactile feedback. The highest frequency was associated with a very strong and uncomfortable sensation. Thus, they preferred the middle intensity (0.3-0.5G).

7.6.2.5 *Discussion*

The results of this study suggest that the participants preferred a localised vibration at the palm, with only one vibration motor being active at a given time. Our findings also suggest that either 0.3G (40Hz) or 0.5G (60Hz) is appropriate for providing tactile feedback at the palm using the developed tactile feedback system. These findings provide first guidelines on how to design tactile feedback for stimulating the palm in an MI-BCI context. In addition, these results can inform the design of feedback for other interactive tasks in HCI which require a similar presentation of feedback to the user.

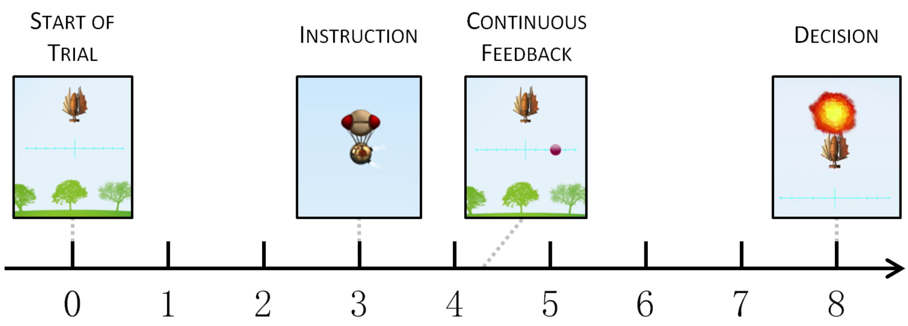


Figure 50 – Timing of a trial.

7.7 TEST OF THE EFFICIENCY OF THE TACTILE FEEDBACK TO IMPROVE MI-BCI USER-TRAINING.

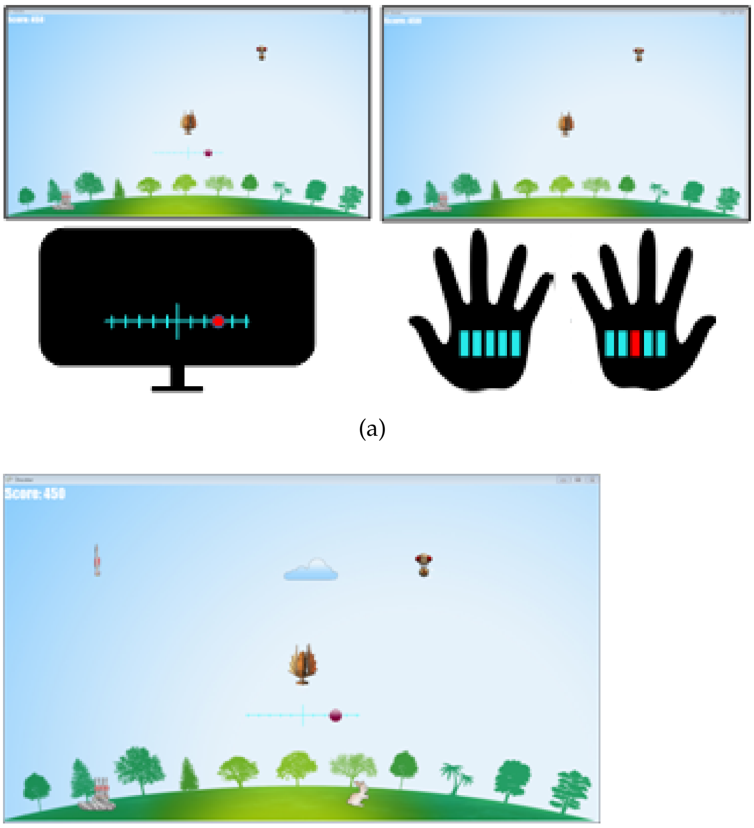
7.7.1 *Description of the Training Environment: Multitasking & Distracters*

BCIs are developed to be used in interactive applications (e.g., video games or navigation tasks), i.e., in a context including distracters and requiring multitasking abilities. Thus, it seems suboptimal to test the efficiency of a feedback outside this kind of context, i.e., in laboratory conditions by doing only an MI-BCI task. This is why we designed a training environment including visual distracters and asked the participants to perform a counting task at the same time they were performing the MI-BCI task (see Figure 51). By adding these elements, we were able to compare the cognitive load required to process each kind of feedback in an interactive situation and to evaluate how cognitive multitasking influences the efficiency of each feedback. In order to include the distracters and the counting task to the MI-BCI task in a consistent environment, we modified the standard MI-BCI training protocol. The standard arrows pointing left or right to inform the user he has to perform a left or right-hand motor-imagery have been replaced by a spacecraft the goal of which was to protect its planet by destroying bombs coming from the left or right (controlled by performing left- or right-hand motor-imagery, respectively) (see Figure 50). Besides, the distracters were appearing randomly in the form of (1) a missile, which was launched in a vertical direction from a tank, (2) a rabbit crossing from the left to the right, or (3) a cloud crossing from the right to the left (see Figure 51). Each distracter appeared for a similar amount of time (approximately 2.5s).

7.7.2 *Materials & Methods*

7.7.2.1 *Participants*

Eighteen healthy volunteers (5 women; aged 27.6 ± 4.8 year-old) participated in the study. Some of them had previously experienced



(a)

(b)

Figure 51 – Two feedback types representing the recognition of a right-hand MI, at level 3 out of 5. (a) Visual feedback was displayed as a red circle moving along the axis and vibrotactile feed-back at the palm was encoded as a vibration of the corresponding motor; (b) Environment visualisation with all elements: an enemy (top right), the spacecraft (centre), and visual feedback (lower centre, below the spacecraft); three distracters: missile (top left), cloud (top centre), and rabbit (bottom centre).

vibrotactile feedback. However, none of them had previous experience with MI-BCI. This study has been approved by the Ethics Committee of the University of Bristol (July 31st, 2014). All the participants signed an informed consent form.

7.7.2.2 *Experimental Paradigm*

Please refer to Figure 52.

7.7.2.3 *Variables & Factors*

The dependent variable considered was the Score obtained as a function of 2 factors: the feedback condition (visual vs. tactile) and the run number. The way the score was computed is explained below.

EXPERIMENTAL PARADIGM	
This experiment was composed of 1 motor-imagery based BCI session of 2.00 hours. The session was divided into 6 runs (1 calibration and 5 training runs), with 40 trials per run. Half of the participants received a visual feedback while the other half received an equivalent tactile feedback.	
BCI EXPERIMENTS – TRAINING PROTOCOL	
TRAINING TASKS	▼ Left-Hand Motor Imagery ▼ Right-Hand Motor Imagery
FEEDBACK	▼ *Modality:* Group 1 = Visual [cursor]; Group 2 = Tactile (see Section 7.6) ▼ *Update Frequency:* 4Hz ▼ *Content:* Classifier output
TRAINING ENVIRONMENT	▼ Gamified Environment Containing Distracters, based on the Standard Graz Training Environment (see Section 7.7.1)
BCI EXPERIMENTS – BRAIN SIGNAL RECORDINGS & PROCESSING	
HARDWARE & EEG SET-UP	▼ BrainVision actiCHamp amplifier (Brain Products, Germany) ▼ See the list in the Materiels & Methods Chapter ▼ Referenced to the right mastoid, grounded to Afz ▼ Sampling of the EEG data: 256Hz
SIGNAL PROCESSING PIPELINE	▼ Band-pass filtering of the EEG data: 8-30Hz *The classifier & CSP are trained on the run 1//* ▼ CSP → 6 band-power features ▼ Probabilistic SVM (fed with the features resulting from the CSP): probabilities of 0 and 1 represent the recognition of a left-hand MI and of a right-hand MI, respectively – this probability was shifted of 0.5 so that negative values [-0.5,0) represent the recognition of a left-hand movement imagination and positive values (0,0.5] represent the recognition of a right-hand movement imagination. ▼ Use of the resulting classifier to discriminate between the 2 tasks for the training runs 1 to 5

Figure 52 – Materials & Methods of the Study aiming at testing the efficiency of our tactile feedback, Section 7.7

.

At the end of each trial, the score was updated according to the following formula:
NEW SCORE = CURRENT SCORE + CLASS LABEL * CLASSIFIER OUTPUT * 200
The CLASS-LABEL was {+1} if a left-hand motor-imagery was recognised and {-1} if a right-hand motor-imagery was recognised. The CLASSIFIER-OUTPUT was the mean classifier output value calculated at the end of the trial: in [-0.5,0) if a left-hand MI was recognised, and in (0,0.5] if a right-hand MI was recognised. Therefore, after each trial, the score was increased or decreased by 100 points maximum, given that to obtain 100 points at one trial, the mean classifier output value of the trial had to be 0.5, which means that the classifier output had to be 0.5 for each of the 15 time windows (the feedback being updated at 4Hz for 3.75s). This value of 0.5 thus means that the classifier was 100% sure that the participant was performing a right-

hand motor-imagery for each of the 15 time windows. This never happens in MI-BCI. Besides, while the mean classifier output is positive, it means that the trial has been correctly classified. Thus, to take an extreme case, a score of 40/4000 at the end of the run (e.g., 1/100 at each of the 40 trials of the run) could be associated with a classification accuracy of 100% (as each mean classifier output was positive, it means that all the trials have been correctly classified). The motor-imagery score corresponded to the sum of the scores obtained in each trial. Furthermore, at the end of each run, the participant was asked to report the number of distracters (rabbits, clouds or rockets) he counted. If this number was correct, the participant was rewarded with 200 points being added to the MI score. If the error was in the order of $\pm$ 1, the score remained unchanged. Otherwise, 200 points were subtracted from the MI score. The final score corresponded to the sum of the MI scores for the 40 trials of the run and the counting task score. While arbitrary, this metric enabled to consider and give a significant weight to both the MI score and the counting task which allowed to evaluate the feedback relevance for both these aspects.

Besides, the participants were asked to complete a customised usability questionnaire assessing 4 dimensions of usability of the system: Learnability/Memorability, Efficiency/Effectiveness, Safety, Satisfaction.

7.7.3 *Results*

The main measurements of interest are (1) the final score (the sum of the motor-imagery task and the counting task scores), (2) the motor-imagery score alone, and (3) the absolute value of the difference between the counted and the actual number of distracters. These measures were analysed using three two-way ANOVAs. We performed a 2-way ANOVA so that we can analyse the interaction between both the feedback condition and the run number. However, given the low number of participants per condition (8 and 9) it was not possible to test the prerequisites for this analysis. Thus, we computed the effect sizes to ensure the robustness of our results. Analyses have been performed on 17 participants: 8 in the visual condition and 9 in the tactile condition. The data from one outlier participant have been removed as his final score (1628.8 ±630.5) differed considerably from his group mean final score (183.0 ±559.5).

The two-way ANOVA on the final score shows a main effect of the Feedback-Condition (visual vs. tactile) [$F(1,15) = 6.327$, $p \leqslant 0.05$, $\eta^2 = 0.291$], a main effect of the Run [$F(1,15) = 3.961$, $p \leqslant 0.01$, $\eta^2 = 0.457$] but no Run * Feedback-Condition interaction [$F(1,15) = 1.476$, $p = 0.243$, $\eta^2 = 0.09$]. The Feedback Condition effect is due to participants in the tactile feedback group having significantly better results than participants in the visual feedback group. Furthermore, concern-

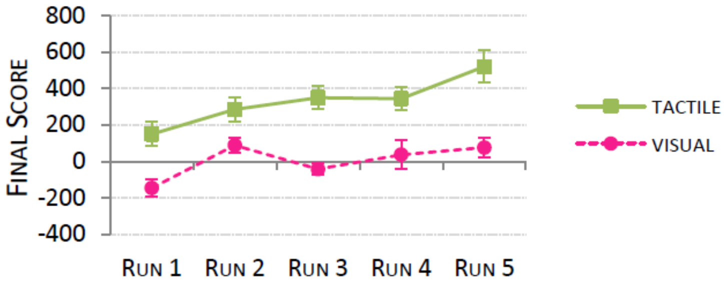


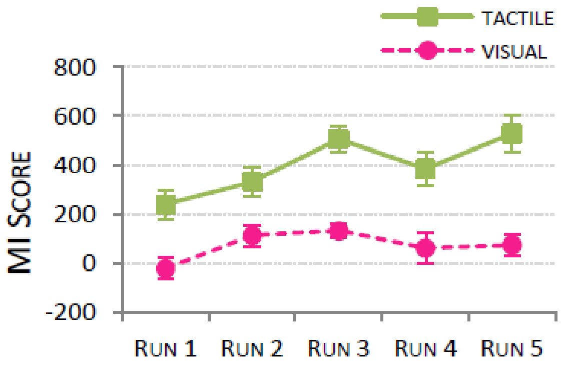
Figure 53 – **Average of the final scores (with standard error): sum of the MI task score and the distracter counting task score (reward and penalty).**

ing the Run main effect, post-hoc analysis shows a significant increase of performance between Run 1 and Run 5 ($p \leqslant 0.005$) (see Figure 54, left) which reveals the learning effect of the performed motor-imagery task, as indicated by the large effect size. The two-factor ANOVA on MI scores (see Figure 54, left) shows strong tendencies towards a Run main effect [$F(1,15) = 3.961$, $p = 0.065$, $\eta^2 = 0.209$] and towards a Feedback Condition effect [$F(1,15) = 4.063$, $p = 0.062$, $\eta^2 = 0.213$], as well as no interaction between these two factors [$F(1,15) = 1.207$, $p = 0.289$, $\eta^2 = 0.074$]. These results indicate a strong tendency towards a better MI score with tactile feedback than with visual feedback and a tendency towards an improved MI score across the Runs. The two-factor ANOVA on the counting task (see Figure 54, right) shows a main effect of the Run [$F(1,15) = 9.806$, $p \leqslant 0.01$] but no main effect of the Feedback Condition [$F(1,15) = 2.860$, $p = 0.111$] and no Run * Condition interaction [$F(1,15) = 0.000$, $p = 0.990$]. Thus, the participants improved their performance across the Runs for the counting task. Indeed, post-hoc analysis shows a significant difference between Run 1 and Run 4 ($p \leqslant 0.001$) and Run 1 and Run 5 ($p \leqslant 0.005$) performances.

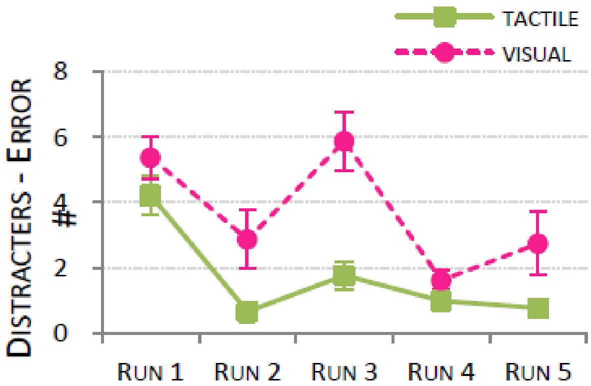
The 1 factor ANOVA did not reveal any differences in terms of usability between the visual and tactile feedback conditions: LM [$\bar{X}_{visual} = 60.47 \pm 10.52$, $\bar{X}_{tactile} = 56.53 \pm 13.46$ – $F(1,17) = 0.444$, $p = 0.515$], EE [$\bar{X}_{visual} = 67.86 \pm 13.72$, $\bar{X}_{tactile} = 56.19 \pm 19.95$ – $F(1,17) = 1.921$, $p = 0.186$], Satifaction [$\bar{X}_{visual} = 67.50 \pm 13.42$, $\bar{X}_{tactile} = 58.70 \pm 20.39$ – $F(1,17) = 1.071$, $p = 0.317$], Safety [$\bar{X}_{visual} = 61.25 \pm 18.08$, $\bar{X}_{tactile} = 55.56 \pm 23.51$ – $F(1,17) = 0.307$, $p = 0.588$].

7.7.4 *Discussion*

While the participants did not find the MI-BCI training easier or more satisfying with the tactile feedback, results suggest that continuous tactile feedback can significantly improve both users' MI-BCI and side visual task performances as compared to an equivalent visual feedback (same timing and update rate). Thus, it seems that a



(a)



(b)

Figure 54 – Left: Average of the MI scores (with standard error) without the counting task (reward and penalty). Right: Average of the distracter errors (difference between the counted and the actual number) for the counting task as a function of Run number and Feedback Condition.

vibrotactile feedback is easier to process and enables to reduce the extrinsic load dedicated to the training protocol and increase the germane load dedicated to the acquisition of knowledge. There are also other potential explanations of our tactile feedback's efficiency. First, this efficiency could be related to more important ERD/ERS in the motor-cortex due to the vibration-motor stimulations on the palms. Another potential explanation is that a feedback on the palms reinforces the control-display mapping, thus leading to a better sense of agency, itself resulting in better performance. These two hypotheses are investigated in the Part III of the current Section.

Link to a video of our vibrotactile gloves: here!

Besides, this study allowed us to determine some parameters the consideration of which could be useful for future designs of a tactile feebdack:

- *Tactile feedback location*: we chose the hand palms for their high spatial accuracy and the consistency with the motor-imagery tasks (left- and right-hand movement) (Thurlings et al., 2012).
- *Tactile feedback update rate*: we used a 4Hz feedback update rate so that each feedback is well perceived by the user (Gescheider, Wright, and Verrillo, 2010).
- *Pattern of vibration*: our first user study suggested that a tactile feedback based on localised stimulation (one motor at the time) is more pleasant and distinguishable than simultaneous vibrations.
- *Intensity of vibration*: our first study suggested that vibration intensities between 0.3G (40Hz) and 0.5G (60Hz) were best: lower intensities did not allow users to perceive the feedback clearly, whereas higher intensities were uncomfortable.

In the future, different elements should be considered in order to increase the validity of this study. First, more participants should be included. Moreover, as long-term use of continuous tactile feedback could result in a palm desensitisation and thus a decrease of performance, it would be important to determine when the feedback is useful or not so that performance can be optimised. Finally, in this study, only the feedback modality is discussed. Yet, much work has to be done on feedback content so that its associated load is decreased. Among others, the feedback should be explanative, supportive and meaningful (Lotte et al., 2013).

PART III - PROSPECTS: WHAT ARE THE PSYCHOLOGICAL & NEUROPHYSIOLOGICAL PROCESSES UNDERLYING TACTILE FEEDBACK EFFICIENCY?

ROADMAP -

QUICK SUMMARY -

Tactile feedback seems efficient to improve MI-BCI performance. We would like to understand the psychological and neurophysiological mechanisms underlying this efficiency. We offer several hypotheses. The first, as suggested before, is related to the fact that freeing the visual channel may avoid overloading cognitive resources, and therefore enable the user to reach a better performance. In the second hypothesis, we speculate that providing vibro-tactile feedback on the hands triggers the motor-cortex, which in turn facilitates the classification of motor-imagery tasks. Finally, the last is that tactile feedback reinforces the control-display mapping and therefore the user's sense of agency. A theoretical analysis of the MI-BCI user-training process that led us to hypothesise a potential role of the sense of agency is first proposed. Then, an experimental protocol aiming at testing the different hypotheses is described.

COLLABORATOR -

Patricia Cornelio (Ph.D Student).

7.8 THEORY - WHAT IS THE RELATIONSHIP BETWEEN EFFICIENCY OF TACTILE FEEDBACK FOR IMPROVING MI-BCI & THE SENSE OF AGENCY?

As explained in Chapter 2, the sense of agency can be defined as “the sense that I am the one who is causing or generating an action” (Gallagher, 2000). The sense of agency is of utmost importance when a person is controlling an external device, since it will influence their affect towards the technology, and thus their commitment to the task and their performance (Vlek et al., 2014). However, in the context of MI-BCIs, experiencing this sense of agency is not straightforward. Indeed, the sense of agency mainly relies on the sensory feedback resulting from a movement. Yet, the absence of proprioceptive feedback when performing mental imagery tasks *a priori* prevents this bodily experience from occurring (Haselager, 2013), and therefore could theoretically inhibit the sense of agency.

Thus, in Section 2.6, we insisted on the importance of the feedback, especially during the primary training phases of the user (McFarland, McCane, and Wolpaw, 1998). Indeed, in the first stages, the technology and the interaction paradigm (through MI tasks) are both new for the user. This is likely to induce pronounced computer anxiety associated with a low sense of agency. Providing the users with a sensory feedback informing them about the outcome of their "action" (MI task) seems necessary in order to trigger a certain sense of agency at the beginning of their training. This sense of agency will in turn unconsciously encourage users to persevere, increase their motivation, and thus promote the acquisition of MI-BCI related skills, which is likely to lead to better performances (Achim and Al Kassim, 2015, Saadé and Kira, 2009, Simsek, 2011).

Different cognitive models have been proposed with the aim of modelling the sense of agency and strengthening the importance of the feedback (also called sensory outcome). Among them, the *comparator model* (Feinberg, 1978), which is also called the *central monitoring theory*, is well adapted to illustrate the sense of agency process in an MI-BCI context. This model, described in Figure 55, suggests that the judgement of agency depends on the level of congruence between the predicted outcome and the sensory outcome of an action. If they are congruent, the person will feel in control while if they are not, the person will not feel in control. The predicted outcome is inferred before the movement is performed, from the motor signals, i.e., the efferent signals generated based on the intentions and motor plan conceived by the person. On the other hand, the sensory outcome follows the movement. Once perceived, this sensory outcome is compared to the predicted outcome. If they are congruent, there will be a feeling of "self-agency". Otherwise, the feeling of "‘self-agency"’ will not be perceived. This model could underlie the (experimentally proven)

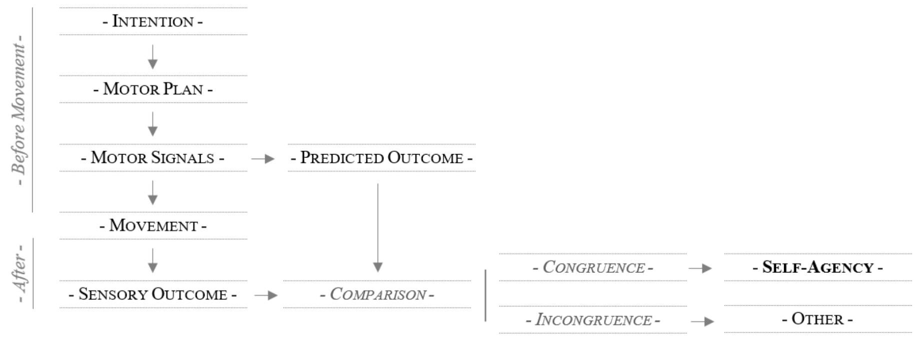


Figure 55 – **Schematic representation of the Comparator Model (Feinberg, 1978).**

efficiency of biased feedback for MI-BCI user-training. Indeed, literature (Barbero and Grosse-Wentrup, 2010; Kübler et al., 2001b) reports that providing MI-BCI users with biased feedback is associated with improved performances, at least while users are novice (experts develop the ability to generate a precise predicted outcome that usually matches the actual outcome: thus, when the feedback is biased, and therefore the predicted and actual outcomes do not match, expert users attribute the discrepancy to external causes more easily).

As explained in Chapter 2, for the sensory outcome, or feedback, to be congruent with the predicted outcome, several principles have to be followed (Vlek et al., 2014): the priority principle (the conscious intention to perform an act must immediately precede the act), the consistency principle (the sensory outcome must fit the predicted outcome) and the exclusivity principle (one's thoughts must be the only apparent cause of the outcome). Also, for the users to feel in control, the feedback should be consistent with the task, which corresponds to the concept of transparent mapping (Beursken, 2012) or control-display mapping (Thurlings et al., 2012). Transparent mapping could enable users to improve their performance on the one hand because they reach a better sense of agency and on the other hand because it allows more resources to be allocated to the task (the task-feedback mapping being more intuitive).

The goal of the study introduced in Section 7.6 was to decrease the workload associated to the feedback by splitting the cognitive resources into two modalities: the visual channel for the application-related information and the tactile channel for the MI-BCI feedback. Also, tactile feedback was provided on the hands in order to improve the transparent mapping between the motor-imagery tasks and the feedback. Therefore, this feedback which was more consistent with the task was also potentially expected to improve users' sense of agency.

The tactile feedback was revealed to be more efficient than an equivalent visual feedback. We hypothesise that the sense of agency played a significant role in the efficiency of tactile feedback. This hypothesis as well as the neural correlates of the sense of agency during MI-BCI training should be explored. The experimental protocol that would enable this test is introduced hereafter. Unfortunately, we did not have enough time to perform the study and provide the results before the time came to submit this thesis.

7.9 TOWARDS AN EXPERIMENTAL PROTOCOL AIMING AT INVESTIGATING THE NEUROPHYSIOLOGICAL AND PSYCHOLOGICAL PROCESSES UNDERLYING THE EFFICIENCY OF TACTILE FEEDBACK.

The goal of this experiment would be to reach a better understanding of why tactile feedback is associated to better MI-BCI performance than an equivalent visual feedback. Our experiment, introduced in Part II, suggests that tactile feedback requires less cognitive resources to be processed than an equivalent visual feedback (most likely because it enables a more transparent mapping). We have two additional hypotheses that could potentially explain this efficiency of improve MI-BCI user-training. First, providing the user with vibrations on the hands is likely to trigger the sensorimotor cortex. This activation could then contribute to the classification and improve its accuracy. The second hypothesis states that by improving control-display mapping, we also increase the sense of agency (as explained in Chapter 2). The first consequence could be to increase the involvement of the user in the task, while the second consequence could be an activation of the premotor cortex (which is a neurophysiological correlate of the sense of agency - as depicted in Chapter 2). This activation, similarly to the activation due to the vibrotactile stimulation, could take part in the classification process and result in a better classification accuracy.

In order to investigate the relevance of these hypotheses, we will have to explore different situations. To investigate the first hypothesis (i.e., motor cortex activation due to the vibrotactile stimulation of the hands), we will have to study the brain patterns when the user: (1) rests, (2) rests but receives vibrotactile stimulations on the hands (mimicking an MI-BCI feedback), (3) performs MI-tasks with vibrotactile feedback. This way, we will be able to determine precisely if there is an additional activation of the motor cortex due to the vibrotactile feedback and how much it contributes to the classification accuracy. In a second instance, to investigate the second hypothesis concerning the role of the sense of agency, we will have to study the brain patterns of the user in the following situations: (1) rest, (2) MI-BCI training with a low sense of agency, (3) MI-BCI with a high sense of agency. We know, based on the literature (Kübler et al., 2001b) that providing novices with a positively biased feedback increases their sense of agency. We will use this trick to study the difference in the neurophysiological activity between situations providing low/high sense of agency while users perform MI-BCI. The effect of the biased feedback will be verified using questionnaires.

Thus, in this experiment we could manipulate two aspects of the feedback: (1) the content: positively biased or non-biased feedback and (2) the modality: tactile vs. visual feedback. Combined, these 2 times 2 manipulations, would give us our four feedback conditions: biased/tactile, biased/visual, non-biased/tactile, non-biased/visual. We hypothesise that biased and tactile feedback would be associated with a better performance (i.e., classification accuracy). We would compare their brain activity during these four conditions with control conditions: rest, rest + visual feedback and rest + tactile feedback.

We have had not enough time to perform this experiment yet. But we intend to carry it out as soon as possible in order to abate the unbearable suspense.

III

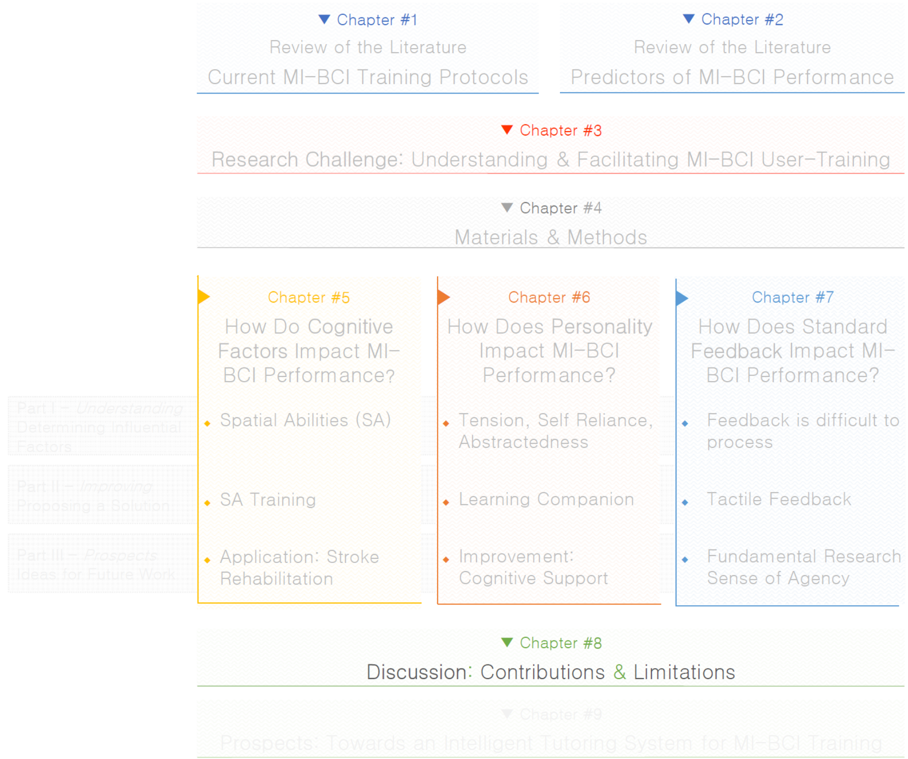
DISCUSSION & PROSPECTS

To complete this manuscript, we first propose a Discussion presenting the contributions and limitations of our work. Then, in the last chapter, we present the future Prospects of a potentially promising approach, which could enable MI-BCI skill acquisition to be investigated as a multifactorial and dynamic process.

8

DISCUSSION

ROADMAP -



QUICK SUMMARY -

The aim of this chapter is to provide a summary of the contributions of this thesis. It also aims at discussing the limitations of our work: small sample sizes, the fact we focused only on young healthy adults, sub-optimal classification algorithms or performance measures that were not always adapted.

8.1 MI-BCI USER-TRAINING - WHERE ARE WE?: CURRENT ADVANCEMENT & RESEARCH CHALLENGES

Although very promising for a wide range of applications, MI-BCIs remain barely used outside laboratories, in particular due to the difficulties users encounter when attempting to control them. Indeed, 10 to 30% of users are unable to control MI-BCIs (so-called "BCI deficiency") while only a small proportion of them reach acceptable control abilities.

On the one hand, the modest average performances of MI-BCI users suggests that current standard training protocols are not optimal to acquire MI-BCI related skills. In Chapter 1, we first reviewed the available literature on MI-BCI training protocols, which gave rise to several guidelines for the design of novel MI-BCI training protocol. As a reminder, these guidelines were the following:

— *Instructions* - It appears necessary to explicitly specify the object of the training process to the user, in particular the fact that the user must learn to generate a stable, specific signal when performing the different MI tasks in order to be able to control the BCI in the long run. Furthermore, it seems important to allow users to experiment independently rather than imposing any particular strategy for performing the tasks. What is more, as far as motor imagery is concerned, it appears that kinaesthetic motor imagery is more effective than visual motor imagery.

— *Training tasks* - Providing tasks that are designed to become progressively increasingly difficult and that are adaptive (specific to each user) seems to facilitate the acquisition of BCI-related skills. The inclusion o self-paced and asynchronous sessions and preparatory training tasks (e.g. meditation) also seems to help.

— *Feedback* - Even though this has not yet been formally shown in a study, visual feedback with emotional connotations (e.g. smiley faces) seems to increase user motivation levels and, consequently, performance. However, visual feedback is not ideal in interactive situations. The same is true for auditory feedback, which does not appear to be truly beneficial except for patients suffering from locked-in syndrome. Tactile feedback is promising, so long as the principles of *control-display mapping* are observed. Indeed, tactile feedback generally produces performances equivalent to visual feedback, but relies on a cognitive channel that is much less saturated in interactive situations. Finally, increasing the quantity and quality of information provided b the feedback (e.g. topography of cerebral activity) seems useful. Another way of improving the feedback would be to adapt the feedback to the user's level.

— *Training environment* - Several studies have shown that gamifying the training process, especially by including elements of virtual reality, increases motivation, and consequently performance.

These guidelines show that several promising avenues regarding the various constituent elements of these training protocols (instructions, training tasks, feedback and training environments) have been explored. Unfortunately, such studies remain few and far between and, critically, their results are rarely taken into account by the BCI community. By building on theories in disciplines such as psychology and instructional design, it is possible to suggest new, promising approaches for improving user performance. Therefore, one of the most important steps seems to be making the effort of understanding each user's cognitive specificities in order to adapt the training protocols to their individual profiles.

In order to reach a better understanding of the profile/state factors impacting MI-BCI skill acquisition and to adapt the training protocols accordingly, the community investigated potential predictors of performance related to users' personality and cognitive profile. Chapter 2 is a literature survey on this topic. This survey enabled us to classify most of the predictors into three categories representing higher-level cognitive concepts: (category 1) the user-technology relationship (which comprises the notions of anxiety and sense of agency during the interaction), (category 2) attention and (category 3) spatial abilities. These three categories appear to be extremely relevant in the context of MI-BCI training. Indeed, the predictors were computed during the early stages of training, i.e., during the first or first few sessions and most studies were performed on BCI-naïve users who were confronted with a BCI for the first time. Yet, the literature suggests that both of these situations (i.e., being in the early training phase and being exposed for the first time to unknown technology) can induce an important level of anxiety, which in turn is associated with a low sense of agency. Both of these have potential negative repercussions on performance (Achim and Al Kassim, 2015, Saadé and Kira, 2009, Simsek, 2011). This justifies the involvement of category 1 predictors, i.e., those related to the users' relationship with the technology. Besides, the Ackerman model (Ackerman, 1988) suggests that during the early stages of learning (phase #1), the inter-user variability in terms of performance is mainly due to differences in "task-appropriate" abilities and high-level cognitive abilities such as attention. These two aspects of the Ackerman model correspond to the two other predictor categories that we identified. Indeed, spatial abilities (category 3), i.e., the ability to produce, transform and interpret mental images (Poltrock and Brown, 1984) can be considered as "task appropriate" abilities in the context of MI-BCI training. Attention (category 2) clearly corresponds to the high-level cognitive abilities which influence inter-user variability according to Ackerman's model. Chapter 2 describes how these three categories were elaborated: we justify the inclusion of each predictor in a different category, we introduce the associated cognitive models and describe the neural correlates related to each concept. This work was intended to provide a better understanding of the different factors impacting MI-BCI training and thus to provide, in the Prospects section (i.e., Section 2.6), a discussion about how these factors could be taken into account when designing future protocols in order to optimise user-training. More specifically, the impact of the training protocol on users' computer anxiety and sense of agency was demonstrated. It has been suggested that a positively biased feedback could increase novice users' sense of agency and thus increase their performance. Also, the significance of respecting the principles of priority, consistency, exclusivity and a transparent mapping between the task and the feedback has been emphasised. Furthermore, it should also be possible to increase BCI training efficiency by considering the user's attention. In particular, attention capabilities can be improved using meditation or neurofeedback. Moreover, attentional resources can be optimally directed towards BCI training by using varied and gamified BCI training tasks, and rich, friendly and multi-modal feedback. BCI efficiency could also be improved by training spatial ability skills, since spatial ability training has proved to enhance performance in many domains (sport, music, surgical practice, etc.). Moreover, enhancing spatial abilities has been shown to be effective, durable, and transferable (to skills that have not been subject to specific training) when the training duration is long enough.

Three research challenges emerged from these reviews of the literature. Literature shows that MI-BCI use is a skill, requiring the user to be properly trained to achieve control. Therefore, rather than improving EEG signal processing alone (which is the most commonly studied factor in the community), the research direction defended in this thesis was to also guide users to learn to master BCI control. Therefore, this thesis addressed a general challenge which consisted in improving and reaching a better understanding of BCI user-training through the consideration of 3 levers: (1) cognitive factors, (2) personality and (3) feedback. Challenges #1 and #2 dealt with the consideration of cognitive factors and personality, respectively, to understand and improve MI-BCI user training. Then, Challenge #3 consisted in considering the impact of the feedback to understand and improve MI-BCI user-training. Each of these challenges was processed in 3 steps, namely (1) understanding which factors impact BCI performance, (2) proposing solutions to improve MI-BCI user-training and (3) introducing potential future applications, further research or theoretical work aiming at understanding why the solutions are efficient. These challenges were summarised in Figure 6.

8.2 CONTRIBUTIONS OF THIS THESIS

This manuscript enabled us to describe the contributions related to the three challenges depicted in Figure 6. These contributions are summarised in the following paragraphs.

Challenge #1 considered cognitive factors to understand and improve MI-BCI user-training. Two studies (Jeunet et al., 2015b; Jeunet, Jahanpour, and Lotte, 2016) revealed a strong correlation between MI-BCI performance (classification accuracy) and spatial abilities (assessed by mental rotation scores). This correlation was shown both for a pure motor-imagery paradigm (left- and right-hand motor-imagery - Jeunet, Jahanpour, and Lotte, 2016) and a 3-MI paradigm (left-hand motor-imagery, mental rotation and mental subtraction - Jeunet et al., 2015b). We have shown that spatial abilities are intimately related with the different mental imagery tasks considered in these studies (see Chapter 5). And most importantly, this result is in line with the predictors described in the literature: different aspects of spatial abilities having been repeatedly suggested to correlate to MI-BCI performance. These results led to question a potential causal relationship between MI-BCI performance and spatial abilities: would increasing spatial abilities (which are malleable abilities, i.e., abilities that can be trained - Uttal et al., 2013) induce an improvement of MI-BCI control abilities? In order to investigate this research question, inspired from the spatial ability literature, we designed a spatial ability training protocol based on mental rotation exercises. In order to comply with instructional design literature, we proposed different exercise types and difficulty levels. A first user study allowed us to rank the different exercises according to their difficulty, while a second user study enabled us to validate the efficiency of our training to improve participants' spatial abilities. Then, we were able to test the efficiency of this spatial ability training protocol to improve MI-BCI performance. Mainly, results suggested that the duration of the spatial ability training as well as the time-lapse between the spatial ability training and the MI-BCI sessions had a significant impact on the efficiency with which spatial ability training improved MI-BCI performance. More specifically, it seems that spatial ability training should be short and intense, and followed by a significant time-lapse before the next MI-BCI session. We also started to investigate the neurophysiological patterns associated with each task with respect to participants' group. Mainly, the high inter-session variability combined with the fact the classifier is only trained on the first session may explain that no improvement in performance was noticed over sessions. Nonetheless, based on descriptive analyses, it seems that participants in the SA group present the highest inter-subject stability in terms of *selected* electrode (i.e., the electrode enabling to discriminate most effectively between rest and task). Also, the results revealed impor-

Contribution #1: Spatial Abilities correlate with MI-BCI performance

Contribution #2: Design, validation & test of a SA training procedure tant clusters around the right motor-cortex for the left-hand motor-imagery task, around the right temporal lobe for the mental rotation task and finally around the left frontal and parietal cortices for the mental subtraction task. In the future, if we manage to associate specific patterns to performance, it will enable us to provide MI-BCI users with cognitive support, i.e., to guide them when they are trying to generate these specific patterns (as discussed in Section 6.6). These promising results encouraged us to think about potential applications of such a spatial ability training process. In particular, it appeared interesting to us to use spatial ability training in stroke rehabilitation procedures. Indeed, MI-BCIs are promising for upper-limb rehabilitation after a stroke as they enable brain-activity to be visualised while the patient is attempting to move. The patient could then be provided with proprioceptive feedback in order to close the sensori-motor loop and favour synaptic plasticity. Nonetheless, this procedure reminds patients they have lost the ability to move their arm which is likely to induce or increase their depressive state. Spatial ability training is known to theoretically trigger the motor-cortex [1] and could be used at least at the beginning of the rehabilitation process, when the patient has no residual movement, to trigger synaptic plasticity in a more *transparent* way for the patient.

Challenge #2 considered personality factors to understand and improve MI-BCI user-training. Our first study (Jeunet et al., 2015b) revealed a robust predictive model of MI-BCI performance including four personality traits: tension (negative impact), self-reliance, abstractedness and the active/reflective dimension of the learning style. As explained in Chapter 6, all these factors were in line with the literature. More specifically, we focused on the tension and self-reliance traits. Indeed, beyond MI-BCI training, highly tense and non-autonomous people have been shown to struggle with *Distant Learning* (i.e., autonomous learning, with no teacher or classmates). Indeed, distant learning lacks social interactions, which are of utmost importance during the learning process, especially for tense and non-autonomous learners. Based on the literature relevant to distance learning, we designed and implemented a Learning Companion, the goal of which is to provide the MI-BCI user with social presence and emotional support in order to facilitate their training process. We called the companion PEANUT for *Personalised Emotional Agent for Neurotechnology User-Training*. The design process enabled us to determine appropriate behaviour and appearance for PEANUT based on a review of the literature, on the analysis of data from a previous experiment and on user-studies. In particular, we determined what the content and the type of each intervention (speech and facial

Contribution #3: Definition of a predictive model of MI-BCI performance based on 4 personality traits.

Contribution #4: Design, implementation & test of a learning companion: PEANUT.

1. We have recorded participants EEG activity while they were performing the SA training; unfortunately we have not had enough time to analyse the data yet. To be continued...

expression) should be depending on the context, i.e., depending on MI-BCI performance and progression. Then, we tested PEANUT's efficiency to improve MI-BCI user-training, both in terms of performance and user-experience. We were unable to conclude as to the impact of PEANUT on performance, due to initial significant differences of classification accuracy between the groups. Nonetheless, results revealed that MI-BCI users who were accompanied by PEANUT rated the system's learnability/memorability as well as their self-efficiency/effectiveness higher than participants who did not receive support from PEANUT. Moreover, the general perception of PEANUT was better when the latter's behaviour was adapted to users' performance and progression (rather than generic). This last result is in line with instructional design literature that insists on the importance of providing support as well as adapted feedback (Shute, 2008). To summarise, PEANUT significantly benefited user-experience during the MI-BCI training process. The next step for PEANUT is to adapt its behaviour not only to the user's performance and progression, but also to their personality/cognitive profile and cognitive/emotional/motivational states. Also, as discussed in the Prospects section of Chapter 6, PEANUT represents a great opportunity to provide the users with a multimodal and explanatory cognitive support (more elaborated than the current feedback). For instance, by coupling PEANUT with TEEGI (Frey et al., 2014b), who would become the user's avatar, PEANUT could provide the learners with indications to help them explore their brain activity (displayed on TEEGI) while performing MI-tasks. Indeed, the literature suggests that autonomy and exploration are necessary to acquire new skills. More details about these future prospects are provided in Chapter 6.

Finally, Challenge #3 considered how feedback could help us understand and improve MI-BCI user-training. Our first object here was to determine the impact of a standard BCI-style feedback (Pfurtscheller and Neuper, 2001) on skill acquisition. We thus decided to use this feedback in an MI-BCI free context, to train participants to perform simple motor tasks: drawing circles and triangles on a graphic tablet. Results showed that around 17% of the participants, who all had the cognitive and motor abilities required to perform the task, failed to find a strategy that allowed the system to recognise the task they were performing. Next, we asked the 10 best and 10 poorest performers from this first study to perform an MI-BCI training session. We hypothesised that if the feedback was partly responsible for participants' performance, there would be a correlation between their performances in motor-tasks and MI-BCI tasks. Results did not reveal such a correlation. Nonetheless, it would seem that participants who faced difficulty during the first experiment, especially women, improved more easily in terms of performance during the second experiment. This could be explained by the fact that facing difficulty in

Contribution #5: Standard feedback requires many cognitive resources to be processed.

the context of a complex task (such as MI tasks, for which we are not trained and for which we do not have any proprioceptive feedback) requires substantial cognitive resources. Thus, these resources are not available to understand how to use the information provided by the feedback. On the contrary, when users face difficulty to find the right strategy in a less complex context (such as performing motor tasks which they know they can do and for which they have proprioceptive feedback) their available resources allow them to pay attention to the feedback and to understand how the latter could be used to improve their performance. Once the process has already been executed, a re-exposition to this protocol would not require as many resources and so could be used efficiently in a more complex context. To summarise, it would seem that the current feedback requires too many resources to be processed in the context of new and complex cognitive tasks such as mental-imagery. We propose two possible solutions to overcome this issue: either to pre-expose the user to the feedback in the context of a task that requires fewer cognitive resources so that they can process the feedback; or to design a new feedback that requires fewer cognitive resources to be processed. Traditionally, MI-BCI training protocols rely mainly on the visual channel. Yet, this channel is overtaxed in interactive situations such as the ones for which BCIs are developed, e.g., spatial navigation or video games. Adding visual feedback is likely to overload the cognitive resources related to this channel and could thus be associated with a decrease in performance. Literature suggests that by splitting information over different sensory channels, the cognitive load could be diminished and thus performance could be preserved. We thus decided to test the efficiency of a feedback similar to the standard visual feedback, but provided on another sensory channel: we chose to provide a vibrotactile feedback on the palms of the hands. Indeed, in the case of hand motor-imagery, providing feedback on the hands will also enable a transparent mapping (or control-display mapping) thus potentially improving the sense of agency and consequently the performance. We designed and implemented gloves embedded with vibrotactile motors. A pre-study enabled us to determine the most appropriate pattern and intensity for the vibrations. Then, we tested the efficiency of our tactile feedback to improve MI-BCI user-training. Results revealed that participants provided with our tactile feedback obtained better MI-BCI performance and better scores at a side task (which suggests that they had more free cognitive resources) than the participants provided with visual feedback. The next step, introduced in the Prospects section of Chapter 7 may consist in investigating the factors underlying the efficiency of our tactile feedback, based on neurophysiological and behavioural data. Results of the previously mentioned study suggest that our tactile feedback requires less cognitive resources to be processed, thus leaving more

Contribution #6: Design, implementation & test of a vibrotactile feedback.

resources to be allocated to the MI-task, which enables the users to acquire better performance. This hypothesis needs to be confirmed. We have two additional hypotheses that could explain the efficiency of tactile feedback: (1) providing tactile feedback on the hands activates the motor-cortex, thus helping the classifier to correctly identify MI tasks ; (2) the transparent mapping between the task and the feedback induces a better sense of agency, itself leading to better performance. The neural correlates of these different elements could allow us to determine if they are involved in the efficiency of tactile feedback for improving MI-BCI training. A future experiment will enable us to test these different hypotheses.

8.3 LIMITATIONS OF THIS PROJECT

We hope this work represents a significant step towards more reliable, efficient and accessible MI-BCI. Nevertheless, some general limitations have to be mentioned. First, we used a basic standard signal processing pipeline (CSP/LDA-SVM). This is certainly not the most advanced technique currently, nor the most successful, but we used it because it is commonly used by the community and most importantly because we were focusing on user-training and thus wanted a general pipeline usable in different contexts. Moreover, the classifier was trained only on the data from the first run of the first session (i.e., on 15 or 20 trials per class). If the experiment comprised several sessions, only the classifier's bias was adapted. We did so in order to avoid users experiencing too much variability in terms of feedback between the sessions. Nonetheless, it would be interesting to assess the impact of re-training the classifier at each session on users' performance and on usability. Limited data as well as the fact the classifier was not re-trained at each session could also explain users' modest performance and progression. Indeed, if users improved over several sessions, and if their brain patterns changed during the process, then not re-training the classifier would prevent them from perceiving their progress, since they did would not have better feedback. In other words, such a classifier is a biased measure of users' skills. Indeed, it uses the data collected on the first run of the first session (i.e., when the user is still novice) to characterise *good skills* that the user should be able to reproduce in order to perform well. However, because the user is performing the tasks for the first time during the calibration run, their BCI skills are very likely not yet reliable, e.g., they are not able yet to produce stable and distinct brain-activity patterns for each task. As a consequence, the patterns used by the classifier to discriminate the different classes may not be the most relevant ones, or may indeed even be noise. Indeed, while users are acquiring BCI skills, their brain patterns are likely to change after the calibration run. Thus, although the user's brain activity patterns could be more stable and distinct than on the first run, they could still be associated with negative feedback. This may explain why the participants of our experiments manage to improve during their first session but do not improve over the sessions. Furthermore, we use classification accuracy as a performance metric, i.e., one value. Yet, such a uni-dimensional metric cannot alone mirror the complexity of MI-BCI performance and skill acquisition. One obstacle to the definition of more appropriate metrics is that we are not yet able to describe *BCI skills*. There is a lack of theoretical and experimental research to determine precisely the skills to be acquired to efficiently control an MI-BCI. Nonetheless, if we use classification accuracy to measure performance, we can easily say that the skills to be acquired are the ability to generate stable and distinct brain-activity patterns for each task. Based on these skills, other performance metrics could be used. More specifically, we could measure the stability of the brain patterns associated with a given task; or measure how distinct each task is from rest, and from the other tasks. To summarise, an effort should be made in order to precisely describe BCI-related skills as well as associated performance metrics.

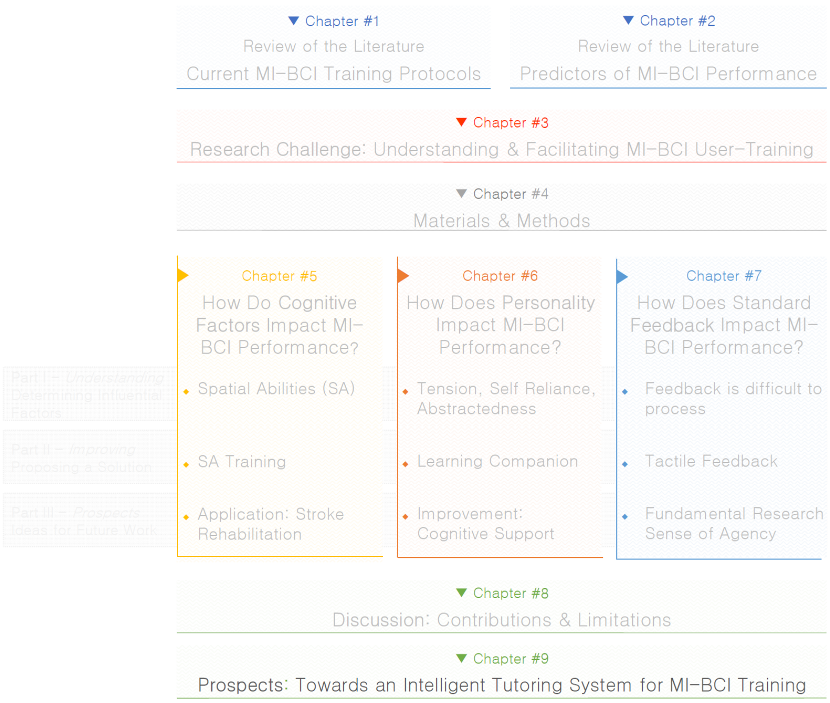
Furthermore, due to the duration of BCI sessions, the inclusion of large samples was difficult. Thus, all our experiments ought to be replicated in order to confirm the results. Again, due to small sample sizes, we decided to use homogeneous populations: young and *healthy* adults (18-30 years old - with no neurological or psychiatric disorders or motor impairments), most of them students, which limits the possibility of extrapolating these results to the whole population. Therefore, on the one hand, other age groups and educational levels should be investigated and on the other hand, the validity of our results should be tested on patients. Indeed, many of our results are introduced as promising in contexts of motor-rehabilitation. However, motor-impaired patients, whatever the cause of their disability, present a huge variability in terms of motor and cognitive functions. For now, we have no ground truth to prove that their profiles and the way they use BCIs is similar to young *healthy* users, and therefore we cannot claim that our findings are relevant for this population. In this view, we started a collaboration with the hospital of Bordeaux and plan to continue investigating MI-BCI user-training on patients, especially in the context of stroke rehabilitation.

Whether for patients or for the general public, we are limited in the investigation of the MI-BCI user-training process and in its improvement due to the lack of theoretical knowledge about this process. Indeed, while the literature describes some factors influencing MI-BCI performance, we have a comprehensive model neither of the skills to be acquired to control an MI-BCI, nor of the factors impacting the acquisition of these skills. The last part of this manuscript is dedicated to future research that could enable us to cope with this shortcoming.

9

PROSPECTS: TOWARDS A MULTIFACTORIAL AND USER-SPECIFIC APPROACH FOR MI-BCI USER-TRAINING USING AN INTELLIGENT TUTORING SYSTEM (ITS).

ROADMAP -



QUICK SUMMARY -

There is great potential for improving MI-BCI performance, but this potential is currently limited by the fact that to go further, we need to adopt a multifactorial and dynamic approach of MI-BCI user-training. We explain why and how an Intelligent Tutoring System (ITS) could enable us to study MI-BCI user-training with such an approach. Then, we argue that, however, we lack theoretical knowledge about the MI-BCI skills to be acquired to develop such an ITS. Consequently, we propose a first, basic cognitive model of MI-BCI tasks.

COLLABORATOR -

Pr. Roger N'Kambou (Ph.D)

RELATED PAPER -

-1- Jeunet, C., N'Kaoua, B., N'Kambou, R., and Lotte, F. (2016). 'Why and how to use an intelligent tutoring system to adapt MI-BCI training to each user?' In: *6th International BCI Conference*.

9.1 INTELLIGENT TUTORING SYSTEMS (ITS) FOR MI-BCI USER-TRAINING: A PROMISING MULTIFACTORIAL & USER-SPECIFIC APPROACH

9.1.1 *Why & How to Use an ITS for MI-BCI User-Training? Research Challenges.*

This thesis focused on MI-BCI user-training. We have shown, both theoretically and experimentally, that current training protocols are suboptimal. Thus, we introduced a review of the research dedicated to improving current MI-BCI user-training and then proposed different levers of improvement, which are summarised in Section 8.2.

Nonetheless, although we obtained some promising results we have not yet reached performances that would enable MI-BCIs to be widely democratised. In fact, we are still far from achieving a complete understanding of the MI-BCI skill acquisition process. It can be argued that this understanding will not be reached while the different factors impacting MI-BCI training are studied independently. As a matter of fact, skill acquisition being a complex multi-factorial process, a global approach should be adopted for its investigation. Yet, current research consists in evaluating the impact of isolated factors on MI-BCI user training in an independent and sequential manner. This approach neglects any potential inter-factor interactions, and also overlooks the evolving dynamics of the impact of these factors throughout the training process (for instance, some emotions -like the frustration- are good for learning at some stages of the training process, while they are detrimental at other stages - Kort, Reilly, and Picard, 2001). Interestingly enough, such a dynamic and multi-factorial approach to understand and improve MI-BCI user-training would be possible using a dedicated Intelligent Tutoring System (ITS), i.e., a computerised adaptive system aiming at supporting learning (Nkambou, Bourdeau, and Mizoguchi, 2010). ITS have the specificity of enabling the training process to be adapted online based on a student model (which includes the learner's profile and an online computation of the learner's state) and on a cognitive model of the task (i.e., theoretical knowledge about the factors impacting the acquisition of target skills). As such, ITS are more and more popular for *Distance Learning* procedures (i.e., situations in which the learner is alone in front of a computer, with no teacher or classmates) because they enable the absence of a teacher to be partially compensated by considering the learner's state and profile to adapt and optimise the sequences of tasks and the support provided to the user. MI-BCI training resembles distance learning as it is performed autonomously and could thus also benefit from ITS. Besides, consistently with distance learning literature, highly anxious and poorly autonomous learners have been shown to struggle with MI-BCI training (see Chapter 6) which is most likely due to the lack of social presence and emotional support inherent to standard MI-BCI training protocols. In order to overcome this drawback, as explained in Part II of Chapter 6, *Learning Companions* have been proposed. As a reminder, learning companions are characters (either virtual or physical) that are able to provide users with different kinds of support (emotional, cognitive, social presence) through facial/bodily expressions and speech (see Chapter 6 and our learning companion PEANUT for an example of emotional support and social presence). Since learning companions have been proven efficient for improving distance learning (Nkambou, Bourdeau, and Mizoguchi, 2010), MI-BCI training may also benefit from them.

To summarise, the strength of ITS lies in (1) a personalised support (that can be provided through a learning companion) and (2) an adaptation of the training process according to the learner's profile, state and skill evolution. Such an ITS represents a promising inter-disciplinary approach for improving MI-BCI performance as it would enable us to gather different levers and articulate them in order to reach a deeper understanding of MI-BCI user-training to allow this process to be optimised.

The architecture of such an ITS dedicated to MI-BCI user-training is depicted in next section.

9.1.2 *Architecture of an ITS for MI-BCI User-Training*

In this section we propose a conceptual framework for an ITS supporting MI-BCI user-training. Traditionally, ITS are composed of 4 modules:

— the *Expert Module* contains the concepts, rules and strategies of the domain to be learned to acquire target skills.

— the *Student Model* is the core component containing information about the user's profile (personality, cognitive profile) and state (cognitive, emotional and motivational states) at any given time during the training process; the skills of the user being included in the cognitive state.

— the *Tutor module* uses input from the two previous modules to select a tutoring strategy, i.e., an appropriate sequence of exercises and appropriate support/feedback.

— the *Interface* provides the user with access to the learning environment; we will not detail the interface in the following sections, since we are at the stage of conceptual reflections rather than HCI development.

In the following paragraphs, we will detail how the first 3 modules would work. Figure 56 is a schematic representation of the architecture of an ITS for MI-BCI user-training.

The Expert module contains a cognitive model of the task that could be represented as an oriented network containing the skills to be acquired as well as all the factors potentially impacting the skill acquisition process (nodes of the network) and the inter-dependencies of these factors (links of the network, that can be positive or negative). This network is represented in Figures 57 & 58 and detailed in Section 9.1.3. The Expert Module would also include a bank of exercises arising from the cognitive model. Once we become familiar with the skills that must be acquired as well as the factors that impact the acquisition of these skills, it will be possible to design exercises that intend to lead the learner, through intermediary steps, towards the acquisition of target skills. In order to comply with recommendations from instructional design (see Chapter 1, or Lotte, Larrue, and Mühl, 2013), these exercises should be varied and offer different levels of difficulty.

We think the Student Model should contain 2 kinds of information. The first is the user's profile (assessed by questionnaires and offline EEG measurements), including spatial abilities, aspects of their personality (e.g., abstractedness, tension and autonomy), or the amplitude of the mu rhythm at rest: all having been shown to be related to MI-BCI performance (see Chapters 5 & 6). The second kind of information the Student Model should contain relates to the state of the user. This includes their cognitive state (fatigue, workload, skills, etc.), motivational state and emotional state (frustration, self-confidence, etc.). However, since the accuracy with which these states can be deduced from EEG/physiological/behavioural data is far from perfect, these measures must be taken with caution. The relevant aspects of the user's state and profile, based on the cognitive model of the task, as well as the intrinsic/extrinsic factors influencing these aspects are put together in a Bayesian network. Based on the cognitive model of the task, on the inputs it receives and on psychological models of learning (such as the model of Kort, Reilly, and Picard, 2001), the Bayesian network could infer the cognitive, motivational and emotional states of the learner. Such a network would enable the student model to be updated online throughout the training process. Concretely, the addition to this network of external factors which influence the states/traits of the user would correspond to the *Cognitive Model of the Task* network (see Section 9.1.3) with probabilities associated with each of its nodes, the nodes being connected to measurable intrinsic/extrinsic factors. The initial probabilities (i.e., probabilities set at the beginning of the training process) could first be defined by experts; the model could then be adapted/improved based on the data collected from the users.

Based on the Student Model, on the Expert module as well as on psychological models (such as the Kort, Reilly, and Picard, 2001 model), the Tutor would select the appropriate exercises and provide users with a suitable support. The sequence of exercises would be determined using dedicated algorithms. For instance, case-based algo-

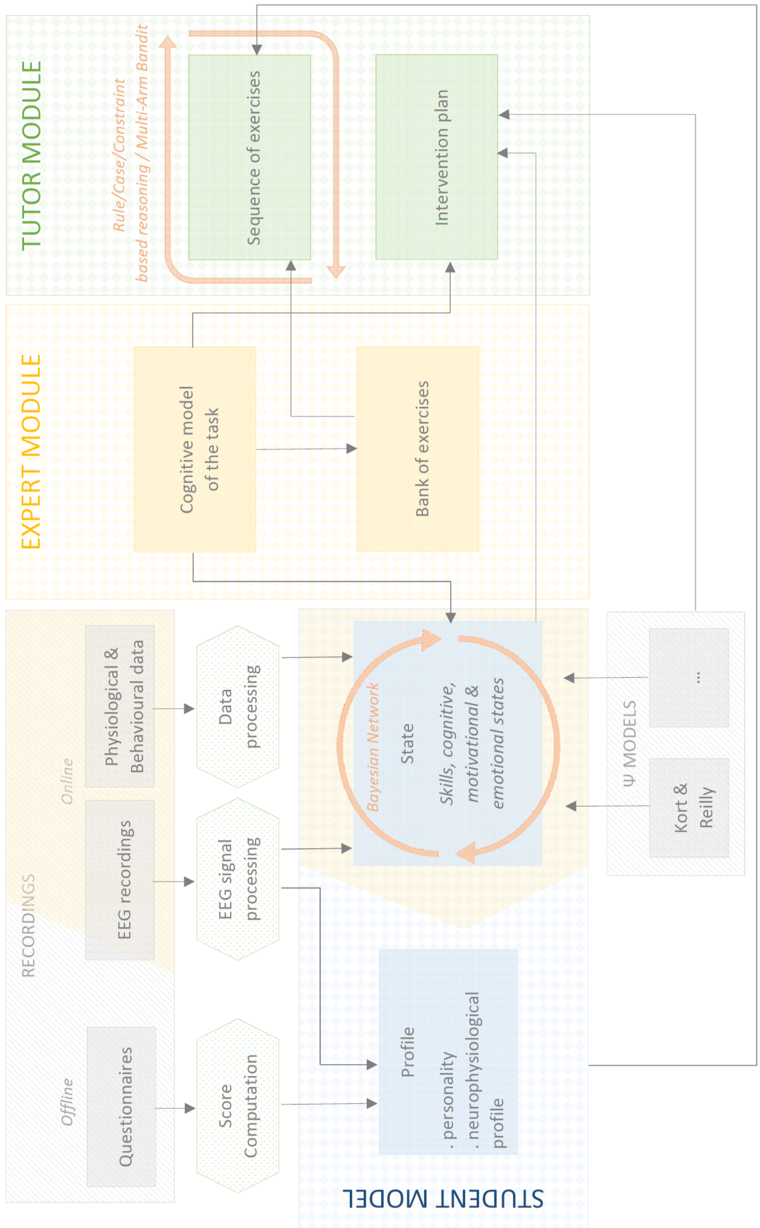


Figure 56 – Architecture of an Intelligent Tutoring System for MI-BCI user-training.

rithms could be used: this would consist in browsing a bank of previous cases and finding situations similar to the current one. Once the system has identified all the similar situations, the algorithm could chose an exercise that appeared to be effective in the previous cases. This is only an example, the choice of the algorithm should be further investigated, since many constraints related to BCIs remain to be addressed (e.g., the fact that it would be difficult to have a large enough data base of previous cases). The sequence of exercises should be adaptive throughout the training process in order to fit the learner's state and optimise the learning process. Concerning support, two kinds could be provided. On the one hand, cognitive support would provide the participant with information about the gap between their current skills and the skills to be acquired, their performance and advice to help them improve (one kind of basic cognitive support is the standard feedback we used in this thesis - Pfurtscheller and Neuper, 2001). On the other hand, emotional support and social presence should be provided in order to overcome the absence of social interactions during the training process. In this thesis, we designed and validated a learning companion, PEANUT, to provide this support. PEANUT is able to provide the user with support adapted to their performance and progression. The next step would consist in adapting this support to the learners' profile, and to the evolution of their emotional and motivational states throughout the training process. Indeed, learners who have high tension and low autonomy levels for instance, have been shown to need more social presence and an emotional support (e.g., empathy) (Ditzen et al., 2008; Reeve et al., 2004); also, women have been shown to appreciate learning companions more than men (Burleson and Picard, 2007).

The architecture described here-above revealed important research challenges related to the design of an ITS for MI-BCI user-training.

First, BCI skills should be explicitly described, as this would allow relevant performance metrics to be determined. A second challenge is to determine and implement relevant algorithms to manage the behaviour of the tutor. The third challenge, which is most closely related to this thesis, is the one we will focus on: the elaboration of a cognitive model of the task.

9.1.3 *Towards a Cognitive Model of the Task of MI-BCI User-Training*

In their book titled "Cognitive Modeling", Jerome Busemeyer and Adele Diederich describe cognitive models as models which aim to scientifically explain one or more cognitive processes or how these processes interact (Busemeyer and Diederich, 2010). Thus, three main features characterise cognitive models: (1) their goal: they aim to explain cognitive processes scientifically, (2) their format: they are described in a formal language, (3) their background: cognitive models are derived from basic principles of cognition (Busemeyer and Diederich, 2010). Cognitive models have three main advantages: they guarantee the production of logically valid predictions, they allow precise quantitative predictions to be made and they enable generalisation (Busemeyer and Diederich, 2010). Different steps are required to build a cognitive model (Busemeyer and Diederich, 2010):

— First, building a cognitive model requires a formal description of the cognitive process(es) to be described based on conceptual theories.

— Next, since the conceptual theories are most likely incomplete, *ad hoc* assumptions should be made to complete the formal description of the targeted cognitive process(es)
— Third, the parameters of the model, e.g., the probabilities associated with each element of the model, should be determined.
— Then, the predictions made by the model should be compared to empirical data.
— Finally, this process should be iterated to constrain and improve the relevance of the model.

Unfortunately, we have not yet had enough time to develop such a complete model of MI-BCI user-training. But it is one of our major research challenges for the future. Hereafter, we provide details concerning the first step.

The field of BCI being rather large, in this model we decided to concentrate on the same focus as the rest of the manuscript: active BCIs, and more specifically Mental-Imagery based BCIs. Also, a decision had to be made about the cognitive processes targeted by the model: we chose to investigate the cognitive processes leading to a good classification accuracy. Indeed, as explained in the previous section, currently, most MI-BCI studies consider the classification accuracy to be a measure of performance. It can be argued that this performance metric corresponds to the ability to produce stable and distinct brain-activity patterns while performing the MI tasks. As such, this model may not be relevant for other BCI skills or performance metrics. Also, we only considered the factors that are supposed to impact performance based on the MI-BCI literature: thus, several relevant factors, that have not yet been studied by the BCI community, are likely to be missing. They will be investigated in the second phase of the construction of this model. Finally, since we are dealing with a model, it is of course only a simplified representation of the complex cognitive processes underlying MI-BCI tasks, and will certainly require to be improved.

To provide a formal description of the cognitive processes leading to good BCI performances, two steps had to be completed. First, we had to describe both the intrinsic factors (i.e., users' states and traits) which impact performance as well as the connections between these factors. Then, the extrinsic elements impacting the users' states/-traits, and consequently their performance, as well as the nature of this impact had to be formalised. These extrinsic elements include design artefacts and different cognitive activities or exercises. Therefore, for more readability, we show two representations of our model: one which shows the intrinsic factors alone; and one which includes extrinsic elements and the intrinsic factors they influence. The next paragraphs are dedicated to the description of both these representations.

9.1.3.1 *Step 1 - Building a Model of the Intrinsic Factors Influencing MI-BCI Performance*

The intrinsic factors included in this model correspond on the one hand to users' cognitive and motivational states and on the other hand to users' traits, i.e., personality traits and malleable cognitive abilities that can be trained. All these factors are represented as hexagons in the model, see Figure 57. The dodecagons represent ways to measure these factors: they are either neurophysiological markers or psychometric test scores. Moreover, vertically juxtaposed hexagons as well as unidirectional arrows represent causal relationships (if factor A is above factor B, then factor A influences factor B). The plus and minus signs indicate if this causal relationship is positive or negative. On the other hand double-sided arrows connect a specific state or trait and the tool used to measure it. Subsequently, we briefly describe all the factors included in the model. For more information about these factors or the studies that revealed their relationship with MI-BCI performance, please refer to the review of the literature dedicated to the predictors of MI-BCI performance, Chapter 2.

This first model can be divided into 2 main parts. On the left and in the middle, the factors related to the user-technology relationship (in orange), to attention (in green) and to mood (in pink) can modulate the user's ability, at a given moment in time, to perform a cognitive task. On the other hand, on the right side of the figure, the factors related to the ability to perform an MI-task are represented in blue. Thus, these factors will determine to what extent users are able to reach good performances. Each of these blocks is described more precisely in the following paragraphs.

Factors pertaining to the user-technology relationship (in orange) are gathered on the left of the schematic representation of the model. First, users showing low self-reliance traits, according to the 16-PF5 test (Cattell and Cattell, 1995), tend to perceive the task as more difficult (Miserandino, 1996). Moreover, the phenomenon of computer anxiety, that is to say the apprehension of the user towards BCI use, has been shown to reduce users' self-efficacy (Simsek, 2011), which in turn will induce a higher perceived difficulty (Brosnan, 1998) and a decreased in performance. On the other hand, by reducing computer anxiety, and consequently improving self-efficacy, it is possible to improve users' engagement towards the task and thus their motivation and performance (Achim and Al Kassim, 2015). This can be explained by the fact that self-efficient users do not consider difficulty as a threat but as a challenge which encourages them to persevere to reach good performance (Achim and Al Kassim, 2015). In order to reduce computer anxiety, the sense of agency should be improved. Besides, a high sense of agency will also increase the feeling of mastery of the system and consequently reduce perceived difficulty, increase motivation and performance (Vlek et al., 2014). Finally, tense or anxious users tend to have lower performances which is due, at least in part, to the fact they devote a lot of resources to off-task considerations (such as worrying about their performance) and thus have fewer resources to allocate to focusing attention on the task (Brosnan, 1998). To summarise, in order to enable users to reach good performance, training protocols should enable them to experience a high sense of agency and a low level of computer anxiety. Also, protocols should be adapted to non self-reliant and highly tense/anxious users so that their personality does not hinder their progress.

Tiredness has a negative impact on motivation, focused attention and mood (in pink). Nonetheless, a good mood positively affects motivation and performance (Nijboer et al., 2007).

Then, the green block in the middle comprises factors related to attention. We have previously shown that engagement towards the task as well as motivation are modulated by the user-technology relationship and by their state (mood and tiredness). Motivation as well as general attentional abilities will determine how much focused attention is dedicated to the MI-BCI task. The more resources are allocated to the task, the better the performance. One neurophysiological predictor has been shown to correlate with attention state: the central gamma power (in attentional networks related to executive control - Grosse-Wentrup, 2011).

Finally, on the right of the model the blue elements represent the various factors that have been suggested to be related to the ability to perform mental-imagery tasks. Indeed, abstractedness abilities correspond to the ability to produce mental images (Cattell and Cattell, 1995). Also, visual-motor coordination is one aspect of spatial abilities, which are described as the ability to produce, manipulate and transform mental images (Poltrock and Brown, 1984). Finally, active learners prefer "learning by doing" and could thus be more prone to producing kinaesthetic mental images, which have been shown to be more efficient than visual ones (Neuper et al., 2005). These abilities can be measure by different scores such as the Kinaesthetic Imagination score or the Visual-Motor Imagination Score (Vuckovic and Osuagwu, 2013) or the Mental Rotation Score (Vandenberg and Kuse, 1978) that we have shown correlates with MI-BCI performance. Moreover, mu rhythms could enable, to a certain extent, to measure the ability to perform motor-imagery. Indeed, Blankertz et al., 2010b have shown that a high mu amplitude at rest correlates with motor-imagery based BCI performance. This can be explained by the fact that a higher amplitude at rest allowed for a greater decrease while performing motor-imagery tasks.

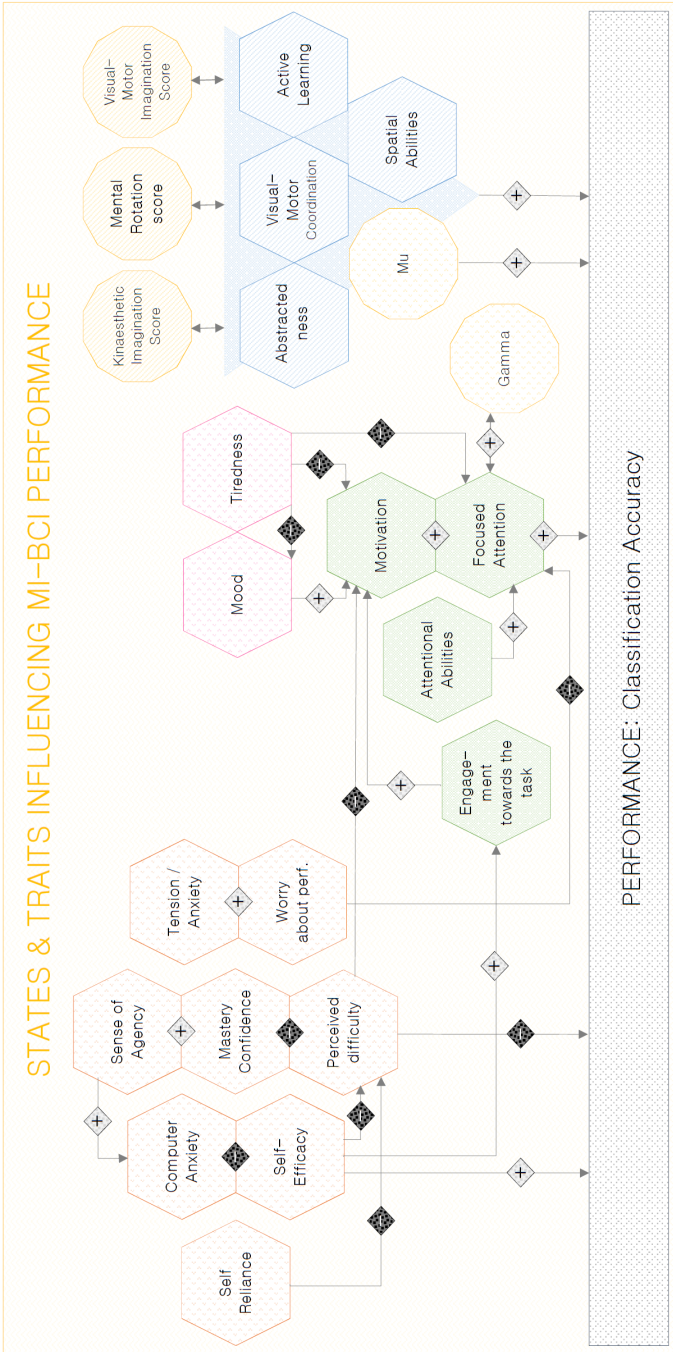


Figure 57 – The States and Traits that Influence a user's BCI Performance.

9.1.3.2 *Step 2 - A First Attempt at a Cognitive Model of the Task*

Once all the intrinsic factors had been integrated into a network, we added the extrinsic elements that can be seen as levers to optimise users' performance, see Figure 58. These extrinsic elements are mainly based on theoretical hypotheses. Their impact on the users' states, traits and performance have not yet been quantified. As a consequence, they should be considered with caution. As stated earlier, these extrinsic elements were of two kinds: design artefacts and cognitive activities/exercises. We determined three types of links between these extrinsic elements and the intrinsic factors:

— "Direct influence on user state" (solid lines): this link connects extrinsic elements in the "design artefacts" category to intrinsic states (mainly). These extrinsic factors are suggested to influence the user's state and, consequently, are likely to have a direct impact on performance. For instance, proposing a positively biased feedback has been suggested to improve (novice) users' sense of agency.
— "Help for users with a specific profile" (dashed lines): this link connects extrinsic elements to traits; they indicate that these extrinsic elements could help users who have a specific profile to improve their performance. For instance, proposing an emotional support has been suggested to benefit highly tense or anxious users.
— "Improved abilities" (dash-dot lines): finally, this link connects extrinsic elements in the "cognitive activities/exercises" category to abilities that could be improved thanks to these activities/exercises. For instance, attentional neurofeedback has been suggested to improve attentional abilities.

The extrinsic elements related to the experimental design that theoretically have a direct impact on the user's state are listed hereafter. First, providing novice users with a positively biased feedback (Kübler et al., 2001b) is thought to improve their sense of agency and consequently decrease perceived difficulty and increase their motivation. Then a transparent mapping (Beursken, 2012), also called control-display mapping (Thurlings et al., 2012) as well as the priority, consistency and exclusivity principles (Vlek et al., 2014) all aim to improve users' sense of agency. Moreover, providing users with emotional support and social presence could improve their motivation (Nkambou, Bourdeau, and Mizoguchi, 2010). Finally, adapting the difficulty and proposing progressive difficulty has also been suggested to improve performance (Wolpaw et al., 2000). On the other hand, meditation, emotional support and social presence could help highly tense and non-autonomous users, as explained in Chapter 6; while cognitive support could help users to produce mental-images that the system can recognise efficiently. Finally, the last type of links (dash-dot links) connect cognitive actvities/exercises to the specific abilities they could benefit. Indeed, video-games, meditation and attentional neurofeedback have been suggested to improve attentional abilities (Brandmeyer and Delorme, 2013); while video-games and spatial-ability exercises may improve the ability to create mental-images.

These two steps represent the first phase in the development of a cognitive model of the BCI task. The next phases consist in making assumptions about the missing factors that should be included, determining the parameters of the model and then repeatedly testing the model by comparing it to empirical data.

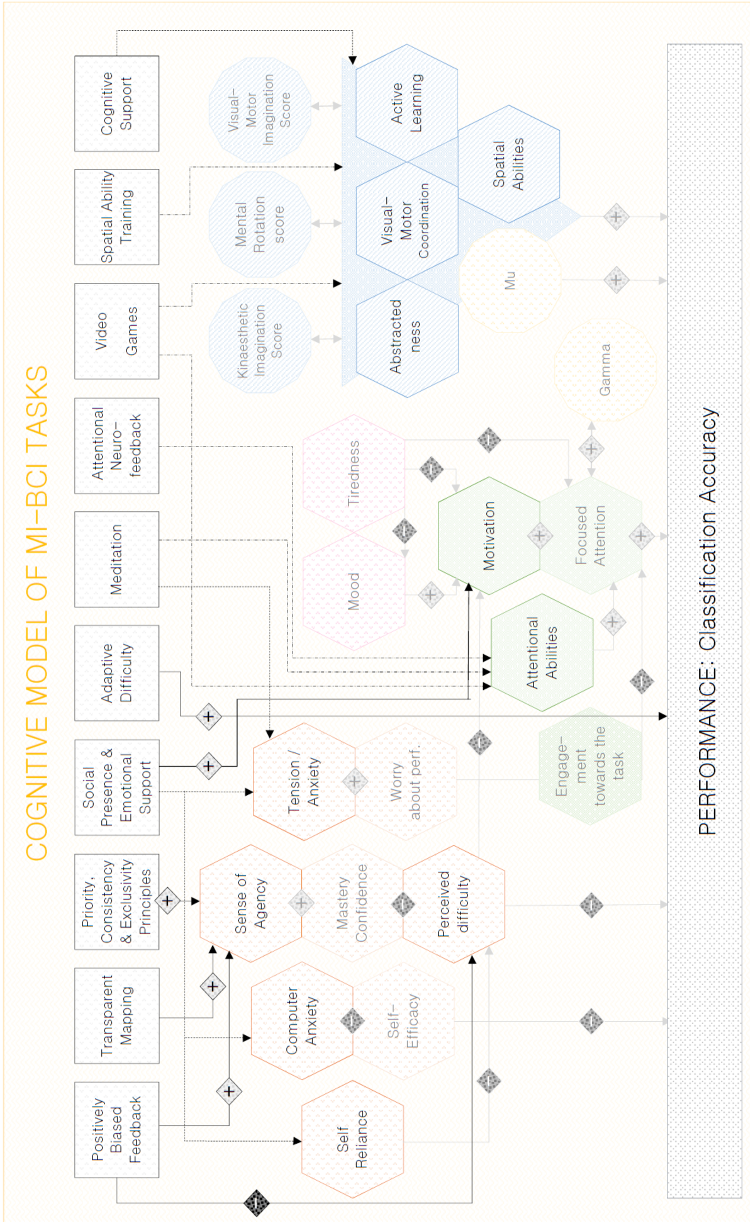


Figure 58 – First phase of the definition of a Cognitive Model of MI-BCI tasks.

CONCLUSION

There is still a long way to go before we are able to propose highly efficient, reliable and accessible BCIs. Therefore the community should of course continue to invest in improving BCI hardware (signal acquisition techniques) and software (signal processing). Nevertheless, even the best EEG recording systems combined with the best signal processing techniques will not suffice to make BCIs efficient and reliable if the user is unable to control the BCI properly. That is why a similar effort should be made by the community to understand and improve MI-BCI user-training. In this thesis, we insist on the importance of acquiring a deep theoretical knowledge about both the skills to be acquired to control a BCI and the factors impacting their acquisition. Building a cognitive model of BCI tasks may certainly enable us to reach a better comprehension of the processes underlying BCI control abilities. Because it would require a huge amount of experimental studies and theoretical work, maybe the ideal solution would be to develop an open platform on which researchers could share their findings (in terms of factors impacting BCI skill acquisition) so that they can be tested by other research teams, in combination with other factors. Beyond the elaboration of such a cognitive model, it is also essential to rethink user-training procedures. As stated in this manuscript (and by many other researchers), current training protocols do not comply with the recommendations from the literature in the fields of psychology, human factors and instructional design. Yet, some early experimental results suggest that better training protocols could significantly benefit BCI performance. To summarise, there is considerable room for improvement and we can reasonably surmise that one day we will achieve sufficient efficiency and reliability to make BCIs accessible and usable. However, improving performance is not enough to make BCIs widely used outside laboratories. Indeed, beyond the BCI system itself, the role of researchers should not be neglected. First, BCI researchers and experimenters should work towards the demystification of BCIs in order to reduce computer anxiety. This can be done through scientific mediation and communication with the media for instance. Second, BCI experimenters should be careful to write clear and informative informed-consent forms and explanations. These should provide participants and patients with an objective estimation of the benefit on risk balance and should regulate any form of hope that may be generated (Nijboer et al., 2013). Finally, the social presence of the experimenter as well as the trust relationship with the user are essential in facilitating the learning process and therefore promote the use of BCI (Kleih et al., 2013).

IV

APPENDIX

A

APPENDIX A: HOME-MADE USABILITY FOR MI-BCI EXPERIMENTS

Questionnaire d'utilisabilité

Ce questionnaire vise à nous aider à comprendre votre ressenti suite à l'utilisation du système.
Il n'y a pas de bonnes ou de mauvaises réponses.
Veillez donc répondre le plus objectivement possible.

*Obligatoire

1. **ID** *

____

2. **Je pense que j'aimerais utiliser ce système fréquemment dans le futur.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

3. **D'une manière générale, je suis satisfait(e) de ce système.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

4. **L'interface du système est plaisante** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

5. **J'aime utiliser l'interface de ce système.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

6. **L'interface du système est visuellement attirante.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

7. **Comment qualifieriez-vous ce système ?** *
Une seule réponse possible.

	1	2	3	4	5	
Terrible						Merveilleux

8. **Comment qualifieriez-vous ce système ?** *
Une seule réponse possible.

	1	2	3	4	5	
Difficile						Facile

9. **Comment qualifieriez-vous ce système ?** *
Une seule réponse possible.

	1	2	3	4	5	
Frustrant						Plaisant

10. **Comment qualifieriez-vous ce système ?** *
Une seule réponse possible.

	1	2	3	4	5	
Monotone						Stimulant

11. **Comment qualifieriez-vous ce système ?** *
Une seule réponse possible.

	1	2	3	4	5	
Rigide						Flexible

12. **J'ai trouvé ce système inutilement complexe.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord						Tout à fait d'accord

13. **J'ai trouvé ce système facile à utiliser.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord						Tout à fait d'accord

14. **La terminologie utilisée dans ce système (symboles) est intuitive.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

15. **Je pense avoir réussi à réaliser ma tâche de manière efficiente (ie. en un temps raisonnable) grâce à ce système.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

16. **Je pense avoir réussi à réaliser ma tâche de manière efficace (ie. avec un bon taux de performance) grâce à ce système.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

17. **J'imagine que la plupart des gens apprennent à se servir de ce système très rapidement.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

18. **Les messages donnés par le système me permettent d'apprendre facilement.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

19. **Apprendre à me servir de ce système a été difficile.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

20. **Faire les tâches qui me sont demandées (imagerie mentale) est simple.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

21. **Le feedback donné (barre bleue) est très utile : il m'aide à réaliser correctement mes tâches.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

22. **Je pense avoir été productif(ve) très rapidement en utilisant ce système.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

23. **L'information donnée par le système est claire.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

24. **J'ai trouvé qu'il y avait de nombreuses inconsistances dans ce système.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

25. **Je me sentais très confiant(e) lorsque j'utilisais ce système.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

26. **Ce système peut facilement être utilisé par n'importe qui.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

27. **Je me sens à l'aise lorsque j'utilise ce système.** *
Une seule réponse possible.

	1	2	3	4	5	
Pas du tout d'accord	◯	◯	◯	◯	◯	Tout à fait d'accord

B

APPENDIX B: TABLES REPRESENTING THE SELECTED ELECTRODE FOR EACH GROUP, SESSION AND TASK, FOR LOW ALPHA, HIGH ALPHA AND HIGH BETA BANDS.

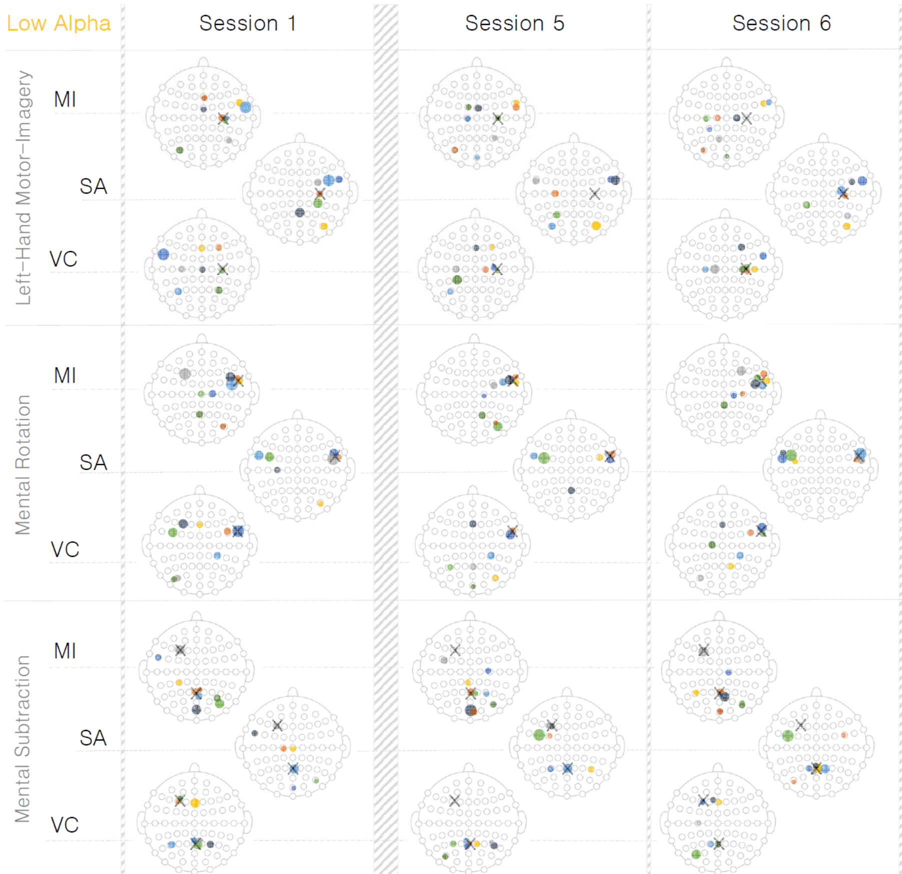


Figure 59 – Table representing the selected electrode as well as its associated coefficient for each participant-group/task/session in the low alpha band, i.e., [8;10]Hz; each head corresponds to one task, on session and one group; on each head are displayed one point by participant: the location of the point represents the selected electrode while the size of the point represents the value of the coefficient for this task/session. The black crosses represent the "theoretical electrode", i.e., the one which is theoretically the closest to the brain region triggered for each of the MI tasks: C4 for the left-hand motor-imagery, FT8 for the mental rotation, F3/Pz for the mental subtraction.

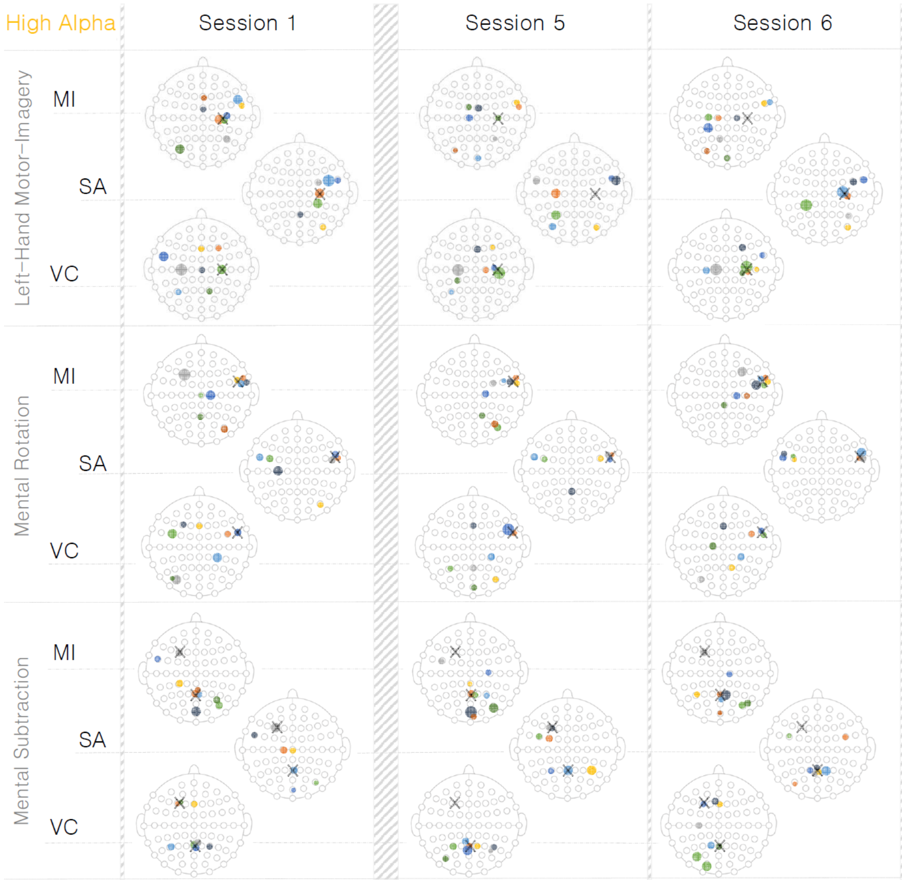


Figure 60 – Table representing the selected electrode as well as its associated coefficient for each participant-group/task/session in the low bata band, i.e., [10;12]Hz; each head corresponds to one task, on session and one group; on each head are displayed one point by participant: the location of the point represents the selected electrode while the size of the point represents the value of the coefficient for this task/session. The black crosses represent the "theoretical electrode", i.e., the one which is theoretically the closest to the brain region triggered for each of the MI tasks: C4 for the left-hand motor-imagery, FT8 for the mental rotation, F3/Pz for the mental subtraction.

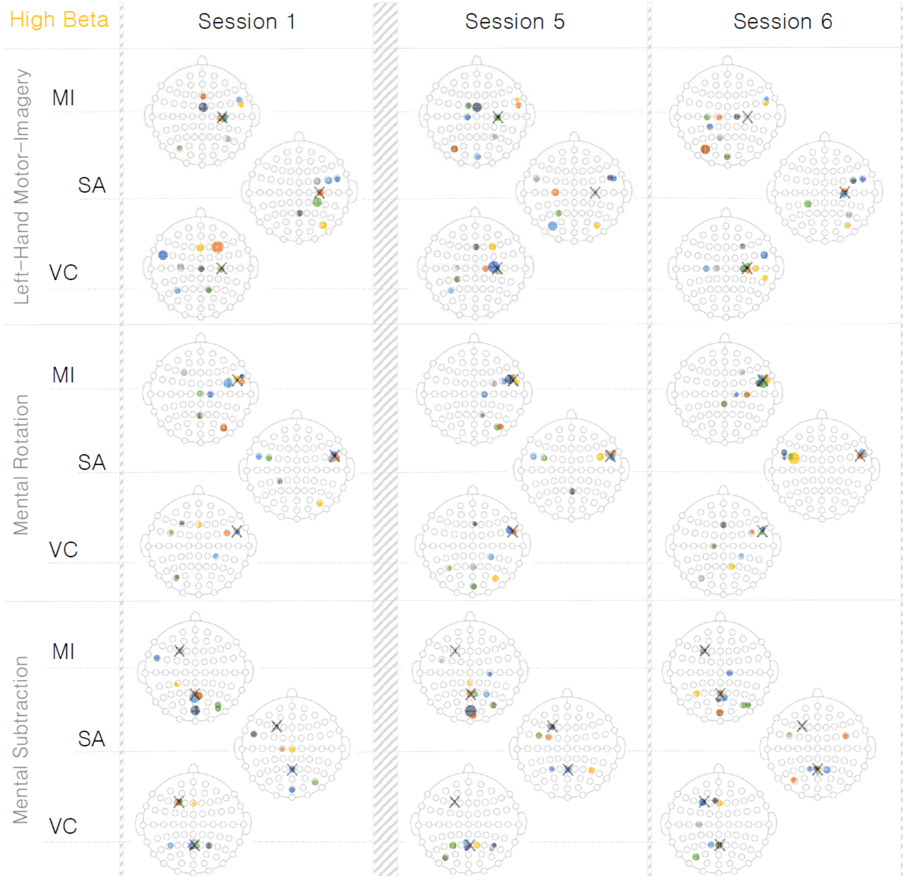


Figure 61 – Table representing the selected electrode as well as its associated coefficient for each participant-group/task/session in the low bata band, i.e., [24;30]Hz; each head corresponds to one task, on session and one group; on each head are displayed one point by participant: the location of the point represents the selected electrode while the size of the point represents the value of the coefficient for this task/session. The black crosses represent the "theoretical electrode", i.e., the one which is theoretically the closest to the brain region triggered for each of the MI tasks: C4 for the left-hand motor-imagery, FT8 for the mental rotation, F3/Pz for the mental subtraction.

C

APPENDIX C: QUESTIONNAIRE ABOUT USERS' PERCEPTION OF PEANUT

Questionnaire sur le Compagnon - PEANUT

Veuillez noter, sur une échelle allant de 1 à 7, à quel point vous êtes d'accord avec les affirmations suivantes.
Il n'y a pas de bonnes ou de mauvaises réponses, nous avons besoin que vous soyez le plus honnêtes et spontanné(e)s possible.

*Obligatoire

1. **Participant ID** *

____

--- Concernant l'APPARENCE du compagnon ---

2. **Je trouve le corps du compagnon approprié (bien proportionné, agréable).** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord	◯	◯	◯	◯	◯	◯	◯	tout à fait d'accord

3. **Je trouve que le visage du compagnon est expressif.** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord	◯	◯	◯	◯	◯	◯	◯	tout à fait d'accord

4. **Je trouve que la voix du compagnon était appropriée (adaptée à son physique).** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord	◯	◯	◯	◯	◯	◯	◯	tout à fait d'accord

5. **Je trouve qu'il est agréable d'avoir le compagnon à ses côtés au cours de l'entraînement.** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord	◯	◯	◯	◯	◯	◯	◯	tout à fait d'accord

--- Concernant le CONTENU des interventions ---

6. **Je trouve que les interventions du compagnon étaient pertinentes.** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord								tout à fait d'accord

7. **Je trouve que les interventions du compagnon étaient claires et appropriées.** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord								tout à fait d'accord

8. **Je trouve que les interventions du compagnon étaient motivantes.** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord								tout à fait d'accord

9. **Je trouve que les interventions du compagnon m'ont permis de rester motivé(e).** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord								tout à fait d'accord

10. **Je trouve que les interventions du compagnon m'ont aidé au cours de mon entraînement à avoir de meilleures performances.** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord								tout à fait d'accord

11. **Je trouve que les interventions du compagnon étaient énervantes / perturbantes.** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord								tout à fait d'accord

--- Concernant la FRÉQUENCE des interventions ---

12. **Je trouve que les interventions du compagnon étaient trop fréquentes, ce qui le rend énervant / dérangeant.** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord	◯	◯	◯	◯	◯	◯	◯	tout à fait d'accord

13. **Je trouve que la fréquence des interventions était appropriée : ce n'est ni énervant, ni dérangeant.** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord	◯	◯	◯	◯	◯	◯	◯	tout à fait d'accord

14. **Je trouve que la fréquence des interventions était appropriée et donc potentiellement utile pour faciliter l'entraînement BCI.** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord	◯	◯	◯	◯	◯	◯	◯	tout à fait d'accord

15. **Je trouve que les interventions du compagnon n'étaient pas assez fréquentes pour être utiles pour faciliter l'entraînement BCI.** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord	◯	◯	◯	◯	◯	◯	◯	tout à fait d'accord

--- D'une manière générale... ---

16. **J'ai aimé être accompagné(e) par PEANUT au cours de mon apprentissage.** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord	◯	◯	◯	◯	◯	◯	◯	tout à fait d'accord

17. **J'ai trouvé que PEANUT permettait de faciliter/améliorer l'entraînement.** *
Une seule réponse possible.

	1	2	3	4	5	6	7	
pas du tout d'accord	◯	◯	◯	◯	◯	◯	◯	tout à fait d'accord

18. **Avez-vous des remarques à ajouter ?**

____
____

____
____

Et voilà c'est fini ! Merci !

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DECLARATION

Put your declaration here.

Bordeaux, 2nd of December, 2016

Camille Jeunet

COLOPHON

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– October 2, 2016