CAMILLE JEUNET

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A Bordeaux,
Le 30 Janvier 2017

Madame, Monsieur,

Veuillez trouver ci-après mon dossier de candidature au pris IFRATH-KAELIS 2016.

J'ai effectué, entre 2013 et 2016, un Doctorat International (label Européen) en Sciences Cognitives, financé par l'IdEx de l'Université de Bordeaux sur le thème des Interfaces Cerveau-Ordinateur. L'objectif était de mieux comprendre et d'améliorer le processus d'apprentissage de l'utilisation d'une interface cerveau-ordinateur, de manière à rendre ces technologies plus fiables, efficientes et donc accessibles, notamment pour les patients atteints d'un handicap moteur sévère. J'étais rattachée à 2 équipes de recherche : le laboratoire Handicap, Activité, Cognition, Santé de l'Université de Bordeaux et l'équipe-projet Potioc d'Inria Bordeaux Sud-Ouest. J'ai aussi effectué 6 mois de mobilité dans le laboratoire de mon codirecteur, actuellement rattaché au Interact Lab de l'Université du Sussex, en Angleterre, et 1 mois de mobilité dans le laboratoire GDAC avec Pr. Roger N'Kambou, UQAM, Canada. Ce doctorat était dirigé par :

Pr. Bernard N'Kaoua – Professeur des Universités en Sciences Cognitives (Univ. Bordeaux)

Dr. Fabien Lotte – Chargé de Recherche en Informatique (Inria Bordeaux Sud-Ouest)

Dr. Martin Hachet – Chargé de Recherche en Informatique (Inria Bordeaux Sud-Ouest)

Pr. Sriram Subramanian – Professeur des Universités en Informatique (Univ. Sussex, UK)

Cette thèse a été évaluée par le jury suivant :

Ass. Pr. Reinhold Scherer – Assistant Professeur en Informatique (TU Graz, Autriche) – Rapporteur & Président du Jury

Pr. Andrea Kübler – Professeur en Psychologie (Univ. Würzburg, Allemagne) – Rapporteur

Pr. Dominique Guehl – Professeur des Unviersités en Neurosciencs, Praticien Hospitalier Neurologue (Univ. Bordeaux, France) – Rapporteur

Dr. Jérémie Mattout – Chargé de Recherche en Neurosciences (INSERM Lyon, France) – Examinateur

Ce Jury, pluridisciplinaire, est justifié par le caractère interdisciplinaire du projet de thèse, alliant psychologie (psychologie cognitive, neuropsychologie), neurosciences (électrophysiologie, neurosciences cognitives) et informatique (interaction homme-machine, traitement du signal).

Ce dossier comprend les pièces suivantes :

- Un CV
- Un résumé du projet de thèse
- Une liste des publications (avec indexation dans Medline et DOI pour les articles de revues scientifiques) accompagnée de la première page de chaque article publié
- Les 4 articles majeurs publiés dans des revues scientifiques
- Les pré-rapports des 3 rapporteurs
- Le rapport de soutenance signé par les membres du Jury
- L'attestation de réussite au Doctorat
- Deux lettres de recommandation, de mon directeur de thèse Pr. B. N'Kaoua et de mon co-directeur, F. Lotte

J'espère avoir associé au dossier toutes les pièces qui vous permettront le l'examiner. Je reste à votre disposition pour tout renseignement complémentaire.

Bien cordialement,

Camille Jeunet

Camille JEUNET, PhD

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FORMATION ▼

02-2017 – 06-2018
Post-Doctorat Inria/EPFL – « Utilisation de la réalité virtuelle et des interfaces cerveau-ordinateur pour améliorer la performance des athlètes de haut niveau » [16 mois]
Equipe Hybrid (Inria Rennes), M2S (Univ. Rennes), Defitech foundation BMI (EPFL, Suisse)

07-2016
Visite dans l'équipe GDAC [1 mois]
UQAM (Université du Québec à Montréal), Canada, avec le Pr. N'Kambou

11-2015 – 01-2016
Visite dans l'équipe « Interact Lab » [3 mois]
Université du Sussex (Brighton), UK, avec le Pr. Subramanian

07-2014 – 09-2014
Visite dans l'équipe « Bristol Interaction and Graphics lab » [3 mois]
Université de Bristol, UK, avec le Pr. Subramanian

10-2013 – 12-2016
Doctorat International IdEx en Sciences Cognitives, label européen - « *Improving Mental-Imagery based Brain-Computer Interface (MI-BCI) User-Training: Towards a New Generation of Efficient, Reliable and Accessible BCI* »
Superviseurs: Bernard N'Kaoua[1], Fabien Lotte[2,] Martin Hachet[2] & Sriram Subramanian[3]
[1]Université de Bordeaux, France, [2]Inria Bordeaux Sud-Ouest, France, [3]Université du Sussex, Angleterre
Jury: Pr. A. Kübler[4], Pr. R. Scherer[5], Pr. D. Guehl[6] & J. Mattout[7]
[4]Univ. Würzburg, Allemagne, [5]TU Graz, Autriche, [6]Univ. Bordeaux, France, [6]Inserm Lyon, France

06-2013
Master 2 en Sciences Cognitives « Handicap & Nouvelles Technologies »
Premier semestre effectué à l'UQAM (Montréal) en Master en Informatique (*A+, 91%) – Mention Très Bien (17,26/20), major de promotion*
Stage : « Estimation du stress et de la relaxation grâce à des marqueurs physiologiques et neurophysiologiques » avec Fabien Lotte & Christian Mühl (Equipe Potioc, Inria Bordeaux)

06-2012
Master 1 en Sciences Cognitives « Handicap & Nouvelles Technologies »
Université de Bordeaux – *Mention Très Bien (16/20), major de promotion*
Stage : « Physiologie et physiopathologie du processus de doute » avec Virginie Lambrecq & Dominique Guehl (IMN, Univ. Bordeaux)
Stage Complémentaire : « Machine Learning » avec Marc-Michel Corsini (Univ. Bordeaux)

06-2011
Licence - MASS (Mathématiques Appliquées au Sciences Sociales), spécialité: Sciences Cognitives,
Université de Bordeaux –*Mention Bien (14,4/20), classée 3ème*

07-2008
Baccalauréat Scientifique (option sport)
Lycée Borda (Dax) – *Mention Bien (15,9/20)*

PRIX & BOURSES ▼

2016	**Bourse de post-doc** Inria / EPFL (classée 1ère)
2016	Talent « **L'Oreal Unesco** pour les Femmes et la Science 2016 »
2016	Prix du **« Meilleur Prof »** décerné par les étudiants de Licence 1 MIASHS
2015	**Best Paper Award** – Colloque des Jeunes Chercheurs en Sciences Cognitives
2015	**Prix du public** & **Prix du jury** au concours « Ma Thèse en 180s »
2013	**Allocation IdEx** Bordeaux (100%) – co-direction internationale

ENSEIGNEMENT & ENCADREMENT ▼

POSTES

2015/2016 – Poste de **Moniteur** en Sciences Cognitives (64h00 de service eqtd)

2013/2014 – Poste de **Moniteur** en Psychologie (64h00 de service eqtd)

Les enseignements ont été dispensés en **Licence Psychologie**, en **Licence MIASHS** (Mathématiques et Informatique appliqués aux Sciences Humaines et Sociales) et en **Master Sciences Cognitives et Ergonomie** de l'Université de Bordeaux.

CONCEPTION SUPPORTS

CM – J'ai moi-même créé, en autonomie, tous les supports pédagogiques de mes CM, soit : 6h00 de CM en Sciences Humaines et Méthodes (L1 MIASHS), 6h00 de CM en Connaissances et Représentations (L3 MIASHS) et 6h00 de CM en IHM et FH (M1 Sc. Cognitives et Ergonomie).

TD – J'ai aussi créé en autonomie les supports de TD pour les UE suivantes : 9h00 de TD en Sciences Humaines et Méthodes, 12h00 de TD d'Introduction aux Sciences Cognitives (que j'ai dispensées en français et en anglais), 9h00 de TD de Connaissances et Représentations (L3 MIASHS) et 9h00 de TD d'IHM et FH (M1 Sc. Cognitives et Ergonomie).

ENCADREMENT STAGIAIRES

***2016* –** Léa Pillette (3A ENSC-EINSEIRB-MATMECA – 6 mois) ; Encadrant principal (50%), co-encadrement avec F. Lotte, B. Mansencal et B. N'Kaoua – Design, Implémentation et Evaluation d'un compagnon d'apprentissage tangible pour améliorer l'apprentissage des interfaces cerveau-ordinateur – Ce stage a donné lieu à la soumission d'un article.

***2016* –** Suzy Teillet (3A ENSC – 6 mois) ; Encadrant principal (60%), co-encadrement avec F. Lotte et B. N'Kaoua –Vers l'utilisation d'interfaces cerveau-ordinateur pour la rééducation post-AVC - Etude de l'impact des habiletés spatiales – Ce stage a donné lieu à un article publié à SMC2016.

***2015* –** Emilie Jahanpour (M1 Sciences Cognitives – 2 mois) ; Encadrant principal (80%), co-encadrement avec F. Lotte – A quel point pouvons-nous apprendre les compétences liées aux ICO grâce au feedback actuel ? – Ce stage a donné lieu à un article paru dans J. of Neural Engineering.

***2014* –** M. Sueur (M1 Sciences Cognitives – 2 mois) ; Encadrement principal (70%), co-encadrement avec F. Lotte et B. N'Kaoua – Entraînement utilisateur pour les ICO.

PROJETS ETUDIANTS

***2015* –** P. Ecoffet, F. Gouet, E. Rhouzlane, M. Seurin (Projet TER L3 MIASHS) ; Encadrement 50%, co-encadrement avec F. Lotte - Détecter la frustration grâce à des marqueurs physiologiques et neurophysiologiques.

***2015* –** I. Ainseba, T. Geral, C. Gouverneur, (TPE 1ère S) ; Encadrement 100% - Interfaces Cerveau-Ordinateur : La technologie peut-elle compenser les déficiences du corps ?

***2014* –** J. Laborie, L. Leitner, M. Pichon, "Interfaces cerveau-ordinateur pour rééducation post-AVC" (TER L3 MIASHS) ; Encadrement 100% - Interfaces Cerveau-Ordinateur pour la rééducation post-AVC.

TITRE THESE	Understanding and Improving Mental-Imagery based Brain-Computer Interface (MI-BCI) User Training Protocols: Towards a New Generation of Reliable, Efficient and Accessible BCIs.
MOTS CLE	Interfaces Cerveau-Ordinateur, Apprentissage, Interaction Homme-Machine, Protocoles d'Entraînement, Profil Cognitif, Personnalité, Neurophysiologie, ElectroEncéphaloGraphie.
ENCADREMENT DE THESE	Ce projet de thèse est profondément interdisciplinaire puisqu'il nécessite de croiser des compétences en informatique, psychologie et neurosciences. Pour cette raison, j'ai été rattachée à deux laboratoires de recherche : le laboratoire Handicap, Activité, Cognition, Santé (Univ. Bordeaux, situé sur le site du CHU, qui m'a permis d'être en contact avec le milieu hospitalier) et l'équipe projet Potioc (Inria Bordeaux Sud-Ouest, où j'ai pu côtoyer des informaticiens et roboticiens). Ainsi, j'ai été encadrée par : Fabien Lotte (CR1-HDR Inria BSO), spécialiste des Interfaces Cerveau-Ordinateur, Martin Hachet (CR1-HDR Inria BSO) et Sriram Subramanian (Professeurs à l'Univ. Sussex, UK), spécialistes de l'Interaction Homme-Machine, et enfin Bernard N'Kaoua (Professeur à l'Univ. Bordeaux), Neuropsychologue, spécialiste de l'EEG et de la cognition spatiale. Ainsi, mes contributions visent à améliorer les conditions de vie de patients grâce à une approche centrée-utilisateur mêlant la psychologie, les neurosciences et l'informatique.
CONTRIBUTIONS MAJEURES	**-1-** Preuve d'une corrélation forte (avec réplication du résultat) entre **habiletés spatiales** et performances de contrôle d'une interface cerveau-ordinateur (ICO) ; design, implémentation et validation d'un entraînement aux habiletés spatiales pour améliorer les performances ICO. Grâce à cet entraînement cognitif, nous espérons qu'il sera plus facile pour les personnes ayant de sévères troubles moteurs d'apprendre à naviguer grâce à un fauteuil roulant contrôlé par une interface cerveau-ordinateur. **-2-** Définition d'un **modèle prédictif de performance** robuste basé sur le profil des utilisateurs suggérant notamment que les utilisateurs tendus et peu autonomes avaient des difficultés d'apprentissage ; nous avons fait l'hypothèse que cela pourrait être dû au fait que ces utilisateurs ont besoin d'un soutien émotionnel et d'une présence sociale lors de l'apprentissage ; ainsi, l'étape suivante consistait à proposer le design, implémentation et validation d'un compagnon d'apprentissage (personnage tangible dont le comportement s'adapte automatiquement au contexte pour fournir aux utilisateurs un soutien émotionnel et une présence sociale). Nous avons appelé ce compagnon PEANUT et sommes actuellement en train de tester son efficacité pour permettre aux patients d'améliorer leur apprentissage en agissant sur 2 fronts : grâce à un soutien émotionnel, primordial pour des patients souvent atteints de troubles de l'anxiété ou de dépression, et grâce à un support pour maintenir l'attention des patients durant l'apprentissage. **-3-** Démonstration du fait que le feedback standard utilisé en ICO requiert trop de ressources cognitives pour être traité ; design, implémentation et validation d'un **feedback tactile** (par des moteurs vibrotactiles) permettant de réduire la charge cognitive liée au traitement du feedback. En effet, en situation de navigation de fauteuil roulant dans un environnement de « la vie de tous les jours », le champ visuel est sollicité pour analyser l'environnement. Nous proposons donc un feedback tactile (plutôt que visuel) qui permettrait de ne pas surcharger la modalité visuelle. **-4-** Proposition d'une classification des prédicteurs de performance ICO et d'un **modèle cognitif de la tâche**, i.e., d'un modèle computationnel des relations entre ces prédicteurs et de leur impact sur les performances. Ce modèle est le premier de son type dans le domaine des ICO et permettra de travailler à l'amélioration de l'apprentissage de l'utilisation des ICO grâce à une approche multi-factorielle prenant en compte des variables de psychologie de la santé, des capacités cogntives mais aussi la motivation par exemple. Le but est d'adapter ce modèle à chaque patient de manière à améliorer l'apprentissage, que ce soit en termes de performance ou d'expérience utilisateur. *Pour de plus amples détails, voici le lien vers mon manuscrit de thèse et ma page professionnelle :* https://hal.inria.fr/tel-01417606/document // camillejeunet.wordpress.com

COLLABORATIONS

Lors de ma thèse, j'ai eu l'opportunité de collaborer avec différents chercheurs internationaux :

. Pr. R. N'Kambou – GDAC (informatique), UQAM, Canada ; Nous avons un papier en commun sur l'utilisation d'un système tutoriel intelligent pour les iCO et planifions de débuter en plus une collaboration avec Dr. M. Martin – Chirurgien Univ. Sherbrooke, Canada – pour améliorer l'entraînement des médecins.

. Pr. S. Subramanian – et son équipe du BIG Lab, Univ. Bristol, UK (notamment C. T. Vi et D. Spelmezan) et du Interact Lab, Univ. Sussex, UK (notamment P. Cornelio).

. Je coordonne actuellement l'écriture d'un chapitre de livre avec Pr. S. Debener & C. Zich (Univ. Oldenburg, Allemagne), S. Kleih (Univ. Würzburg), R. Scherer (TU Graz, Autriche).

RESPONSABILITES COLLECTIVES & ADMINISTRATIVES ▼

ORGANISATION DE WORKSHOPS

05-2017- Co-organisation d'un cours (3 session de 80min) sur les ICO à CHI2017, Denver, USA (taux acceptation : 40%) – CHI est la plus importante et sélective des conférences en Interaction Homme-Machine au monde, avec autour de 3000 participants par an.

10-2016 - Co-organisation de la "BMI Workshop special session on Human factors for BMI training and operation" @ SMC (Systems, Men and Cybernetics) 2016, Budapest, Hongrie.

05-2016 - Co-organisation du Open-BCI Workshop, événement satellite du 6th International BCI Meeting, Asilomar, USA.

10-2015 - Co-organisation de la "BMI Workshop special session on user-training in EEG-based BCIs" @ SMC 2015, Hong Kong.

RESPONSABILITES INTERNATIONALES

J'ai été (ou vais être) membre de plusieurs **comités de programme** de conférences internationales ; Dans ce cadre, je sollicite des chercheurs renommés pour qu'ils soumettent leurs travaux, puis je participe au recrutement des comités de relecture et à la sélection des articles acceptés pour publication et présentation à la conférence.

09-2017 – Membre du comité de programme de la Graz BCI Conference 2017 (Graz, Autriche) ; une des deux conférences sur les ICO (ou BCI en anglais pour Brain-Computer Interface) les plus importantes au monde ; elle réunit toute la communauté internationale une fois tous les 2 ans.

10-2016 – Membre du comité de programme de SMC 2016 (Budapest, Hongrie)

10-2015 – Membre du comité de programme de SMC 2015 (Hong Kong)

REVIEW

J'ai été sollicité pour être relectrice d'une douzaine articles :

Articles de Revues Scientifique – PLOS ONE, Journal of Visualized Experiments, International Journal of Psychophysiology, IEEE Transactions on Human Machine Systems

Articles de Conférences – CHI 2017, SMC2016, CHI 2016, SMC 2015.

RESPONSABILITES ADMINISTRATIVES

2016 – Participation à la création d'un MOOC sur l'Intégrité Scientifique, tourné par l'Université de Bordeaux et destiné dans un premier temps aux doctorants, puis aux chercheurs, ingénieurs, etc. ; Mon rôle a été de réfléchir comment rendre le MOOC attractif, ce qui s'est concrétisé en un tournage d'un « micro campus » (micro trottoir sur le campus universitaire bordelais) et une interview sur des bonnes pratiques.

2014/2015 – Elue représentante des doctorants au conseil de l'Ecole Doctorale SP2 ; mon rôle était de faire l'interfaçage entre les doctorants, le comité des doctorants et le conseil de l'école doctorale lors des conseils de l'EDSP2 (1 fois par mois).

2013 à 2O15 – Membre du comité des doctorants de mon Ecole Doctorale SP2 ; Avec les autres membres, nous avons cherché à mettre en place des solutions pour faciliter le contact entre les doctorants et l'équipe dirigeante de l'ED. Notamment, nous avons mis à disposition une adresse mail et un groupe facebook, nous avons aussi organisé chaque année les journées de l'ED.

Depuis 2014 – Promotion des carrières de la recherche auprès des lycéens (intervention au lycée de Borda, Dax, participation au salon Aquitec, Bordeaux)

VIE ASSOCIATIVE	Depuis 2014 – Membre de l'Association des Doctorants de l'EDSP2 2014 – Membre fondateur de l'Association des Doctorants de l'EDSP2 ; Avec 4 collègues doctorants, nous avons voulu créer une Association dans le but de faire vivre notre jeune école doctorale et de rassembler les doctorants issus de disciplines a priori éloignées. Nous avons mis en places plusieurs événements, dont le Gala de l'EDSP2, qui depuis a lieu tous les ans. Aujourd'hui, l'association comprend une centaine de membres.
MEDIA-TION	*2016* – Conférencière invitée à Pint of Science 2016 *2016* – Conférencière invitée pour la 3ème conférence "Media Science" à l'ENSCBP *2015* – Participation au concours « Ma thèse en 180s » *2014* – Conférencière invitée au "Café de la Connaissance"
MEDIA	*2017* – Interview dans le Complément Sud-Ouest sur l'offre de formation de l'Université de Bordeaux *2016* – Interview dans Plug'In, magasine interne Inria *2016* – Interview radio : L'œuf ou la Poule sur la radio de l'UQAM (Canada)

COMPRENDRE & FACILITER L'APPRENTISSAGE DES INTERFACES CERVEAU-ORDINATEUR BASEES SUR L'IMAGERIE MENTALE :

VERS UNE GENERATION D'INTERFACES CERVEAU-ORDINATEUR FIABLES, EFFICACES ET ACCESSIBLES

Une Interface Cerveau-Ordinateur basée sur l'Imagerie Mentale (IM-ICO), est une neurotechnologie permettant à son utilisateur d'interagir avec l'environnement uniquement via son activité cérébrale (souvent mesurée par ElectroEncéphaloGraphie – EEG) de par la réalisation de tâches d'Imagerie Mentale (IM). Par exemple, avec une IM-ICO, imaginer des mouvements de la main gauche/droite peut permettre de déplacer un objet, tel qu'un fauteuil roulant, vers la gauche/droite. Les IM-ICO sont réellement prometteuses, notamment dans l'optique de créer des technologies d'assistance (par exemple des fauteuils roulants, comme expliqué dans l'exemple précédent, ou des neuroprothèses) permettant aux personnes souffrant d'un handicap moteur sévère d'accéder à une certaine autonomie [1]. Malgré cela, les IM-ICO demeurent peu utilisées par les patients dans le besoin, entre autres en raison de leur manque de fiabilité : 15% à 30% des utilisateurs sont incapables de les contrôler, et parmi ceux qui y arrivent, les performances de contrôle restent souvent modestes, ne permettant un pas un usage sûr dans des conditions de vie réelle [2]. Il est reconnu qu'un apprentissage approprié est essentiel pour acquérir les compétences nécessaires au contrôle d'une IM-ICO. Or, les protocoles d'entraînement actuels sont théoriquement inappropriés car ils ne suivent pas les recommandations issues de l'ingénierie pédagogique [3]. Malheureusement, la composante « humaine » des IM-ICO n'a été que peu considérée pour l'amélioration de la fiabilité de ces technologies : la plupart des recherches du domaine se concentrent sur la composante « machine » en essayant d'améliorer les algorithmes traduisant l'activité cérébrale en commandes. Or, si les patients n'arrivent pas à produire une activité cérébrale claire pour la machine, s'ils n'arrivent pas à apprendre à se servir d'une ICO, les meilleurs algorithmes du monde ne suffiront pas à rendre les ICO utilisables. Ainsi, l'objectif principal de ma thèse consistait à aborder la problématique de l'amélioration de la fiabilité et de l'accessibilité des ICO avec un angle différent : une approche centrée utilisateur. Ainsi, dans un premier temps, nous avons cherché à comprendre les facteurs impactant la performance de contrôle des utilisateurs, puis dans un second temps, nous avons proposé de nouvelles approches pour concevoir des protocoles d'entraînement innovants, adaptés au profil de chaque utilisateur. Dans une dernière partie, de synthèse, nous avons proposé le premier modèle cognitif de la tâche d'apprentissage ICO. Ce travail pourrait constituer le pilier d'une nouvelle génération d'IM-ICO fiables et accessibles. Démocratisées, les IM-ICO pourraient jouer un rôle déterminant dans l'amélioration des conditions de vie des patients atteints de sévères troubles moteurs et de leur entourage, notamment en offrant une autonomie de mouvement et de déplacement.

PREMIERE PARTIE ▼ **COMPRENDRE LES FACTEURS IMPACTANT LA PERFORMANCE**

Nous avons pris le parti de traiter cette première question, fondamentale, selon deux axes :

A. Comment les protocoles d'entraînement impactent-ils les performances aux IM-ICO ?
B. Comment le profil (cognitif, neurophysiologique, personnalité) impacte-t-il ces performances ?

A. Il semblait d'abord nécessaire d'évaluer concrètement l'impact des protocoles d'entraînement standards sur la capacité des utilisateurs à contrôler une ICO. En effet, jusqu'alors, cet impact, n'avait été que suggéré de par des comparaisons théoriques avec les recommandations issues de l'ingénierie pédagogique [3]. Or, les ICO sont sujettes à de nombreux autres éléments qui pourraient expliquer les performances modestes des utilisateurs, p.ex., la non-stationnarité et le faible ratio signal/bruit de l'EEG. Nous avons donc réalisé une étude [4] au cours de laquelle nous avons utilisé un protocole standard dans un contexte exempt d'ICO pour apprendre à des participants à réaliser de simples tâches motrices, i.e., dessiner des triangles et des cercles sur une tablette graphique. Comme cela aurait été le cas pour des tâches d'imagerie mentale (pour lesquelles il faut déterminer l'amplitude et la vitesse d'imagination du mouvement de la main appropriées), ils devaient trouver les stratégies adéquates (taille et vitesse d'exécution des gestes) de manière à ce que le système reconnaisse la tâche exécutée. Nos résultats montrent que 17% des sujets n'ont pas réussi à apprendre à réaliser ces tâches simples [5]. Plus particulièrement, le feedback fourni aux apprenants, trop difficile à traiter, ne semble pas approprié pour l'acquisition de compétences.

B. Il s'agissait donc ensuite de comprendre pourquoi certains utilisateurs réussissent mieux que d'autres à apprendre à contrôler une IM-ICO, alors que tous utilisent les mêmes protocoles. Cette grande variabilité inter-sujets en terme de performance a soulevé la question du potentiel impact de la personnalité, du profil cognitif et des marqueurs neurophysiologiques de l'utilisateur sur ses capacités de contrôle d'une ICO. Nous avons réalisé une étude [6] qui a mis en avant deux résultats principaux. Premièrement, une forte corrélation entre les performances obtenues par les participants et leurs habiletés spatiales (i.e., capacité à produire et manipuler une image mentale) a été révélée. Deuxièmement, cette étude a permis d'identifier pour la première fois un modèle prédictif de la performance, issu d'une régression linéaire, permettant d'expliquer plus de 80% de la variance des performances de nos participants. Ce modèle, qui inclut notamment les niveaux de tension et d'autonomie de l'apprenant, s'est non seulement révélé être cohérent avec la littérature, mais aussi très stable et fiable. Il suggère que les personnes anxieuses/tendues et peu autonomes sont celles ayant le plus de difficultés pour utiliser une ICO, ce qui semble pertinent puisque ce sont les personnes qui ont le plus besoin d'une présence sociale et d'un soutien émotionnel, or, aucun soutien de ce type n'est proposé pendant l'apprentissage actuellement.

SECONDE PARTIE ▼ PROPOSER DES SOLUTIONS POUR AMELIORER L'APPRENTISSAGE

Cette seconde partie consistait à proposer de nouvelles approches, basées sur les résultats fondamentaux présentés ci-dessus, dans le but d'améliorer l'entraînement au contrôle des IM-ICO. A nouveau, nous avons traité cette question selon deux axes :

- **A.** Améliorer les protocoles d'entraînement standards.
- **B.** Adapter le protocole d'entraînement en fonction du profil de chaque apprenant.

A. Nos études ont montré que les protocoles d'entraînement standards n'étaient pas adaptés pour acquérir une compétence. Plus spécifiquement, elles ont suggéré que le feedback fourni aux utilisateurs, pour les informer de la tâche d'imagerie mentale reconnue par le système, pourrait être trop difficile à traiter. En d'autres termes, ce feedback nécessiterait trop de ressources cognitives pour être traité. Nous avons donc proposé un feedback intuitif sous forme de stimulations vibrotactiles au niveau des mains : vibrations sur la main gauche/droite lors de la reconnaissance par le système de l'imagination d'un mouvement de la main gauche/droite, respectivement [8]. En plus d'être intuitif, ce feedback semblait être plus adapté qu'un feedback visuel dans un contexte de navigation en fauteuil roulant. En effet, lors d'une tâche de navigation, la modalité visuelle est extrêmement sollicitée pour analyser l'environnement. Il n'est donc pas recommandé d'ajouter une information, ici le feedback, devant être traitée par cette même modalité. Ce feedback tactile s'est avéré être associé à de meilleures performances qu'un feedback visuel équivalent : les utilisateurs ont mieux appris à se servir de l'ICO.

B.1. Premièrement, nos résultats ont suggéré une corrélation entre Habiletés Spatiales (HS) et les capacités de contrôle d'une IM-ICO. Nous voulons maintenant savoir si une relation causale existe entre ces deux éléments, ou, en d'autres termes : si une amélioration des HS résulterait en une amélioration des capacités de contrôle d'une IM-ICO ? Nous menons actuellement une étude [9] afin d'investiguer les processus sous-tendant ce lien. Nos premiers résultats montrent, sous certaines conditions, un lien entre entraînement HS et progression aux tâches de contrôle d'une ICO ce qui suggère qu'un entraînement des HS des patients pourrait les aider à améliorer leurs capacités de contrôle d'une ICO. Au-delà de l'application pour les personnes atteints d'un trouble moteur sévère, nous nous intéressons aussi à cet entraînement aux HS, notamment en terme de plasticité synaptique au niveau du cortex moteur, dans le cadre de la rééducation de patients ayant subi un AVC. En effet, de par son effet sur le cortex moteur, un entraînement aux HS représente une approche innovante et prometteuse pour la rééducation motrice post-AVC, en particulier pour les patients sans mobilité résiduelle, puisqu'il permettrait de stimuler le cortex moteur sans demander aux patients de réaliser des tâche d'IM qui ont tendance à leur rappeler la perte de mobilité de leur membre et donc d'accentuer leur état dépressif.

B.2. Deuxièmement, nous souhaitons aussi adapter le protocole d'entraînement à la personnalité de l'apprenant. Plus spécifiquement, nous avons montré que la tension et l'autonomie de l'apprenant influençaient sa capacité à utiliser une IM-ICO. Inspirés de la littérature sur l'apprentissage à distance, nous avons développé un compagnon d'apprentissage tangible (petite marionnette imprimée en 3D dotée d'expressions faciales et de synthèse vocale, que nous avons appelée PEANUT) dont le but est de fournir aux apprenants un support émotionnel et une présence sociale visant à pallier de forts niveaux d'anxiété et faibles niveaux d'autonomie, respectivement. Le comportement du compagnon est adapté au profil de l'apprenant et à l'évolution de ses performances au cours du processus d'apprentissage. Ce compagnon a été développé grâce à une approche de design participatif et testé dans le contexte d'un apprentissage ICO. Nous pensons que PEANUT est très prometteur pour favoriser l'apprentissage de l'utilisation d'ICO pour la navigation, dans le cas de patients avec troubles moteurs, mais aussi lors de rééducation post AVC. En effet, nombre de patients souffrent d'anxiété et de dépression. Ce compagnon permettrait de leur fournir un soutien émotionnel qui pourrait faciliter l'apprentissage en favorisant les émotions positives et en maintenant le niveau attentionnel et la motivation.

TROISIEME PARTIE ▼ **VERS UN MODELE COGNITIF DE LA TACHE D'APPRENTISSAGE DES ICO**

Cette thèse a permis d'apporter des éléments fondamentaux nouveaux, et donc d'avancer un peu plus vers la compréhension des processus impliqués dans l'apprentissage de l'utilisation des ICO. Cependant, pour atteindre une réelle compréhension approfondie de ces processus, une approche multifactorielle est indispensable. En effet, un apprentissage est le fruit de l'interaction de différents facteurs cognitifs intervenant dans un contexte émotionnel et motivationnel particuliers. Il est donc nécessaire de comprendre comment ces facteurs interagissent et comment ils peuvent être manipulés pour atteindre une meilleure performance. Grâce à une synthèse de la littérature, à la fois sur le plan théorique et expérimental, nous avons proposé le premier modèle cognitif de la tâche d'apprentissage des BCI. Ce modèle comprend des facteurs liés à la relation entre la personne et la technologie, à l'attention/motivation, et aux habiletés spatiales [9]. Nous avons cherché à comprendre comment ces facteurs interagissent et comment nous pourrions les influencer grâce à des facteurs extérieurs (tels que le design de l'expérience ou des entraînements cognitifs spécifiques) de manière à améliorer la performance des utilisateurs.

Ce travail concoure notoirement à l'amélioration de la fiabilité des IM-ICO, et donc à leur acceptabilité. Ainsi, ces technologies pourraient contribuer de manière significative à améliorer la rééducation post-AVC, et donc les conditions de vie de ces patients et de leur entourage.

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Triées en fonction du type de publication et de la date de publication (de la plus récente à la plus ancienne)

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Why standard brain-computer interface (BCI) training protocols should be changed: an experimental study

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Abstract

Objective. While promising, electroencephaloraphy based brain–computer interfaces (BCIs) are barely used due to their lack of reliability: 15% to 30% of users are unable to control a BCI. Standard training protocols may be partly responsible as they do not satisfy recommendations from psychology. Our main objective was to determine in practice to what extent standard training protocols impact users' motor imagery based BCI (MI-BCI) control performance. *Approach.* We performed two experiments. The first consisted in evaluating the efficiency of a standard BCI training protocol for the acquisition of non-BCI related skills in a BCI-free context, which enabled us to rule out the possible impact of BCIs on the training outcome. Thus, participants ($N = 54$) were asked to perform simple motor tasks. The second experiment was aimed at measuring the correlations between motor tasks and MI-BCI performance. The ten best and ten worst performers of the first study were recruited for an MI-BCI experiment during which they had to learn to perform two MI tasks. We also assessed users' spatial ability and pre-training μ rhythm amplitude, as both have been related to MI-BCI performance in the literature. *Main results.* Around 17% of the participants were unable to learn to perform the motor tasks, which is close to the BCI illiteracy rate. This suggests that standard training protocols are suboptimal for skill teaching. No correlation was found between motor tasks and MI-BCI performance. However, spatial ability played an important role in MI-BCI performance. In addition, once the spatial ability covariable had been controlled for, using an ANCOVA, it appeared that participants who faced difficulty during the first experiment improved during the second while the others did not. *Significance.* These studies suggest that (1) standard MI-BCI training protocols are suboptimal for skill teaching, (2) spatial ability is confirmed as impacting on MI-BCI performance, and (3) when faced with difficult pre-training, subjects seemed to explore more strategies and therefore learn better.

Keywords: brain-computer Interface, user-training, standard training protocol, spatial ability, electro-encephalography

(Some figures may appear in colour only in the online journal)

1. Introduction

Brain–computer interfaces (BCIs) are communication and control systems that allow users to interact with the environment using only their brain activity [47], which is often measured using electroencephalography (EEG). A prominent type of BCI, called motor imagery based BCIs (MI-BCIs), makes use of control signals sent via the execution of motor imagery tasks, such as imagining hand movements. They are indeed very promising, in particular

CHAPTER

1

Advances in user-training for mental-imagery-based BCI control: Psychological and cognitive factors and their neural correlates

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Abstract

While being very promising for a wide range of applications, mental-imagery-based brain–computer interfaces (MI-BCIs) remain barely used outside laboratories, notably due to the difficulties users encounter when attempting to control them. Indeed, 10–30% of users are unable to control MI-BCIs (so-called BCI illiteracy) while only a small proportion reach acceptable control abilities. This huge interuser variability has led the community to investigate potential predictors of performance related to users' personality and cognitive profile. Based on a literature review, we propose a classification of these MI-BCI performance predictors into three categories representing high-level cognitive concepts: (1) users' relationship with the technology (including the notions of computer anxiety and sense of agency), (2) attention, and (3) spatial abilities. We detail these concepts and their neural correlates in order to better understand their relationship with MI-BCI user-training. Consequently, we propose, by way of future prospects, some guidelines to improve MI-BCI user-training.

Keywords

Brain–computer interfaces, Interuser variability, User-training, Predictors of performance, Neural correlates, Sense of agency, Computer anxiety, Attention, Spatial abilities, Improving training protocols

PLOS ONE

RESEARCH ARTICLE

Predicting Mental Imagery-Based BCI Performance from Personality, Cognitive Profile and Neurophysiological Patterns

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Abstract

Mental-Imagery based Brain-Computer Interfaces (MI-BCIs) allow their users to send commands to a computer using their brain-activity alone (typically measured by ElectroEncephaloGraphy—EEG), which is processed while they perform specific mental tasks. While very promising, MI-BCIs remain barely used outside laboratories because of the difficulty encountered by users to control them. Indeed, although some users obtain good control performances after training, a substantial proportion remains unable to reliably control an MI-BCI. This huge variability in user-performance led the community to look for predictors of MI-BCI control ability. However, these predictors were only explored for motor-imagery based BCIs, and mostly for a single training session per subject. In this study, 18 participants were instructed to learn to control an EEG-based MI-BCI by performing 3 MI-tasks, 2 of which were non-motor tasks, across 6 training sessions, on 6 different days. Relationships between the participants' BCI control performances and their personality, cognitive profile and neurophysiological markers were explored. While no relevant relationships with neurophysiological markers were found, strong correlations between MI-BCI performances and mental-rotation scores (reflecting spatial abilities) were revealed. Also, a predictive model of MI-BCI performance based on psychometric questionnaire scores was proposed. A leave-one-subject-out cross validation process revealed the stability and reliability of this model: it enabled to predict participants' performance with a mean error of less than 3 points. This study determined how users' profiles impact their MI-BCI control ability and thus clears the way for designing novel MI-BCI training protocols, adapted to the profile of each user.

Introduction

A brain computer interface (BCI) is a hardware and software communication system that enables humans to interact with their surroundings without the involvement of peripheral

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EEG-based workload estimation across affective contexts

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Workload estimation from electroencephalographic signals (EEG) offers a highly sensitive tool to adapt the human–computer interaction to the user state. To create systems that reliably work in the complexity of the real world, a robustness against contextual changes (e.g., mood), has to be achieved. To study the resilience of state-of-the-art EEG-based workload classification against stress we devise a novel experimental protocol, in which we manipulated the affective context (stressful/non-stressful) while the participant solved a task with two workload levels. We recorded self-ratings, behavior, and physiology from 24 participants to validate the protocol. We test the capability of different, subject-specific workload classifiers using either frequency-domain, time-domain, or both feature varieties to generalize across contexts. We show that the classifiers are able to transfer between affective contexts, though performance suffers independent of the used feature domain. However, cross-context training is a simple and powerful remedy allowing the extraction of features in all studied feature varieties that are more resilient to task-unrelated variations in signal characteristics. Especially for frequency-domain features, across-context training is leading to a performance comparable to within-context training and testing. We discuss the significance of the result for neurophysiology-based workload detection in particular and for the construction of reliable passive brain–computer interfaces in general.

Keywords: workload, stress, brain–computer interface, classification, electroencephalography, passive brain computer interface

INTRODUCTION

The increasing complexity and autonomy of information systems rapidly approaches the limits of human capability. To avoid overload of the users in highly demanding situations, a dynamic and automatic adaptation of the system to the user state is necessary. Reliable knowledge about the user state, especially his workload, is a key requirement for a timely and adequate system adaptation (Erp et al., 2010). Examples are systems supporting air traffic control, pilots, as well as medical and emergency applications.

Conventional means of workload assessment, such as self-assessment and behavior, are intrusive or limited in their sensitivity, respectively (Erp et al., 2010). Physiological sensors, assessing for example the galvanic skin response (GSR) or elecrocardiographic activity (ECG), offer an unobtrusive and continuous measure that has been found sensitive to workload (Verwey and Veltman, 1984; Boucsein, 1992). In the last two decades, neurophysiological activity became popular as a modality for the measurement of mental states in general and of workload in specific. So-called "passive brain-computer interfaces" (pBCI, Zander and Kothe, 2011) are able to measure neuronal activity in terms of the electrophysiological activity of neuron populations as in the case of EEG or the oxygination of the cerebral blood flow as for functional near-infrared spectroscopy (fNIRS). Both approaches have been found informative regarding the detection of cognitive load (Brouwer et al., 2012; Solovey et al., 2012), and there is evidence for a partially superior sensitivity of neural measurements compared to other physiological sensors (Mathan et al., 2007) or self-report (Peck et al., 2013).

Most experiments on passive BCI use a very controlled approach, which naturally limits the range of real-world conditions they reflect. While this control is necessary to ensure the psychophysiological validity of the mental state detection, their results lack a certain ecological validity, they can not be generalized to other contexts. This might be one of the most impeding problems for the creations of passive BCI systems that work in the real world, since daily life is characterized by the variability of the conditions we function under. A prominent example are changes of affect while working, for example working under the pressure of an impending evaluation vs. work without pressure. A system that is supposed to work in such contexts needs to be calibrated and tested in them. Previous research in the domain of pBCI largely ignored the problem. To shed light on the interaction of mental state classification and change of affective context, we devised a protocol that recreates conditions of work, requiring different effort, during relaxed conditions and under psychosocial stress in a controlled environment. To study the resilience of a state-of-the art workload detection system to changes in affective context, we train subject-specific classifiers in either stressed or non-stressed context and test their performance within the same and in the other context.

In summary, the contributions of this paper for the study of the effect of affective context on workload classification are:

Towards a Spatial Ability Training to Improve Mental Imagery based Brain-Computer Interface (MI-BCI) Performance: a Pilot Study

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***Abstract*—Although Mental Imagery based Brain-Computer Interfaces (MI-BCIs) seem to be very promising for many applications, they are still rarely used outside laboratories. This is partly due to suboptimal training protocols, which provide little help to users learning how to control the system. Indeed, they do not take into account recommendations from instructional design. However, it has been shown that MI-BCI performances are significantly correlated to certain aspects of the users' cognitive profile, such as their Spatial Abilities (SA). Thus, it remains to be elucidated whether training the SA of BCI users would also improve their BCI control performance. Therefore, we proposed and validated an SA training that aimed at being included in an MI-BCI training protocol. Our pre-studies indeed confirmed that such a training does increase people's SA abilities. We then conducted a pilot study with 3 participants, one with a standard MI-BCI training protocol, one with the proposed SA training integrated into a standard MI-BCI training, and another control integrating another training, here verbal comprehension tasks, into a standard MI-BCI training. While such a small population cannot lead to any strong result, our first results show that SA training can indeed be integrated into MI-BCI training and is thus worth being further investigated for BCI user training.**

***Index Terms*—Brain-Computer Interfaces, Training, Spatial Abilities, Mental Rotation**

I. Introduction

Brain-computer interfaces (BCIs) are communication and control systems enabling users to interact with their environment using their brain activity alone [1] which is often measured using Electroencephalography (EEG). A prominent type of BCI, called Mental-Imagery based BCI (MI-BCI), makes use of control signals sent via the execution of mental-imagery tasks, such as imagining movements of the left hand vs. right hand. Such technologies are very promising, notably in the context of stroke rehabilitation [2]. However, MI-BCIs remain barely used outside laboratories due to their lack of reliability [1]. Two main factors responsible for this low reliability have been identified. The first, extensively investigated, concerns brain signal processing with current classification algorithms being still imperfect [3]. The second concerns the users themselves: between 15% and 30% cannot control a BCI at all (so-called "BCI deficiency"), while most of the remaining 80% obtain relatively modest performances [3].

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It is now accepted that 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 MI-tasks [4], [5]. Just as with any skill, appropriate training is required to acquire these skills [4]. Yet, current standard training protocols, which do not take into account the recommendations from psychology and instructional design (such as offering adaptive and progressive tasks or explanatory, supportive and multimodal feedback), appear to be theoretically inappropriate, and thus might be partly responsible for BCI illiteracy and modest user performance [6].

In a previous study, we showed that the user's profile could be related to MI-BCI control abilities based on a 6-session protocol (i.e., over 6 different days) [7]. In this experiment, the participants (N=18) had to learn to perform 3 MI tasks: left-hand motor imagery, mental rotation and mental calculation. The results stressed the correlation between mental rotation scores (measured using questionnaires, [8]) which reflect Spatial Abilities (SA), and mean MI-BCI performance [$r=0.696$, $p\leq0.05$]. SA are the mental capacities which enable the construction, transformation and interpretation of mental images. Based on these results, it seems that users with high mental rotation scores perform better when using an MI-BCI than users with low mental rotation scores. Recently, a second study [9], involving 20 healthy participants training to control a 2-class MI-BCI (left- and right-hand movement imagination), revealed a similar correlation between peak MI-BCI performance and mental rotation scores [$r=0.464$, $p\leq0.05$], thus reinforcing the hypothesis of a close relationship between spatial abilities and MI-BCI control performance.

With a view to improving users' MI-BCI control abilities, further investigating this relationship between MI-BCI performance and SA seems promising. More specifically, beyond the correlation, it would be interesting to assess whether a causal relationship exists between SA and MI-BCI performance. In other words, does an improvement in SA lead to improved MI-BCI performance? This raised the idea of a new approach for MI-BCI training by targeting the improvement of users' SA. Therefore, we implemented an SA training (composed of 6 sessions: 1 standard MI-BCI session - 3 sessions of SA training

Why and How to Use Intelligent Tutoring Systems to Adapt MI-BCI Training to Each User.

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Introduction: While Mental Imagery based BCIs (MI-BCIs) are promising for many applications, their usability "out-of-the-lab" has been questioned due to their lack of reliability: literature reports that 15% to 30% of users cannot control such a technology, while most of the remaining users obtain only modest performances [1]. Standard MI-BCI training protocols have been suggested to be partly responsible for these modest performances as they do not comply with general human learning principles [2]. The modest performances as well as the flaws in the protocols led to the investigation of solutions to improve MI-BCI training by adapting it to each user. Such an approach is possible using Intelligent Tutoring Systems (ITS), i.e., computerised systems aiming at supporting learning [3]. Hence, we show **why** ITS are relevant for MI-BCI training and **how** this technology could be used.

Why? – MI-BCI training resembles *distance learning* (DL) as it is performed autonomously, with neither teacher nor classmates. Consistently with DL literature, highly anxious and poorly autonomous learners have been shown to struggle with MI-BCI training [5]. Since ITS have been proven efficient for improving DL [3], MI-BCI training may also benefit from ITS. The strength of ITS lies in (1) a personalised support provided by a learning companion [3] and (2) an adaptation of the training process according to the learner's profile and skill evolution.

How? - We are proposing the conceptual framework for an ITS which would support MI-BCI user-training. ITS comprise 4 modules. First, the *Student Model* is the core component containing information about the user's personality and cognitive profile and state. Second, the *Expert module* contains the concepts, rules and strategies of the field to be learned. Third, the *Tutoring module* uses input from the two previous modules to select a tutoring strategy, and finally the *Interface* provides the user with access to the learning environment. Each module will be described in an MI-BCI training context (see Fig.1). The *Student Model* contains 2 kinds of information: 1) the user-profile, as assessed by questionnaires, and more specifically spatial abilities and personality traits (e.g., abstractness, tension or autonomy), which have been shown to be related to MI-BCI performance [4]; and 2), the user's cognitive state, e.g., fatigue and workload levels and MI-BCI skill development, provided by the BCI system through classification-accuracy measures. The *Expert module* contains a cognitive model of the skills to be learned, e.g., the ability to generate stable and distinct brain-activity patterns while performing the MI-tasks. It also includes a bank of exercises with different levels of difficulty [6], which would help the user to acquire these skills. Based on the *Student Model* and on the *Expert module*, and using specialised algorithms [3], the *Tutor* selects the appropriate exercises and provides the users with a suitable support, i.e., adapted to their performance and profile. This support will be provided using a physical learning companion [3], which has been proven to increase motivation and learning [3]. In particular, this companion will provide any users who have high tension and low autonomy levels [4] with a social presence and an emotional support (e.g., empathy). We are currently designing and evaluating the content of these different modules.

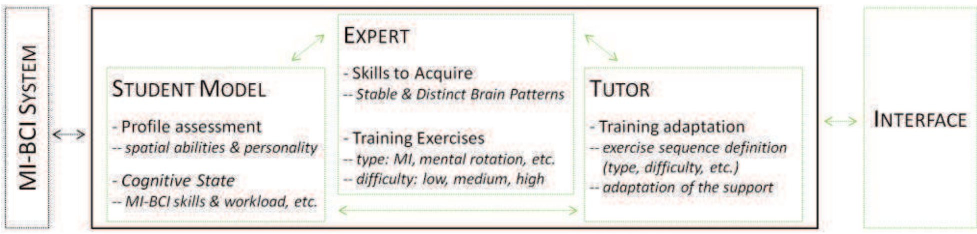

Figure 1. *Diagram representing the conceptual architecture of an ITS supporting MI-BCI training.*

Discussion: ITS may be very useful for MI-BCI user training, especially if the *Student Model* and *Expert module* are reinforced. The former could include more detail on the user's profile and cognitive state, while the latter could be improved by a better fundamental understanding of MI-BCI related skills and how they are acquired.

Significance: Such an ITS represents a promising pluridisciplinary approach for improving MI-BCI performance as it would enable to gather different levers and articulate them in order to optimise the user-training process.

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Spatial Abilities Play a Major Role in BCI Performance

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Introduction: Despite their promising potential impact for many applications, Mental-Imagery based BCIs (MI-BCIs) remain barely used outside laboratories. One reason is that 15% to 30% of naïve users seem unable to control them [1] and only a few reach high control abilities. Although different predictors of BCI performance (i.e., command classification accuracy) have been investigated to explain this huge inter-user variability [2, 3], no strong predictive model has yet been determined. This could be due to (a) the often small samples used (N=5 or 6) and (b) the fact that these predictors have been mostly determined based on one-session experiments. Yet there is no evidence that performance obtained at the first session is predictive of users' MI-BCI control ability.

Material, Methods and Results: In [4], we investigated the impact of the user's personality and cognitive profile on MI-BCI performance based on a 6-session experiment. Averaging performances over these sessions reduced the intra-subject variability (e.g., due to fatigue or external factors), and thus led to a better estimation of participants' MI-BCI control ability. Each session comprised 5 runs during which the participants (N=18) had to learn to perform 3 MI tasks: left-hand motor imagery, mental rotation and mental calculation. The results stressed the impact of mental rotation scores (measured using questionnaires), and which reflect Spatial Abilities (SA), on mean MI-BCI performance [$r=0.696$, $p<0.05$] (see Fig. 1[A]). SA are the mental capacities which enable the construction, transformation and interpretation of mental images. In a more recent study (to be published), we trained 20 participants to control a 2-class MI-BCI by performing motor-imagery of their left- and right-hands, within 1 session of 5 runs. Results confirmed the role of SA: mental rotation scores were correlated with peak MI-BCI performance [$r=0.464$, $p<0.05$]. This suggests that SA are a generic predictor of MI-BCI performances.

Figure 1. *[A] Diagram representing the mean classification accuracy for the different subjects as a function of their mental rotation score; [B] 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.*

Spatial Ability Training: The strong correlation between SA and MI-BCI performance raised a new research question: Is there a causal effect between SA and MI-BCI performance? In other words: Would an improvement of users' SA result in an increase of their MI-BCI control abilities? We implemented an SA training protocol (see Fig. 1[B]) including different exercise types and difficulties. In the coming weeks, we will test this protocol efficiency in terms of MI-BCI performance improvement by comparing it to a standard MI-BCI training approach. We will also investigate the neurophysiological correlates of the SA training (notably the implication of the motor cortex) to improve the understanding of the relationship between SA and MI-BCI performance.

Perspectives for Stroke Rehabilitation: If a causal link between SA and MI-BCI performance is confirmed, this would be a promising way to improve MI-BCI performance and thus MI-BCI-based applications such as stroke rehabilitation [5]. Also, current MI-BCI based stroke rehabilitation procedures [5] require the execution of MI tasks which can induce (or increase) a depressed state in patients by reminding them of the loss of movement in their limb. Since SA training and mental rotation tasks activate the motor cortex [6], they might also be used as a more transparent way to indirectly induce synaptic plasticity in the motor cortex during rehabilitation.

Significance: Through SA, we propose a new approach for MI-BCI training that could offer promising perspectives for MI-BCI and stroke rehabilitation. We are currently evaluating and validating this approach.

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Training Users' Spatial Abilities to Improve Brain-Computer Interface Performance: A Theoretical Approach

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Abstract—**Mental-Imagery based Brain-Computer Interfaces (MI-BCIs) allow their users to send commands to a computer using their brain activity alone (typically measured by ElectroEncephaloGraphy - EEG), which is processed while they perform specific mental tasks. While very promising MI-BCIs remain barely used outside laboratories because of the difficulty encountered by users to control them. Indeed, although some users obtain good control performances after training, a substantial proportion remains unable to reliably control an MI-BCI. This huge variability in user performance led the community to look for predictors of MI-BCI control ability. Mainly, neurophysiological and psychological predictors of MI-BCI performance have been proposed. In this paper, a newly-depicted lever to increase MI-BCI performance is introduced: namely a spatial ability training. The aims of this paper are to clarify the relationship between spatial abilities and mental imagery tasks used in MI-BCI paradigms, and to provide suggestions to include a spatial ability training in MI-BCI training protocols.**

I. Introduction

A brain computer interface (BCI) is a hardware and software communication system that enables its user to interact with surroundings without the involvement of peripheral nerves and muscles, i.e., by using control signals generated from electroencephalographic (EEG) activity [1]. More specifically, this paper focuses on BCIs for which these control signals are sent via the execution of *mental tasks* (e.g., motor imagery): so-called Mental-Imagery based BCIs (MI-BCIs). MI-BCIs represent a new, non-muscular channel for relaying users' intentions to external devices such as computers, assistive appliances or neural prostheses [2]. Unfortunately, most of these promising BCI-based technologies cannot yet be offered on the public market since a notable portion of users (estimated to be between 15 and 30%) does not seem to be able to learn to control such a system [3]: this phenomenon is often called "BCI illiteracy" or "BCI deficiency". This high "BCI illiteracy" rate could be due on the one hand to several EEG-related flaws like non-stationarity, poor signal/noise ratio or imperfect classification algorithms [3]. On the other hand, standard training protocols [4] have also been questioned [5] as they do not follow recommendations from instructional design and psychology. Nonetheless, although there is a large proportion of "illiterates", some users perform excellently [6] and the EEG-related flaws and unsuitable protocols do not explain the important variability in performance . From this observation emerged the idea of a relation between users' characteristics and their ability to control an MI-BCI, which led the community to look for predictors of MI-BCI performance (i.e., the rate of correctly recognised MI tasks). The training process to learn to control an MI-BCI being time- and resource-consuming, being able to predict users' success (or failure) could avoid important loss of time and energy for both users and experimenters. From another perspective, knowing these predictors could guide the design of new training protocols that would be adapted to users' characteristics. In this paper, a newly-depicted lever to increase MI-BCI performance is introduced: namely a spatial ability training. This factor seems to be a very promising predictor of MI-BCI performance as it appeared to be stable and reliable. The aims of this paper are to clarify the relationship between spatial abilities and mental imagery tasks used in MI-BCI paradigms, and to provide suggestions to include a spatial ability training in MI-BCI training protocols.

II. Predictors of MI-BCI Performance

A. Neurophysiological Predictors

Recently, evidence was presented that the amplitude of sensorimotor-rhythms (SMRs) at rest is a good predictor of subsequent BCI-performance in motor-imagery paradigms [7]: a correlation (r=0.53) was found between a new neurophysiological predictor based on the μ (about 9-14 Hz) rhythm over sensorimotor areas and BCI performance (N = 80). Moreover, Grosse-Wentrup et al. [8] demonstrated that the modulation of SMRs was positively correlated with the power of frontal and occipital γ-oscillations, and negatively correlated with the power of centro-parietal γ-oscillations. Besides, Grosse-Wentrup and Schölkopf [9] showed that high-frequency γ-oscillations originating in fronto-parietal networks predicted variations in performance on a trial-to-trial basis. This finding was interpreted as empirical support for an influence of attentional networks on BCI performance via the modulation of SMRs. Furthermore, Ahn et al. [10] found that BCI-illiterate show higher θ- and lower α-power levels than BCI-literate. Statistically significant areas were frontal and posterior-parietal regions for the θ-band and the whole cortex area for the α-band. A high positive correlation between γ-activity and motor-imagery performance was also shown in the prefrontal area [11]. Finally, [12] demonstrated that having higher frontal θ and lower posterior α prior to performing motor-imagery,

Predicting Mental-Imagery Based Brain-Computer Interface Performance from Psychometric Questionnaires

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ABSTRACT

Mental-Imagery based Brain-Computer Interfaces (MI-BCIs) allow their users to send commands to a computer via their brain activity, measured while they are performing specific mental tasks. While very promising (e.g., assistive technologies for motor-disabled patients) MI-BCI remain barely used outside laboratories because of the difficulty encountered by users to control such systems. Indeed, although some users obtain very good control performance after training, a substantial proportion remains unable to reliably control an MI-BCI. This huge variability led the community to look for predictors of MI-BCI control ability. In this paper, we introduce two predictive models of MI-BCI performance, based on a dataset of 17 participants who had to learn to control an MI-BCI by performing 3 MI-tasks: mental rotation, left-hand motor imagery and mental subtraction, across 6 sessions. These models include aspects of participants' personality and cognitive profiles, assessed by questionnaires. Both models, which explain more than 96% and 80% of MI-BCI performance variance, allowed us to define user profiles that could be associated with good BCI performances.

Keywords

Brain-Computer Interfaces, Mental Imagery, Performance Predictors, Personality, Cognitive Profile

1. INTRODUCTION

A brain computer interface (BCI) is a hardware and software communication system that enables its user to interact with the surroundings without the involvement of peripheral nerves and muscles, i.e., by using control signals generated from electroencephalographic (EEG) activity [16]. More specifically, this paper focuses on BCIs for which these control signals are sent via the execution of *mental tasks*: so-called Mental-Imagery based BCIs (MI-BCIs). MI-BCIs represent a new, non-muscular channel for relaying users' intentions to external devices such as computers, speech synthesizers, or neural prostheses [10]. Unfortunately, most of these promising BCI-based technologies cannot yet be offered on the public market since a notable portion of users (estimated to be between 15 and 30%) does not seem to be able to learn to control such a system [1]: this phenomenon is often called "BCI illiteracy" or "BCI deficiency". This high "BCI illiteracy" rate could be due to several BCI-related flaws like EEG non-stationarity, poor signal/noise ratio or imperfect classification algorithms [1]. Standard training protocols [13] have also been questioned [8] as they do not follow recommendations from instructional design. However, although there is a large proportion of "illiterates", some users perform excellently [5] and the previous elements do not explain the important variability in users' ability to control an MI-BCI. From this observation emerged the idea of a relation between users' characteristics and their ability to control an MI-BCI. It led the community to look for predictors of MI-BCI control performance. Indeed, the training process to learn to control an MI-BCI being time- and resource-consuming, being able to predict users' success (or failure) could avoid important loss of time and energy for both users and experimenters. From another perspective, knowing these predictors can guide the design of new training protocols that would be adapted to users' characteristics. The main contribution of this paper is to propose, for the first time, a predictive model of MI-BCI performance generated from the data of 17 participants who were trained to perform 3 mental tasks (mental rotation, mental subtraction and left-hand motor imagery) for 6 sessions.

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2. RELATED WORK

Mood, motivation [12] and the locus of control score related to dealing with technology [2], have been shown to be correlated with motor-imagery based BCI performance. Fear of the BCI system has also been shown to affect performance [2][11]. In [4], attention span, personality and motivation play a moderate role for one-session motor-imagery based

Towards Explanatory Feedback for User Training in Brain–Computer Interfaces

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***Abstract*—Despite their potential for many applications Brain–Computer Interfaces (BCI) are still rarely used due to their low reliability and long training. These limitations are partly due to inappropriate training protocols, which includes the feedback provided to the user. While feedback should theoretically be explanatory, motivating and meaningful, current BCI feedback is usually boring, corrective only and difficult to understand. In this study, different features of the electroencephalogram signals were explored to be used as a richer, explanatory BCI feedback. First, based on offline mental imagery BCI data, muscular relaxation was notably found to be negatively correlated to BCI performance. Second, this study reports on an online BCI evaluation using muscular relaxation as additional feedback. While this additional feedback did not lead to significant change in BCI performance, this study showed that multiple feedbacks can be used without deteriorating performance and provided interesting insights for explanatory BCI feedback design.**

***Index Terms*—Brain-Computer Interfaces, Training, Feedback**

I. Introduction

Brain-Computer Interfaces (BCI) are systems that enable their users to control an external device such as a computer without the need for any muscular movement [1]. Instead they only rely on a measure of brain signals, e.g., electroencephalography (EEG). BCI systems can be used as assistive technology to restore communication with patients who have severe motor disabilities. Despite their potential in this and many other areas, most BCIs are still not used outside laboratory settings due to their low reliability and long training times. Furthermore, roughly 15–30% of users fail to gain any control over a BCI [1]. Recently, [2] have identified potential reasons for these limitations in the usability of BCI systems. They argue that since BCIs are co–adaptive systems, the two parts of the system might be sources of bad performance and hence are possible targets for improvement: the user and the machine. The user has to learn to produce specific brain patterns by performing mental tasks while at the same time the machine has to learn to recognize and classify these brain patterns by undergoing machine learning.

While there has been a lot of research exploring new signal processing approaches to improve the machine learning component of BCIs, this study will focus on the user's side. BCI use can be seen as a skill and requires training [1]. Training is particularly important in the case of spontaneous BCIs which rely on the voluntary modulation of certain brain patterns by the user. An example of such a paradigm is a mental imagery–based BCI (MI-BCI) where users try to modulate their brain activity by performing different mental imagery tasks, e.g. the imagination of movements. BCI user training can be divided into three parts: the instructions, the task and the feedback. While all these aspects are potential targets for improvement [2] this study will focus on the feedback that is provided to the user. Feedback is essential for learning to operate a BCI since it is generally not clear to the user from the beginning what exactly they are required to do in order for the computer to be able to pick up useful signals. In a classical MI-BCI the user is asked to perform different mental imagery tasks such as the imagination of a left or a right hand movement. On the basis of a calibration period a classifier is trained to distinguish between the classes by learning the differences in the recorded brain patterns which underlie the execution of the tasks. During subsequent runs feedback is given to the users to inform about their current performance. The classical feedback that is used in MI-BCIs is shown in form of a moving bar which corresponds to the strength and direction of the output of the previously trained classifier [2]. The feedback thus indicates whether the classifier was able to identify the correct class and the certainty of the classifier in its decision.

Several aspects of this feedback are not in line with current opinions on good feedback from educational research [2]. Generally speaking, while feedback should be explanatory (i.e., explain what was good or bad and why), motivating, supportive, meaningful, specific, and multimodal [3], currently used BCI feedback is usually boring, corrective only (i.e., only indicates whether it was good or bad), not meaningful to people who are not familiar with the concept of a classifier, and limited to the visual modality. Thus, there are a lot of possibilities for improvement some of which have already been explored in previous studies. While most BCI systems use visual feedback, several studies explored the auditory and haptic modalities. Giving haptic feedback either leads to comparable results as visual feedback [4] or leads to higher performances [5], [6]. Using the auditory modality for feedback does not seem to be as promising, the performances are either comparable to visual feedback [7] or lower [8]. Regarding the motivational aspect of feedback several studies have shown that virtual reality

Continuous Tactile Feedback for Motor-Imagery Based Brain-Computer Interaction in a Multitasking Context

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Abstract. Motor-Imagery based Brain Computer Interfaces (MI-BCIs) allow users to interact with computers by imagining limb movements. MI-BCIs are very promising for a wide range of applications as they offer a new and non-time locked modality of control. However, most MI-BCIs involve visual feedback to inform the user about the system's decisions, which makes them difficult to use when integrated with visual interactive tasks. This paper presents our design and evaluation of a tactile feedback glove for MI-BCIs, which provides a continuously updated tactile feedback. We first determined the best parameters for this tactile feedback and then tested it in a multitasking environment: at the same time users were performing the MI tasks, they were asked to count distracters. Our results suggest that, as compared to an equivalent visual feedback, the use of tactile feedback leads to a higher recognition accuracy of the MI-BCI tasks and fewer errors in counting distracters.

Keywords: Brain-Computer interaction · Tactile feedback · Multitasking

1 Introduction

Brain-Computer Interfaces (BCIs) are communication and control systems allowing users to interact with their environment using their brain activity alone [27]. BCIs based on ElectroEncephaloGraphy (EEG, i.e., recording neurons' electrical activity on the scalp) are increasing in popularity due to their advantages of having high temporal resolution while being non-invasive, portable and inexpensive compared to BCIs based on other brain sensing techniques (e.g., functional Magnetic Resonance Imaging). In particular, sensorimotor rhythms (SMRs), i.e., oscillations in brain activity recorded from cortical somatosensory and motor areas (detectable in the 8–30 Hz frequency

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Towards Improved BCI based on Human Learning Principles

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***Abstract*—Although EEG-based BCI are very promising for numerous applications they mostly remain prototypes not used 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. This paper presents some of our current work that aims at addressing the latter, i.e., at guiding users to learn BCI control mastery. First, this paper discusses some psychological models about human learning to illustrate the limitations of current standard BCI training approaches and thus the need for alternative ones. We will show that such theoretical limitations are confirmed by actual experiments. To try to address these limitations, we conducted a study to explore what kind of users can use a BCI and why, and will present the main results. We also present new feedback types we designed to help users to learn BCI control skills more efficiently.**

I. Introduction

ElectroEncephaloGraphy (EEG)-based Brain-Computer Interfaces (BCI) make computer control possible without any physical activity [?]. As such, they have promised to revolutionize many applications areas, including assistive devices or human-computer interaction [?][?]. Despite this promising potential, such revolutions have not been delivered yet, and BCI are still barely used outside laboratories [?]. The main reason for this failed promise is the substantial lack of reliability of current BCI [?]. In particular, BCI too often fail to correctly recognize the users mental commands. Moreover, it is estimated that roughly 20% of BCI users cannot control the system at all (the so-called BCI illiteracy/deficiency) [?].

To operate a BCI, the user has to produce EEG patterns, typically using mental imagery tasks[1], which the machine has to recognize by using signal processing. So far, to address the reliability issue of BCI, most research efforts have been focused on EEG signal processing only [?][?]. While this has contributed to increased performances, improvements have been relatively modest, with BCI accuracy being still relatively low and BCI illiteracy still high [?][?]. Thus, the reliability issue of BCI is unlikely to be solved by focusing on signal processing alone. Indeed, BCI control is known to be a skill that needs to be learned and mastered by the user [?]. This means that 1) the BCI performances of a user become better with practice and thus that 2) the user needs to learn how to produce stable, clear and distinct brain activity patterns to successfully control a BCI. With poor users BCI control skills, even the best signal processing algorithms will fail to recognize the users mental commands. Unfortunately, how to train users to BCI control has been rather scarcely studied in the BCI literature so far. As a consequence, the best way to train users to master BCI control skills is still unknown [?][?].

This paper aims at convincing the reader that changing BCI design to enable their users to master BCI control skills is a very promising direction to improve BCI reliability. Indeed, this paper first identifies the theoretical and practical limitations of current standard BCI training protocols, which may explain, at least in part, the current high rate of BCI illiteracy/deficiency and their overall modest performance. It then presents our ongoing work towards improving these training protocols. It notably presents some results about what kind of users can use mental imagery-based BCI and why. It also introduces new feedback types and new training environments targeted at improving the user's understanding of BCI use as well as his/her motivation to learn the BCI skill. Overall, this paper shows that we can improve BCI reliability by improving how users learn a BCI skill and that much still needs to be explored in that direction.

II. Theoretical and practical limitations of current BCI training approaches

BCI control being a skill, it has to be mastered by the BCI user [?]. Typically, standard BCI training is perform by asking the user to control an object on screen by modulating his/her brain activity in a specific way (e.g., using motor imagery). The feedback provided to the user about his/her task performance is thus generally a uni-modal (generally visual) feedback indicating the mental task recognized by the classifier together with the confidence in this recognition. It is generally represented by an extending bar or a moving cursor [?]. Typically, the bar/cursor extends in the required direction if the mental task is correctly recognized and extends in the opposite direction otherwise. 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 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.

A. Theoretical limitations

Unfortunately, such standard training approaches satisfy very few of the guidelines provided by human learning and instructional design principles to ensure an efficient learning

[1] Note that BCI based on Event Related Potentials are not considered in this paper as they involve very little or no human training [?]

(What) Can We Learn With Standard BCI Training Approaches? A Pilot Study.

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Abstract

While being very promising, brain-computer interfaces remain barely used outside laboratories because they are not reliable enough. One study [3] suggested that current training approaches may be partly responsible for the poor reliability of BCIs as they do not satisfy recommendations from psychology and are thus inadequate. To determine to which extent such BCI training approaches (standard -S- and partially self-paced -PSP-) are suitable to learn a skill, we used them in another context (without a BCI) to train people to perform simple motor tasks. Results show that 15% of the participants are unable to learn to perform these simple motor tasks, which is close from the BCI-illiteracy rate [1]. Moreover, usability questionnaires suggest that while it is not more pleasant to learn with a PSP approach, it is easier than with a S approach.

1 Introduction

Brain-computer interfaces (BCIs) are communication systems allowing users to interact with the environment, using only their brain activity [6]. BCIs, although very promising, remain barely used outside laboratories because they are not reliable enough [6]. Two main reasons have been identified. The first one, extensively investigated, concerns brain signal processing, with current classification algorithms being still imperfect [1]. The second one concerns the users themselves. Indeed, many users seem unable to acquire good BCI skills (i.e. the capacity to generate specific and stable brain activity patterns): around 20% cannot control a BCI at all (the so-called "BCI illiteracy"), while most of the remaining 80% have relatively modest performances [1]. An appropriate training is needed to acquire these skills, especially for Mental Imagery-based BCI (MI-BCI). The study [3] suggested that currently used training and feedback protocols, which do not take into account the recommendations from psychology to optimise human learning, might be partly responsible for BCI illiteracy and poor user performance. For instance, it has been shown that, for efficient learning, training protocols have to fit the user learning style and propose an increasing and adpative difficulty [3]. Yet standard BCI training protocols are the same for all users [3]. While instructive, these studies only provide theoretical considerations about training approaches. It is therefore necessary to concretely assess whether training approaches used in BCI are appropriate to train a skill. Moreover, it is necessary to perform this evaluation independently of BCI, to rule out possible biases due to BCI complexity, non-stationarity and poor signal-to-noise ratio. Thus in this work, we propose to study these BCI training approaches without using a BCI: participants were asked to learn specific and simple motor tasks using BCI-like training approaches. We then studied whether and how well they could learn such motor tasks to assess the quality of the training approaches, independently of BCI use. We studied here two different approaches: 1) the training approach

Design and Validation of a Mental and Social Stress Induction Protocol
Towards Load-Invariant Physiology-Based Stress Detection

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Keywords: Mental Stress, Psychosocial Stress, Cognitive Workload, Physiological Computing, ECG, GSR, EEG

Abstract: Stress is a major societal issue with negative impacts on health and economy. Physiological computing offers a continuous, direct, and unobtrusive method for stress level assessment and computer-assisted stress management. However, stress is a complex construct and its physiology can vary depending on its source: cognitive workload or social evaluation. To study the feasibility of physiology-based load-invariant *psychosocial* stress-detection, we designed a stress-induction protocol able to independently vary the relevant types of psychophysiological activity: mental and psychosocial stress. Here, we validate the efficacy of our protocol to induce psychosocial and mental stress. Our participants (N=24) had to perform a cognitive task associated with two workload conditions (low/high mental stress), in two contexts (low/high psychosocial stress), during which we recorded subjects' self-reports, behaviour, physiology and neurophysiology. Questionnaires showed that the subjectively perceived level of stress varied with the psychosocial stress induction, while perceived arousal and mental effort levels vary with mental stress induction. Behaviour and physiology further corroborated the validity of our protocol. Heart rate and skin conductance globally increased after psychosocial stress induction relative to the non-stressful condition. Moreover, we demonstrated that higher workload tasks (mental stress) led to decrease in performance and a marked increase of heart rate.

1 INTRODUCTION

Stress is a universal societal issue, affecting both economy and health. Thus, it is easy to understand why many people invest in finding ways to deal with stress (Regehr et al., 2013): how to help people manage their stress is becoming a major preoccupation in many countries. Computer-assisted stress management is one way to support coping with stress. However, it requires reliable stress level assessment (van den Broek and Westerink, 2012).

Besides psychological questionnaires, many devices are available to assess stress levels. They measure stress-related physiological markers such as heart rate, skin conductance or blood pressure, which are increased during a stressful episode (see Section 1.1). The availability of cheap sensor technology and small, portable computing devices allows to automatically and continuously monitor the level of stress in every-day contexts, as during driving (Healey and Picard, 2005) and work (Kusserow et al., 2012), or in clinical contexts (Hogervorst et al., 2013).

However, there are still several challenges that have to be addressed to be able to successfully monitor stress levels with physiological sensors. One of the most notorious is the definition of the relationship between physiological measurements and the psychophysiological construct of stress. For example, it is known that modifications of the above physiological markers are characteristic of psychosocial stress, but not exclusively affected by it (Dickerson and Kemeny, 2004). For example cardiovascular measures, like heart rate and its variability, are known to respond to stress as well as to high cognitive workload or to exciting situations. The same is true for several frequency bands in the electroencephalogram (EEG): for example the alpha frequency band has been shown to covary with stress/relaxation, but is also known to respond strongly to sensory stimulation, attention and cognitive workload (see Section 1.1). Therefore, the relationship between measurements and psychophysiological constructs is a complex many-to-many mapping for which great care has to be taken in the aim of finding the right mapping parameters to avoid confusion between episodes of psychosocial stress and those of high cognitive worload, i.e., of mental stress.

Chapitre 11

Apprentissage humain pour les interfaces cerveau ordinateur

11.1. Introduction

Les BCI sont définies par Wolpaw [WOL 02] comme étant des outils de communication et de contrôle permettant à un utilisateur d'interagir avec son environnement uniquement via son activité cérébrale. Cette définition met en avant l'aspect fondamental des BCI, c'est-à-dire, l'interaction entre deux composantes : le cerveau de l'utilisateur et l'ordinateur. Il s'agit donc de faire en sorte que ces deux composantes (cerveau et ordinateur) « se comprennent », et s'adaptent l'une à l'autre afin d'optimiser les performances du système (souvent mesurées en terme de taux de bonne classification).

De ce fait, l'architecture du fonctionnement d'une BCI [WOL 02] fait apparaître une boucle composée de deux grandes étapes, faisant suite à l'envoi d'une commande par l'utilisateur via son activité cérébrale (que l'on appellera ÉTAPE 0). Au cours de l'ÉTAPE I, l'ordinateur essayera de *comprendre* la commande envoyée par l'utilisateur en opérant généralement une extraction de l'information pertinente suivie par une classification. Puis, lors de l'ÉTAPE II, c'est l'utilisateur qui tentera de *comprendre* au mieux la signification du feedback généré par l'ordinateur, qui indique la façon dont ce dernier a reconnu la commande qui lui a été adressée. Afin d'illustrer le fonctionnement de cette boucle, plaçons-nous dans le cadre d'un protocole BCI standard basé sur l'imagerie motrice [PFU 01]. Dans ce protocole, l'utilisateur a la possibilité d'effectuer deux tâches d'imagerie motrice, « imaginer un mouvement de la main gauche » ou « imaginer un mouvement de la main droite », qui sont associées à deux commandes distinctes. Afin de guider l'utilisateur, le système fournit également un feedback, souvent sous forme de barre, indiquant la tâche reconnue par le système. La direction de

Chapitre rédigé par Camille JEUNET, Fabien LOTTE et Bernard N'KAOUA.

Impact Of Cognitive And Personality Profiles On Mental-Imagery Based Brain-Computer Interface-Controlling Performance

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Background

People suffering from severe motor disabilities are victims of social isolation and they lack autonomy. Thus, developing tools such as Brain-Computer Interfaces (BCIs) appears very promising for improving their living standards.
BCIs are control and communication tools allowing users to interact with their environment, using only their brain-activity (Wolpaw 2002). More particularly, Mental-Imagery-based- BCIs (MI-BCI) allow users to control a device (i.e. a wheelchair) by doing different mental tasks, which are then translated into commands. MI-BCIs, although very promising, remain barely used outside laboratories because they are not reliable enough. Indeed, around 20% of people cannot control a MI-BCI at all (so-called “BCI-illiteracy”), while most of the remaining 80% achieve relatively modest performances (Allison & Neuper 2010).
Two main reasons for this have been identified. The first one, extensively investigated, concerns brain signal processing, with current classification algorithms being still imperfect (Alison & Neuper 2010); while the second one, much less investigated, concerns both the mental tasks used and the user’s characteristics (cognitive and personality profiles).
In this context, the aims of our study are 1) to determine if some mental tasks are more efficient than others to optimise performance and 2) to determine a relationship between users’ cognitive and personality profiles and their ability to perform different mental tasks.

Method

18 participants (9 males and 9 females, aged 21.5±1.2) have been trained to perform three mental tasks, using an existing MI-BCI training protocol including 3 mental tasks (Friedrich et al. 2013): “imagination of a left-hand movement”, “mental-subtraction” and “mental-rotation”. Participants were also asked to complete psycho-technical tests to determine their cognitive and personality profiles.

Results & Discussion

Preliminary results suggest that some mental tasks are better performed by the participants, and that these performances seem to be related to some aspects of the participants’ cognitive and personality profiles such as locus of control, learning style or anxiety.
These results suggest that performance at MI-BCI control does not only depend on classification algorithms efficiency, but also on the user’s cognitive and personality profiles.

Conclusion

In line with our preliminary results, we will develop training protocols that will be adapted to different cognitive and personality profiles to optimise users’ performance at MI-BCI control. Another promising approach we are interested in is to make these training protocols adaptable in real-time to the cognitive, motivational and emotional states of the user in order to make BCI training faster, easier and more pleasant.

Presented by: JEUNET, Camille

Conception et validation d'un protocole pour induire du stress et le mesurer dans des signaux physiologiques

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INTRODUCTION

Le stress est un problème majeur pour l'économie et la société, nécessitant de concevoir des outils pour le gérer [3]. En plus de questionnaires psychologiques, il existe des outils mesurant le niveau de stress grâce à des signaux physiologiques comme le rythme cardiaque ou la réponse électrodermale (RED), qui augmentent avec le stress [3]. Ces mesures sont cependant peu robustes car leurs variations ne sont pas nécessairement dues au stress [3]. C'est pourquoi il semble pertinent d'estimer le stress à la source, c'est-à-dire grâce à une analyse temps-réel de l'activité cérébrale, mesurée par ÉlectroEncéphaloGraphie (EEG). Dans ce but, la première étape est de créer un protocole rigoureux pour induire le stress. Ceci permet en effet d'avoir accès à une vérité terrain ainsi qu'aux signaux physiologiques (dont EEG) correspondants. Ce poster présente et valide un tel protocole.

ÉTAT-DE-L'ART

Le stress peut être défini comme une réponse de l'organisme à une situation environnementale perçue comme négative, qui peut être réelle ou imaginée [3]. Le stress peut être physique (e.g., dû à des températures extrêmes), psychologique (e.g., dû à des tâches cognitives difficiles), ou encore psychosocial (dû à une évaluation sociale, e.g., parler en public) [3].

Différents travaux ont exploré l'impact du stress sur les signaux EEG, tels que [4, 6]. Cependant, ils ont uniquement étudié des mesures moyennes de l'EEG sur une large période de temps, ce qui ne permet pas une estimation temps-réel du niveau de stress. Riera et al. se sont eux intéressés à une mesure du stress en temps-réel [7]. Ils ont ainsi proposé un protocole mesurant les signaux EEG lors d'une tâche stressante ou lors d'une phase de repos. Le problème de ce protocole est que de nombreux paramètres (notamment comportementaux) varient entre ces deux conditions, à cause de tâches différentes, ce qui peut donner lieu à des variations des signaux EEG indépendemment du niveau de stress. Enfin, dans ces différents travaux, un seul type de stress est étudié, ce qui ne permet pas d'identifier une mesure générique du stress. C'est pourquoi nous avons conçu un protocole dans lequel 1) le seul paramètre changeant d'une condition à l'autre est le niveau de stress, et 2) ce niveau de stress varie selon deux types de stress : psychologique (induit par des tâches cognitives difficiles impliquant différents niveaux de charge mentale) et psychosocial (induit par des tâches de présentation en public, avec évaluation).

MÉTHODE

14 sujets (dont 4 femmes, âge moyen : 26.46 ± 9.75 ans) participèrent à notre expérience. Lors de celle-ci, différents signaux physiologiques ont été enregistrés, dont l'EEG, le pouls et la RED. Avant l'expérience, les sujets devaient remplir le questionnaire "State-Trait Anxiety Inventory" (STAI) Y-A, qui mesure le niveau d'anxiété [8]. En effet, le score au questionnaire STAI Y-A augmente lors d'une situation de stress psychologique. Ensuite, les capteurs étaient installés, puis l'expérience commençait dans l'un des quatres scénarios possibles, afin de contrebalancer les conditions pour éviter tout effet d'ordre (voir Figure 1). Chaque scénario est composé de deux blocs (un bloc stress et un bloc non-stress, présentés dans un ordre aléatoire), séparés par une mesure du questionnaire STAI Y-A. De même, l'expérience commence aléatoirement par une tâche de charge mentale basse ou élevée. Dans chaque bloc, le sujet effectue 6 fois chaque condition de charge mentale (basse/elevée), avec une courte pause après 6 tâches. Enfin, une fois les 2 blocs complétés, le sujet remplissait une dernière fois le questionnaire STAI Y-A.

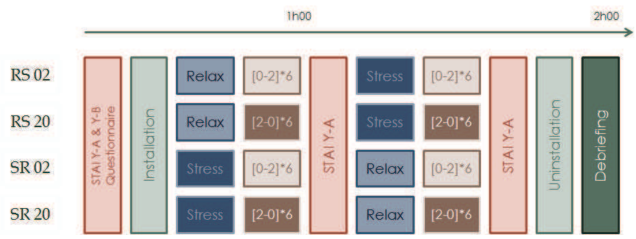

Figure 1. Chronologie du protocole expérimental (R=Non-stress (Relaxation); S=Stress; 0= tâche 0-back; 2= tâche 2-back).

Pour induire du stress psychosocial, notre protocole se base sur l'approche validée du "Trier Social Stress Task" [2]. L'induction du stress nécessite la participation d'un comité de personnes présentées comme des experts du langage corporel (et jouant ce rôle) et se déroule comme suit : tout d'abord, un membre du comité demande au sujet de préparer un entretien d'embauche fictif pendant 5 minutes. Ensuite, le comité lui demande de faire cet entretien et de parler de lui pendant 5 minutes. Les membres du

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Why standard brain-computer interface (BCI) training protocols should be changed: an experimental study

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Abstract

Objective. While promising, electroencephalography based brain–computer interfaces (BCIs) are barely used due to their lack of reliability: 15% to 30% of users are unable to control a BCI. Standard training protocols may be partly responsible as they do not satisfy recommendations from psychology. Our main objective was to determine in practice to what extent standard training protocols impact users' motor imagery based BCI (MI-BCI) control performance. *Approach.* We performed two experiments. The first consisted in evaluating the efficiency of a standard BCI training protocol for the acquisition of non-BCI related skills in a BCI-free context, which enabled us to rule out the possible impact of BCIs on the training outcome. Thus, participants ($N = 54$) were asked to perform simple motor tasks. The second experiment was aimed at measuring the correlations between motor tasks and MI-BCI performance. The ten best and ten worst performers of the first study were recruited for an MI-BCI experiment during which they had to learn to perform two MI tasks. We also assessed users' spatial ability and pre-training μ rhythm amplitude, as both have been related to MI-BCI performance in the literature. *Main results.* Around 17% of the participants were unable to learn to perform the motor tasks, which is close to the BCI illiteracy rate. This suggests that standard training protocols are suboptimal for skill teaching. No correlation was found between motor tasks and MI-BCI performance. However, spatial ability played an important role in MI-BCI performance. In addition, once the spatial ability covariable had been controlled for, using an ANCOVA, it appeared that participants who faced difficulty during the first experiment improved during the second while the others did not. *Significance.* These studies suggest that (1) standard MI-BCI training protocols are suboptimal for skill teaching, (2) spatial ability is confirmed as impacting on MI-BCI performance, and (3) when faced with difficult pre-training, subjects seemed to explore more strategies and therefore learn better.

Keywords: brain-computer Interface, user-training, standard training protocol, spatial ability, electro-encephalography

(Some figures may appear in colour only in the online journal)

1. Introduction

Brain–computer interfaces (BCIs) are communication and control systems that allow users to interact with the environment using only their brain activity [47], which is often measured using electroencephalography (EEG). A prominent type of BCI, called motor imagery based BCIs (MI-BCIs), makes use of control signals sent via the execution of motor imagery tasks, such as imagining hand movements. They are indeed very promising, in particular for the rehabilitation of stroke patients [3], for controlling assistive technologies such as neuroprosthetics or smart wheelchairs [31], or even for gaming for healthy users [23]. However, MI-BCIs are barely used outside laboratories due to their lack of reliablility [47]. The two main factors responsible for this low reliability have been identified. The first, extensively investigated, concerns brain signal processing with current classification algorithms being still imperfect [2]. The second concerns the users themselves: between 15% and 30% cannot control a BCI at all (so-called BCI illiteracy or BCI deficiency), while most of the remaining 80% display relatively modest performance [2]. It is known that controlling an MI-BCI requires the acquisition of specific skills, and in particular the ability to generate stable and distinct brain activity patterns while performing the different MI tasks [36, 46]. Just as with any skill, appropriate training is required to acquire BCI control [36]. Yet, current strandard training protocols, which do not take into account the recommendations from psychology and instructional design (such as proposing adaptive and progressive tasks, or explanatory, supportive and multimodal feedback), do not seem to be theoretically appropriate, and thus might be partly responsible for BCI illiteracy and modest user performance [27, 28].

However, while being instructive, insights such as those presented in [27, 28] only provide theoretical considerations about the flaws associated with the training approaches used in MI-BCI that could be responsible for modest user performance and BCI illiteracy. It is therefore necessary to concretely assess whether the standard training protocols used in MI-BCI paradigms are appropriate for training in a skill, and how much they impact BCI performance and BCI skill acquisition. Moreover, it is necessary to perform this evaluation independent of MI-BCIs, to rule out possible biases due to BCI complexity, EEG non-stationarity and poor signal-to-noise ratio. Indeed, if 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 of the user due to the orientation of the user's cortex, for instance. Therefore, to study the impact and usefulness of a given training protocol, it is necessary to study it without the possible confounding factors originating from the BCI design.

Thus, the objective of this paper is to evaluate the efficiency of a standard training protocol [40] for the acquisition of MI-BCI related skills. In particular, we have focused here on the MI-BCI training protocol proposed by the Graz group [40], which is a widely used BCI training protocol [36]. Moreover, most other existing MI-BCI training protocols can be seen as variants of the Graz training protocol, as they use similar timings, feedback and training tasks, see, e.g., [4, 32].

In order to acheive this objective, two experiments were conducted. The first consisted in studying the efficiency of a standard MI-BCI training protocol [40] for skill acquisition in an MI-BCI-free context: participants ($N = 54$) were asked to learn specific and simple motor tasks, i.e. drawing circles and triangles on a graphic tablet, using this standard training approach[3] [40]. The second experiment was aimed at studying the correlations between motor task performance and MI-BCI performance. The ten best and ten worst performers of the first study were selected to participate in an MI-BCI experiment during which they had to learn to perform two MI tasks: left- and right-hand movement imagination. We hypothesised that poor performers in the first experiment would also experience difficulties in the MI-BCI experiment, while the best performers of the first experiment would also perform well in the second.

In the following sections, we first present the details of the standard training protocol initially proposed by the Graz group [40], on which we based our study. Then we present a quick review of the literature that has been published on human training in BCI, and more particularly on the impact of user profile on performance, and on the improvement of training protocols and feedback. Subsequently, both experiments are introduced and their results presented and discussed.

2. Description of a standard training approach: the Graz protocol [40]

This protocol was first proposed by the Graz BCI group as an alternative to the operand conditioning (OC) approach, enabling us to provide the participants with a shorter training period. 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 [41]. 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 are 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 that 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

[3] Preliminary results ($N = 20$ participants) of this first study have been published in a short conference paper [18].

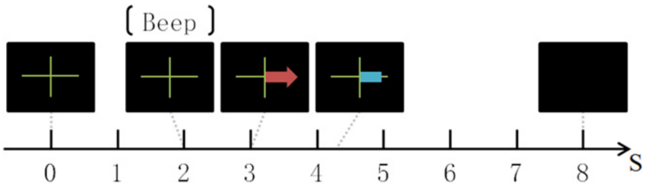


Figure 1. Timing of one trial in the Graz protocol.

another). 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 whichMI 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 such 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 min 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 8 s. 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 s long rest period (which is usually used as a reference period for event-related synchronisation and desynchronisation calculation). Then, after 2 s, a beep is used to trigger the attention of the user and prepare him/her for the oncoming instruction. One second later, at $t = 3$ s, 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 $t = 3.250$ s, feedback is provided for 4 s 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 1.

3. Related work: human training in MI-BCI

Research on human training in MI-BCI mainly focuses on two aspects: (1) the influence of the user's profile on his/her MI-BCI control performance and (2) the enhancement of the communication/comprehension between the user and the system by improving the training protocols and feedback. A brief state of the art of these two points of interest is presented in this section.

3.1. Impact of the user's profile on BCI performance

The important inter-subject and inter-session variability in terms of MI-BCI performance led the community to look for predictors of performance. Two main categories of predictors have been studied: neurophysiological and psychological predictors. A review of neurophysiological predictors is presented in [1]. Among them, a prominent one, whose usefulness has been reproduced and confirmed across multiple experiments [14, 15], is the predictor proposed by Blankertz *et al* [5]. They showed that the amplitude of sensorimotor rhythms (SMRs) at rest was a good predictor of subsequent BCI performance in motor imagery paradigms: a correlation ($r = 0.53$) was found between this neurophysiological predictor based on the μ rhythm (about 9–14 Hz) over sensori-motor areas and MI-BCI performance ($N = 80$). Furthermore, concerning psychological factors, mood and motivation [39], as well as the locus of control score related to dealing with technology [8], have been shown to be correlated with MI-BCI performance. Fear of the BCI system has also been shown to affect performance [8, 38]. The study of Hammer *et al* [14] revealed that attention span, personality and motivation played a moderate role for one session MI-BCI performance, but a significant predictive model of performance, including visuo-motor coordination and the degree of concentration, was proposed. They tested this model in a four session experiment within a neurofeedback paradigm [15]. Results revealed that these parameters explained almost 20% of the BCI performance within a linear regression, even if visuo-motor coordination failed significance. Finally, we recently showed a strong and significant correlation between users' spatial ability (assessed using the mental rotation test [44]) and mental imagery based BCI performance ($r = 0.696$) [17, 19]. We also defined a predictive model of MI-BCI performance ($R^2_{adj} = 0.809$), which included four parameters: tension, abstractness ability, self-reliance and the active/reflective dimension of the learning style [19].

3.2. MI-BCI training protocols

Different training protocols have been proposed in the literature, most of them being based on the Graz protocol described here, or similar to it. They focus on improving either the instructions provided to the user at the beginning of the experiments, the training tasks proposed to the participant to control the MI-BCI, the feedback provided concerning the system's decision (i.e. about which MI task was recognised) or the training environment. Only two studies considered the instructions and showed that it is beneficial to incite the users to perform kinaesthetic-motor imagery [37] and to not give them over-specific strategies so that their cognitive resources are not overtaxed [22]. Concerning the training tasks, several studies have proposed using either progressive or adaptive tasks, instead of fixed and repetitive tasks, to increase performance [11, 35, 45]. The feedback certainly is the aspect of training protocols for which the most alternatives have been tested. Indeed, the bar representing the classifier output has been replaced by smileys [25] to increase motivation, or by auditory [13, 16, 30, 39] or tactile [9, 10, 20, 21, 24] feedback in order to reduce cognitive workload related to the overtaxed visual channel. While auditory feedback seems to be the best solution for locked-in patients, tactile feedback appeared to be at least as efficient as visual feedback, and more efficient in interactive contexts [20]. Finally, concerning the training environment, some authors have proposed to 'gamify' the training process to increase motivation and improve user

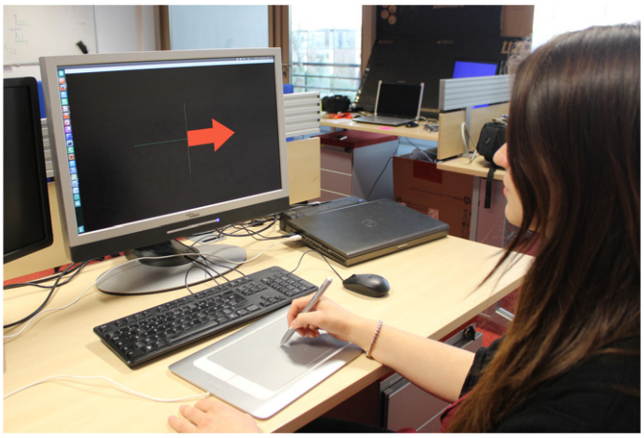


Figure 2. Picture of a participant during the experiment. The instruction (red arrow pointing right) indicates that the participant has to draw triangles on the graphic tablet.

experience [30], and some have even integrated virtual reality (for a review, see [23, 26]), which appeared to efficiently improve performance.

It should be noted that the vast majority of the research on training protocols aims at improving the Graz training protocol or similar protocols. Similarly, a large proportion of the work performed to determine predictors of mental imagery based performance are based on experiments in which either the Graz protocol, or protocols that can be seen as variants of it, were used. Yet, the efficiency of this type of training approach has not been questioned nor extensively evaluated. Thus, before improving these protocols, it would be worth testing their efficiency in terms of skill acquisition. This is what we aimed to do with the two experiments we present in the next sections.

4. Experiment 1: using a standard MI-BCI training protocol for learning to perform simple motor tasks

The objective of this first study was to evaluate the impact of a standard training approach (the Graz protocol, introduced above [40]) on participants' ability to acquire a skill in an MI-BCI-free context.

4.1. Materials and method

Participants were asked to learn to perform two motor tasks: drawing triangles and circles with a pen on a graphic tablet (see figure 2), using the Graz protocol [40] (i.e. same instructions, tasks 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 that 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 [40] 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 [28]. Interestingly enough, the study described in [35] obtained promising results when providing more autonomy to a single BCI user. These two approaches are described here after.

4.1.1. Participants. 54 BCI-naive and healthy participants (20 females, 34 males; aged 25.1 ± 4.6 years old) took part in this study, which was conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki. All the participants signed an informed consent form at the beginning of the experiment.

4.1.2. Experimental protocol. Each participant ($N = 54$) had to learn to do two 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 2 s, an auditory cue (a beep) triggered the attention of the participant towards the red arrow, which was displayed at 3 s for 1 s, 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. This picture was visible at all times to ensure subjects could refer to it whenever needed. At 4.25 s, a blue feedback bar appeared and was updated at 16 Hz for 3.75 s. 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 four 7 min long s-runs. The other half learned using the partially self-paced (PSP) training approach: the first and fourth runs were s-runs, while the second run was replaced by a 3.5 min long sp-run followed by a shortened s-run (ten trials per task, 3.5 min), and the third run was replaced by a shortened s-run followed by a 3.5 min long sp-run. The total training duration was the same in both conditions. We studied the impact of the condition, S versus PSP, on the recognition accuracy of triangles and circles by the system and on subjective experience (measured by a usability questionnaire, UQ).

4.1.3. 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 1s long time window (in a sliding window scheme, with a 1/16 s 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 five 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 two people (one left-handed, one right-handed). The resulting classifier could discriminate triangles from circles with 73.8% classification accuracy (ten-fold cross-validation on the training set), which is an accuracy equivalent to the average accuracy of an MI-BCI [5]. 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 of the classifier.

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

4.2. Results

4.2.1. Performance analyses. Results (depicted in figure 3) showed that 45 out of 54 participants managed to learn the task, i.e. obtained more than 70% average performance[4], classification accuracy, [34] ($\bar{X} = 89.09\%$; 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 is of the same order of magnitude as the BCI illiteracy rate (between 15% and 30% [2]). Thus, one can hypothesise that BCI illiteracy is not only due to the user, but also partly to the training protocol. Indeed, it has been hypothesised that BCI illiteracy/deficiency could be due to the user, who may generate noisy or non-stationary signals, who may have a cortex whose orientation prevents the relevant neural signals from reaching the scalp and thus EEG sensors, or who may fail to produce the desired EEG patterns [2]. Our experiment suggests that some subjects may fail to reach BCI control because the training protocol is not suited to everyone.

Furthermore, we performed a two-way ANOVA for repeated measures to evaluate the impact of the condition on motor performance according to the run number. Checking the assumptions revealed that the normality (skewness test: $s_{\text{run1}} = -0.203$; $s_{\text{run2}} = -1.295$; $s_{\text{run3}} = -1.709$; $s_{\text{run4}} = -1.961$) and equality of variance (Levene test: $p_{\text{run1}} = 0.044$; $p_{\text{run2}} = 0.024$; $p_{\text{run3}} = 0.160$; $p_{\text{satisfaction}} = 0.128$) were not totally respected. Nonetheless, given that the results were close to the threshold and the ANOVA being a robust analysis [43] , we decided to use this analysis. The two-way ANOVA revealed neither a main effect 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 run1 and run2 ($perf_{\text{run1}} = 72.88\%$, $perf_{\text{run2}} = 84.48\%$; $p \leqslant 0.001$) and between run2 and run3 ($perf_{\text{run2}} = 84.48\%$, $perf_{\text{run3}} = 87.62\%$; $p \leqslant 0.005$] but not between run3 and run4 ($perf_{\text{run3}} = 87.62\%$, $perf_{\text{run4}} = 89.11\%$; $p = 0.277$].

4.2.2. Usability questionnaires. Each participant was asked to complete a UQ at the end of the experiment. This questionnaire measured four dimensions: LM, EE, safety and satisfaction. Four one-way ANOVAs were performed to evaluate the impact of the condition (S versus PSP) on these dimensions. The prerequisites of the ANOVA were satisfied: all the dimensions had a normal distribution (skewness test, $s_{\text{LM}} = -0.072$; $s_{\text{EE}} = 0.046$; $s_{\text{safety}} = 0.098$; $s_{\text{satisfaction}} = 0.232$) and the variances were equal (Levene

[4] 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 [2].

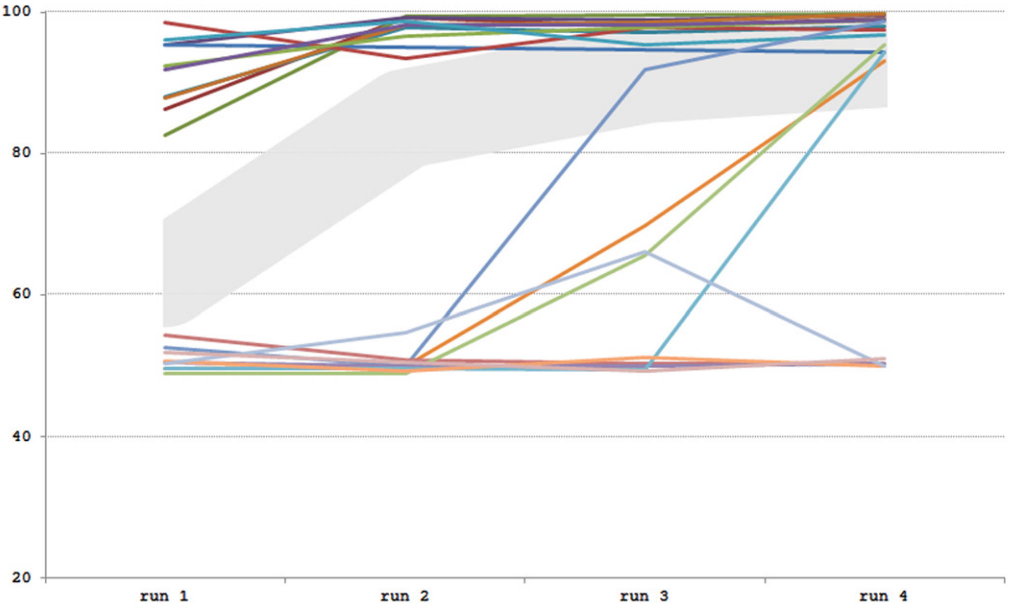


Figure 3. Graphic representing the performance of the participants (mean classification accuracy) as a function of the run. We chose to represent the ten best and ten worst performers, who took part in the next experiment. The average performance of the 34 other participants is represented by the large grey line.

test, $p_{\mathrm{LM}} = 0.938$; $p_{\mathrm{EE}} = 0.415$; $p_{\mathrm{safety}} = 0.861$; $p_{\mathrm{satisfaction}} = 0.143$). However, the 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 ($F(1,53) = 0.895$; $p = 0.349$).

4.3. Discussion

The aim of this first study was to concretely assess whether training approaches used in BCI are 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 versus 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 four 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 four runs). It is noteworthy that this rate is of the same order of magnitude as the BCI illiteracy rate (between 15% and 30% [2]). Thus, it seems most likely that a substantial proportion of illiterates are illiterate partly due to the training protocols, given the fact that all subjects were cognitively able to understand the instructions and had the motor ability to perform the tasks. This result emphasises the fact that such protocols should be improved to enable 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 protocol 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 here after.

5. Experiement 2: investigating the relationship between motor performance and MI-BCI performance

This second experiment was aimed at investigating 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 training approach: the

Graz protocol [40]. Indeed, we hypothesised that there could be a positive correlation between the performance obtained at the motor tasks (introduced in experiment 1) and MI-BCI performance. Indeed, we hypothesised that subjects who could learn motor tasks using the Graz training protocol would be likely to learn MI tasks using the same protocol as they managed to learn a skill using this approach. 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, namely spatial ability and the Blankertz SMR predictor. We thus selected the ten best and the ten worst performers from the first experiment, 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.

5.1. Materials and method

5.1.1. Participants. 20 BCI-naive participants (10 females; aged 24.7 ± 4.0 years 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. Participants were selected from the first experiment and divided into two groups, the good and the bad performers. The ten best performers of the first experiment ($\bar{X} = 96.00\%$ of performance–classification accuracy; SD = 1.13) were in the good group while the ten 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 five women and five men each. Moreover, in each group, seven participants were using the S conditions and three were under the PSP conditions during the first study. Considering the results of the first experiment as well as the distribution of the conditions in the groups, we decided not to consider this variable (S versus PSP) in this second experiment. In other words, the MI-BCI training only comprised standard runs.

5.1.2. Experimental protocol. Each participant (N = 20) had to learn to do 2 MI tasks, namely imagining left- and right-hand movements, so that they were recognised by the system. Participants first had to complete a 'calibration' run which aimed at providing the system with examples of EEG patterns associated with each of the MI tasks. This run and the whole classifier training process are explained here after (see section 5.1.5). Then, as in the first experiment, user training lasted 4 runs, each of them being composed of 20 trials per task. As shown in figure 1, at the beginning of each trial a green cross was displayed. After 2 s, an auditory cue (a beep) triggered the attention of the participant towards the red arrow, which was displayed at t = 3 s for 1 s, and indicated which task the participant had to perform (imagining right- or left-hand movements upon appearance of a right or left arrow, respectively). At 4.25 s, a blue feedback bar appeared and was updated at 16 Hz for 3.75 s. Its direction indicated the imagined movement recognised by the classifier and its length was proportional to the classifier output. This was thus exactly the same training protocol as used in the first experiment.

Here as well, 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 motor task you are doing, which will concretely correspond to having the feedback bar as long as possible in the correct direction: left for left-hand and right for right-hand movements'.

Added to these MI tasks, participants were asked to complete a mental rotation questionnaire which is depicted in the next section.

5.1.3. Spatial ability assessment using the mental rotation test. Participants were asked to complete the mental rotation test [44], which is a validated paper and pen psychometric questionnaire assessing spatial ability, at the beginning of the experiment. Spatial ability has been related to mental imagery based BCI performance [17, 19], but not yet to purely motor imagery based BCI. This test is composed of two sets of ten items. Each set has to be completed in 3 min maximum. An item consists in a 3D shape on the left and four 3D shapes on the right of the page. Among the four 3D shapes, two are the same as the one presented on the left with a rotation of 60°, 120° or 180° around the vertical axis (see figure 4). The other two are mirror-reversed and rotated images of the 3D shape on the left. For each item, the participant has to find the two 3D shapes that are the same than the one on the left (i.e. only rotated). Since there is a strong gender effect associated with this test (men usually perform better than women), we had to take the participants' gender into account in the analyses in order to study the impact of spatial ability on performance.

5.1.4. The Blankertz SMR predictor of MI-BCI performance. The Blankertz SMR predictor [6] is currently one of the most replicated and reliable neurophysiological predictors of MI-BCI performance (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 us 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 long baseline had been recorded with our protocol, we used the 40 3 s long pre-trial time windows (3000 ms before the instruction) of each run, which gave a 2 min long time window and enabled us to compute the predictor on this sequence. More precisely, we computed the power spectrum of each 3 s long time window, averaged these spectrums (i.e. over time windows), and computed the predictor on this averaged spectrum.

5.1.5. EEG recordings and signal processing. The EEG signals were recorded using two g.USBamp amplifiers (g.tec, Graz, Austria), using 30 scalp electrodes (F3, Fz, F4, FT7,

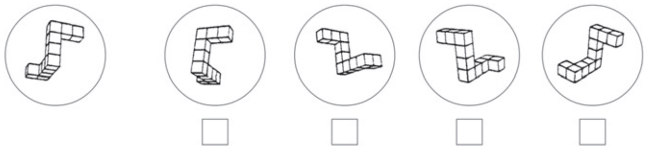


Figure 4. First item of the Vandenberg and Kuse mental rotation test [44].

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) [12], referenced to the left ear and grounded to AFz. Such electrodes cover the sensori-motor cortex, where EEG variations due to MI can be measured. EEG signals were sampled at 256Hz. First, EEG signals were band-pass filtered in 8–30 Hz (containing the SMRs) [40]. The first run (20 trials per MI task) was used to train the classifier. While 20 trials per class is not much, it has been shown to be sufficient to set up a motor imagery classifier [7, 29]. For instance, in [12], a successful mental imagery BCI classifier was setup with only 10 trials per class. Moreover, here we do not focus on the impact of the classifier but on the impact of the training protocol. Thus, at the end of the first run, which served for training the classifier, a common spatial pattern algorithm [33] was used for each user on the collected data, to find six spatial filters whose resulting EEG power was maximally different between the two MI tasks. The spatially filtered EEG signal power (computed on a 1s time window, with 250 ms overlap between consecutive windows) was used to train an LDA classifier [33]. The LDA was then used online to differentiate between left- and right-hand MI during the five user training runs.

5.1.6. Analyses. In this study, we analysed the effect of the group of the first experiment (two modalities: good versus bad; independent measures), of the run (four modalities: run1, run2, run3 and run4; repeated measures), of the mental rotation score (continuous covariable) and of the gender (two modalities: men versus 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.

5.2. Results

5.2.1. MI-BCI performance. In our analysis aiming at evaluating the effect of the group (bad versus good performers in the first experiment), gender (men versus 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 is the typical performance measure used with the Graz protocol, see, e.g., [42], and (2) the mean classification accuracy over the whole feedback period of all trials. We thus performed two ANCOVAs. Note that as the mean accuracy is 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 the participant's ability to produce a long and stable BCI control signal.

5.2.1.1. Peak performance . The average peak performance of the 20 participants was 66.95% (SD = 6.24; range = [57.09; 82.69]). Assumption checking is depicted in figure 5. 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 [43]). 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. Post hoc analyses (student t-tests for paired measures) on the tendency towards a run main effect revealed a significant increase in peak performance, on average, between the first and the last runs ($t = -2.360$; $p \leqslant 0.05$) thus suggesting a learning effect. 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 accross the runs. Second, a run–gender interaction ($F(1,15) = 7.936$; $p \leqslant 0.05$; $\eta^2 = 0.346$) (see figure 6), which suggests that if we consider performance independently from participants' spatial ability, while men'(s) MI-BCI performance was stable accross the four 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 ability, 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 7). Finally, this ANCOVA revealed a strong tendency towards a run–gender–group interaction ($F(1,15) = 4.221$; $p = 0.058$; $\eta^2 = 0.220$) (see figure 8) but no

	Normality	Linearity	Homogeneity of Regression Slots	Equality of Variances
Mental Rotation Scores	s = 0.049		p = 0.155	
Run 1	s = 0.676	p = 0.090		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 5. Table representing the assumption checking for the ANCOVA on peak performance.

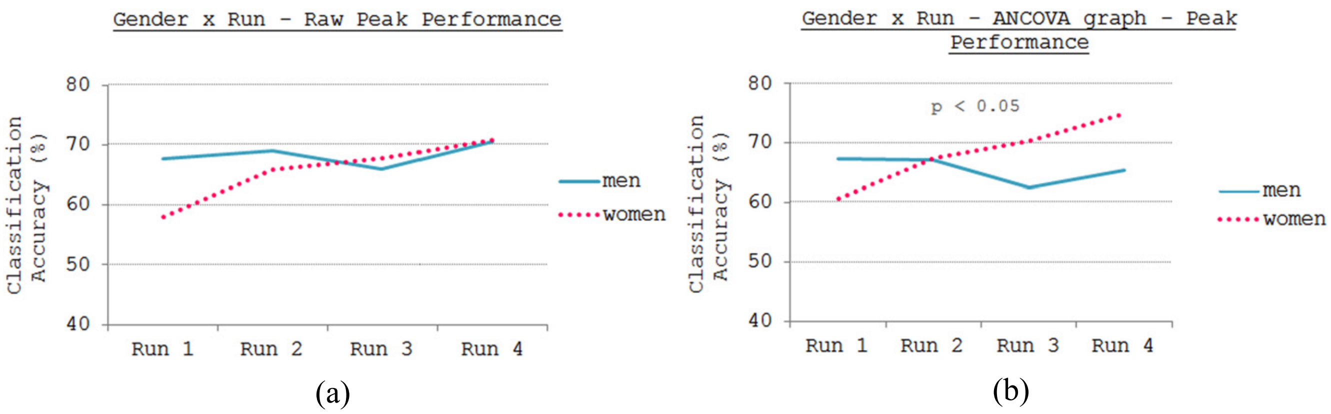


Figure 6. (a) Graph representing participants' raw MI-BCI peak performance (i.e. without the ANCOVA correction) as a function of their gender and of the run. (b) Graph representing the ANCOVA results for the gender–run interaction ($p < 0.05$), considering the mental rotation scores as a covariable. When considering the performance independently from the mental rotation scores, women increase in performance accross the four runs while men do not.

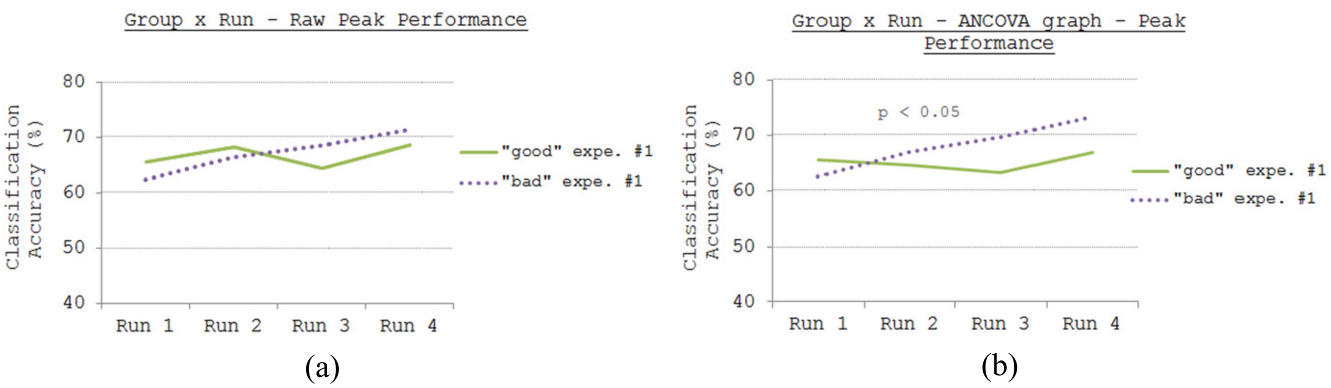


Figure 7. (a) Graph representing participants' raw MI-BCI peak performance (i.e. without the ANCOVA correction) as a function of their group from experiment 1 and of the run. (b) Graph representing the ANCOVA results for the group–run interaction ($p < 0.05$), considering the mental rotation scores as 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.

gender–group interaction ($F(1,15) = 2.982$; $p = 0.105$; $\eta^2 = 0.166$).

5.2.1.1. 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 assumption satisfaction for the ANCOVA are represented in figure 9. Mental rotation scores as well as mean performance of run1, run2 and run4 satisfied the criteria for a normal distribution, but run3 did not. As stated in the previous paragraph, this can be explained by the low number

Figure 8. (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 accross the runs while all the other participants do not.

of participants per group and should not impact the analysis reliability [43]. 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 ($F(1,15) = 5.817$; $p \leqslant 0.05$; $\eta^2 = 0.279$) as well as a strong tendency towards a main effect of the run ($F(1,15) = 4.100$; $p = 0.061$; $\eta^2 = 0.215$). However, no main effect of the group ($F(1,15) = 0.403$; $p = 0.535$; $\eta^2 = 0.026$) or of the gender ($F(1,15) = 2.965$; $p = 0.106$; $\eta^2 = 0.165$) was revealed. Concerning the strong tendency towards a run main effect, post hoc analyses (student t-tests for paired measures) revealed a significant increase in the mean performance between the first and the last runs (t = -2.542; $p \leqslant 0.05$) thus suggesting a learning effect, as was the case in the peak performance analyses. This ANCOVA also revealed several significant interactions. First, there was a run–mental rotation scores interaction ($F(1,15) = 7.545$; $p \leqslant 0.05$; $\eta^2 = 0.335$). Second, the run–gender interaction ($F(1,15) = 7.381$; $p \leqslant 0.05$; $\eta^2 = 0.330$) suggests that while men's MI-BCI performances (corrected so that they are independent from spatial ability scores) were stable across the four runs, women's increased significantly (see figure 10). Furthermore, the run–group interaction ($F(1,15) = 6.376$; $p \leqslant 0.05$; $\eta^2 = 0.298$) revealed that, considering performance independently from participants' spatial ability, 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 11), 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 12) but no run–gender–group interaction ($F(1,15) = 2.319$; $p = 0.149$; $\eta^2 = 0.134$).

5.2.2. MI-BCI performance and spatial ability. First, there was a clear gender effect on the mental rotation score, consistent with the literature: $mean_{\text{men}} = 30.5 \pm 7.12$; $mean_{\text{women}} = 20.7 \pm 7.21$ (t-test; $t = 3.058$; $p \leqslant 0.01$). Then, both the ANCOVAs (on mean and peak performance) revealed the important impact of spatial ability with a main effect of mental rotation scores on performance. Moreover, while mental rotation scores were not correlated with mean MI-BCI performance ($r = 0.266$; $p = 0.257$), they were correlated with the peak MI-BCI performance ($r = 0.464$; $p = 0.039$). These results confirm the important impact of spatial ability on MI-BCI performance that was demonstrated in [17, 19]. More specifically, the positive correlation indicates that people with better spatial ability (i.e. higher mental rotation

	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 9. Table representing the assumption checking for the ANCOVA on mean performance.

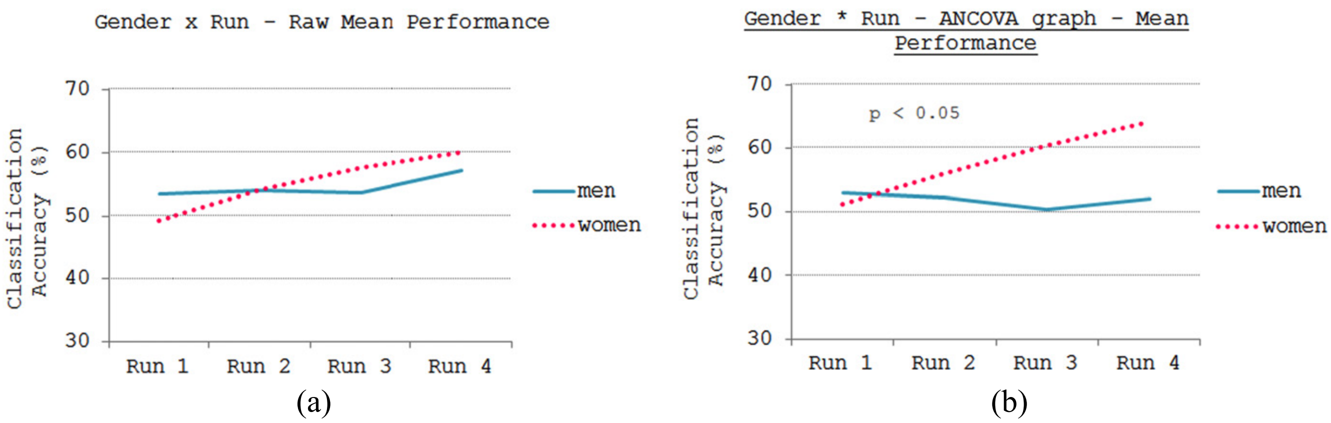


Figure 10. (a) Graph representing participants' raw MI-BCI mean performance (i.e. without the ANCOVA correction) as a function of their gender and of the run. (b) Graph representing the ANCOVA results for the gender–run interaction ($p < 0.05$), considering the mental rotation scores as a covariable. When considering the performance independently from the mental rotation scores, women's performance increases while men's does not.

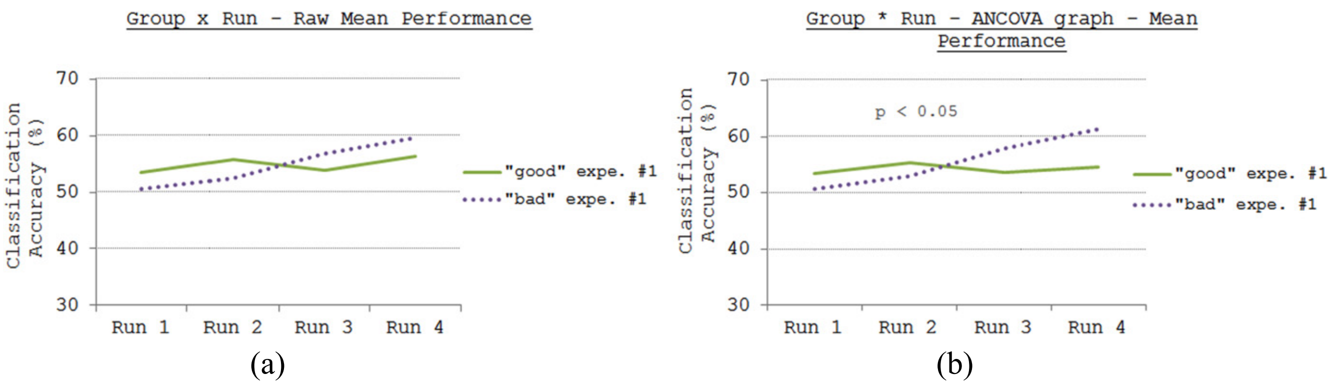
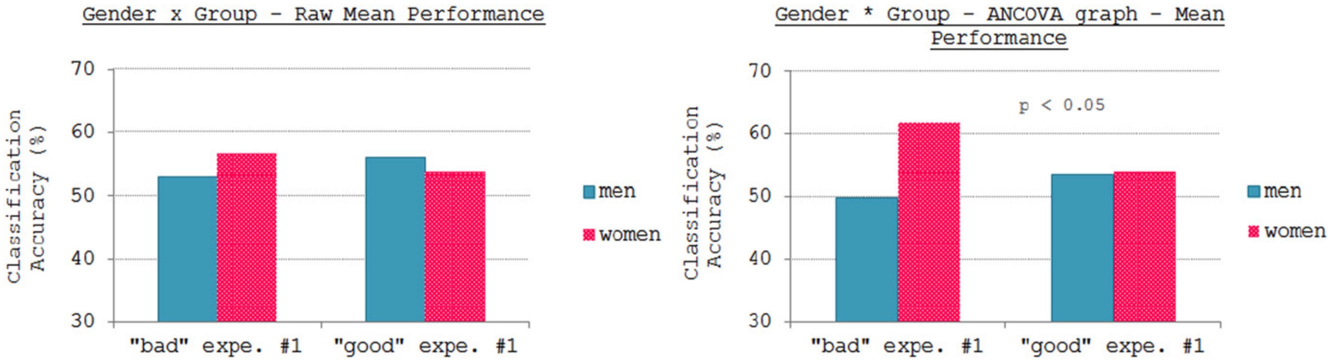


Figure 11. (a) Graph representing participants' raw MI-BCI mean performance (i.e. without the ANCOVA correction) as a function of their group from experiment 1 and of the run. (b) Graph representing the ANCOVA results for the group–run interaction ($p < 0.05$), considering the mental rotation scores 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.

scores in this instance) obtain higher MI-BCI control performance.

5.2.3. MI-BCI performance and the Blankertz SMR predictor. We performed bivariate Pearson correlation analyses to assess the relation between users' mean and peak MI-BCI performance and the mean Blankertz SMR predictor (averaged over the four runs). Results revealed no significant correlation between the predictor and the mean MI-BCI performance ($r = 0.151$; $p = 0.525$)



(a) (b)

Figure 12. (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. This 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 outperform all the other participants.

	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 13. Table representing the assumption checking for the ANCOVA. It should be noticed that all the assumptions but the linearity were respected.

nor with the peak MI-BCI performance ($r = 0.078$; $p = 0.743$).

5.2.4. Usability questionnaires. We also evaluated the score associated with the four dimensions of the UQ (LM, EE, safety and satisfaction) as a function of the participant's group (good versus bad), gender (men versus women) and of their mental rotation score. We thus performed four ANCOVAs. The prerequisite checking is depicted in figure 13. 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. No effect of the group, of the gender nor an interaction of both was revealed for the LM, the safety and the satisfaction dimensions. For the EE dimension however, two strong tendencies were revealed: a tendency towards a main effect 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 EE of the MI-BCI protocol as the same whatever their performance in the first experiment, while women evaluated this dimension with lower scores when they had difficulties in the first experiment, and with higher scores when they managed in the first experiment. The fact we only have tendencies could be due to the relatively low number of participants ($N = 20$, i.e. only 5 per group–gender).

5.3. Discussion

This second experiment aimed at assessing the relationships existing between MI-BCI performance, motor task performance (obtained in the first experiment) and spatial ability (measured by the mental rotation test). Participants globally obtained modest performance, probably due to the fact they only took part in one session, while several sessions are necessary to acquire MI-BCI skills and thus improve in terms of performance. Nonetheless, 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 ability on BCI performance that was suggested in our previous papers for mental imagery based BCI (not purely motor ones) [17, 19]. The important role of spatial ability 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 ability 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 performance in the second experiment but their performance 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 subtantial cognitive resources. Thus, these resources are not available to understand how to use the information provided by the training protocol or by the feedback. By contrast, when users face difficulty in finding the right strategy in a less complex context (such as performing motor tasks that they know they can do and for which they have proprioceptive feedback) their available resources allow them to pay attention to 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.

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 learned 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 ability than men on average, and that spatial ability is correlated to BCI performance, they have more room for improvement, which could explain why they improved over the runs while men did not. 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.

6. General discussion

The two experiments we conducted provide a number of relevant insights regarding MI-BCI training with standard training protocols. Our first experiment used a standard BCI training protocol, the widely used Graz group protocol, to teach non-BCI related sills, simple motor tasks in this case. It showed that with such training tasks and feedback, a substantial proportion of subject, here 16.67%, i.e. 9 subjects out of 54, failed to acquire the targeted skills despite their simplicity (drawing triangles and circles). This suggests that such a training protocol is suboptimal for skill teaching, and therefore, that BCI illiteracy/deficiency is most likely due, at least in part, to the limitations of the training protocol. In particular, many participants reported that the feedback they received, i.e. the bar feedback, provided too little information to help them to improve. Thus, future research aimed at reducing BCI illiteracy/deficiency and improving BCI training should consider providing richer and more explanatory feedback, which helps users identify what they should change in their EEG patterns and mental strategies to achieve successful BCI control. Interestingly enough, this is also what is theoretically recommended for successful training in human learning and education psychology literature [28].

Our second experiment was aimed at measuring possible relationships between the performance obtained during the motor task training (first experiment) and MI-BCI training performance (second experiment). To do so, we trained the ten best and ten worst participants from the first experiment, to perform left-hand and right-hand MI. Contrary to our hypothesis, this second experiment did not reveal any significant linear correlation between motor task performance (first experiment) and MI-BCI performance. It also did not reveal significant performance differences between the ten best and tem worst participants from the first experiment. This may be due to the fact that different tasks were performed in the first and second studies, which could represent a limitation. However, the same protocol (in terms of instructions and feedback) was used in both studies. Moreover, in retrospect, this is not so surprising since, as mentioned before, when dealing with BCIs, a number of factors other than the training protocol and users' learning ability appear to affect BCI performance. In particular, the EEG signal-to-noise ratio, the participants' ability or experience at performing motor imagery or the orientation of their sensori-motor cortex with respect to the scalp, among others, can all impact the quality of the EEG patterns, which in turn can impact BCI performance, independently from the training protocol and the users' learning ability. Furthermore, our results revealed no relationship between MI-BCI performance and the Blankertz SMR predictor. 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 min long baseline was recorded the predictor was computed based on the concatenation of all the 3 s long pre-trials of the runs, which could impact its performance. Nonetheless, this second experiment did reveal some other interesting insights. First it confirmed that spatial ability is related to mental imagery based BCI performance. 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 paper suggests that spatial ability also plays a role in purely motor imagery based BCI performances, in which no mental rotation tasks are involved. This thus confirms the importance of spatial ability for successful BCI control, and reinforces the idea that spatial ability training should be explored for BCI training. Second it showed that when subjects are faced with a pre-training session they perceive as difficult (here motor learning tasks for subjects with poor performance), they seem to explore more strategies and therefore learn better in a subsequent training task, here MI-BCI training. This is an interesting result as it suggests that in the future it would be worth exposing naive BCI subjects to pre-training that forces them to explore multiple strategies that might in turn help them to find a better MI strategy in subsequent classical BCI training. Such an approach should be explored in the future. Finally, this second experiment suggests that, when spatial ability is controlled for, women (especially the ones who faced difficulty in the first experiment) seem to improve over time whereas men do not with such short term training. However, this might be explained by women having more room for improvement than men and/or different cognitive approaches to learning. Further studies (both experimental and theoretical) should be performed to elucidate this observation.

In summary, our studies have shown that current standard BCI training protocols such as the Graz training protocol are suboptimal and most likely responsible for a substantial part of observed BCI illiteracy/deficiency. They should therefore be changed, in particular by providing more explanatory feedback. Our two experiments also revealed the importance of spatial ability and of a pre-training session on subsequent MI-BCI performance. This therefore suggests that exploring spatial ability training and specific pre-training tasks for MI-BCI training are promising future prospects. Altogether, our studies have opened the door to several new research questions aimed at improving MI-BCI training and thus at further increasing the reliability and potential of MI-BCIs.

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CHAPTER

Advances in user-training for mental-imagery-based BCI control: Psychological and cognitive factors and their neural correlates

1

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Abstract

While being very promising for a wide range of applications, mental-imagery-based brain–computer interfaces (MI-BCIs) remain barely used outside laboratories, notably due to the difficulties users encounter when attempting to control them. Indeed, 10–30% of users are unable to control MI-BCIs (so-called BCI illiteracy) while only a small proportion reach acceptable control abilities. This huge interuser variability has led the community to investigate potential predictors of performance related to users' personality and cognitive profile. Based on a literature review, we propose a classification of these MI-BCI performance predictors into three categories representing high-level cognitive concepts: (1) users' relationship with the technology (including the notions of computer anxiety and sense of agency), (2) attention, and (3) spatial abilities. We detail these concepts and their neural correlates in order to better understand their relationship with MI-BCI user-training. Consequently, we propose, by way of future prospects, some guidelines to improve MI-BCI user-training.

Keywords

Brain–computer interfaces, Interuser variability, User-training, Predictors of performance, Neural correlates, Sense of agency, Computer anxiety, Attention, Spatial abilities, Improving training protocols

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1 INTRODUCTION

Brain–computer interfaces (BCIs) are communication systems that enable their users to send commands to computers by means of brain signals alone (Wolpaw and Wolpaw, 2012). These brain signals are usually measured using electroencephalography (EEG), and then processed by the BCI. For instance, a BCI can enable a user to move a cursor to the left or to the right of a computer screen by imagining left- or right-hand movements, respectively. Since they make computer control possible without any physical activity, EEG-based BCIs have promised to revolutionize many application areas, notably to control assistive technologies (eg, control of text input systems or wheelchairs) for motor-impaired users (Millán et al., 2010; Pfurtscheller et al., 2008) and rehabilitation devices for stroke patients (Ang and Guan, 2015) or as input devices for entertainment and human–computer interaction (Graimann et al., 2010), to name but a few (Van Erp et al., 2012). Despite this promising potential, such revolutions have not yet been delivered, and BCIs are still barely used outside research laboratories (Van Erp et al., 2012; Wolpaw and Wolpaw, 2012). The main reason why current BCI fail to deliver is their substantial lack of reliability and robustness (Van Erp et al., 2012; Wolpaw and Wolpaw, 2012). In particular, BCI too often fail to correctly recognize the user's mental commands. For example, in a study with 80 users, the average classification accuracy was only 74.4%, for a BCI using two imagined movements as commands (Blankertz et al., 2010). Moreover, it is estimated that between 10% and 30% of BCI users, depending on the BCI type, cannot control the system at all (so-called BCI illiteracy/deficiency) (Allison and Neuper, 2010).

BCIs, as the name suggests, require the interaction of two components: the user's brain and the computer. In particular, to operate a BCI, the user has to produce EEG patterns, eg, using mental imagery tasks, which the machine has to recognize using signal processing and machine learning. So far, to address the reliability issue of BCI, most research efforts have been focused on EEG signal processing and machine learning (Allison and Neuper, 2010; Bashashati et al., 2007; Makeig et al., 2012). While this has contributed to increased performances, improvements have been relatively modest, with classification accuracy being still relatively low and BCI illiteracy/deficiency still high (Allison and Neuper, 2010; Wolpaw and Wolpaw, 2012). To make BCI truly reliable and thus useful, it is also necessary to ensure the user can produce clear, stable, and distinct EEG patterns. Indeed, BCI control is known to be a skill that must be learned and mastered by the user (Wolpaw and Wolpaw, 2012). This means that (1) the BCI performances of a user become better with practice and thus that (2) the user needs to learn how to produce these stable, clear, and distinct EEG patterns to successfully control a BCI (Lotte et al., 2013a; Neuper and Pfurtscheller, 2010). This need for training is particularly salient for BCI based on mental-imagery (MI) tasks. With the so-called mental-imagery-based brain–computer interfaces (MI-BCIs), users send mental commands by performing MI tasks, eg, movement imagination or mental mathematics, which are then recognized by the BCI and translated into commands for the application.

In this chapter, we focus on this type of BCI which is prominent in many BCI applications such as stroke rehabilitation (Ang and Guan, 2015), the control of wheelchairs or prosthetics (Millán et al., 2010), and entertainment applications (Lotte et al., 2013b), among many others.

Designing a reliable MI-BCI thus requires that the MI-BCI user has been properly and specifically trained to control that BCI. Current training approaches have been rather similar across the different MI-BCI designs so far, and can be divided into two main families: the operant conditioning approach (Wolpaw et al., 1991) and the machine learning approach (Millán et al., 2002). While these two training approaches differ in the way the classifier is defined (manually defined vs optimized on EEG data), both approaches require to provide feedback to user. Such feedback is generally visual, indicating both the mental task recognized by the classifier together with the system's confidence in the recognized task. A typical and very popular example is the Graz BCI protocol (Pfurtscheller and Neuper, 2001). In this protocol, users are instructed to perform kinesthetic imagination of left- or right-hand movements following the on-screen display of an arrow pointing either left or right, respectively. They then receive visual feedback in the form of a bar extending toward the left or the right, depending on whether a left- or right-hand movement was recognized by the BCI. The length of the bar is proportional to the classifier output. Users are typically trained with such an MI-BCI protocol over several sessions (ie, on several days), each session being composed of 4–6 runs, and a run comprising about 15–20 trials per mental task.

However, even with state-of-the-art signal processing and classification algorithms, 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; Kübler et al., 2013; Wolpaw and Wolpaw, 2012). 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, ie, 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 and Jeunet, 2015; Lotte et al., 2013a). 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). This survey allowed the identification of different predictors that can be organized 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 3, attention is discussed in Section 4 and spatial abilities are attended to Section 5. Finally, Section 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 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 (ie, 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 et al. (1988) as "temporary, brief, and caused by external circumstances." The second group gathers the factors related to the users' *Traits*, characterized as "stable, long-lasting, and internally caused" with respect to one's environment and experience (Chaplin et al., 1988). Finally, the third group comprises the factors that can be qualified neither as *Traits* nor as *States*, ie, demographic characteristics, habits, and environment-related factors.

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. (2008) have shown that mood (measured using a subscale of the German Inventory to assess Quality of Life—Averbeck et al., 1997) correlates with BCI performance. On the other hand, both attention (Daum et al., 1993; Grosse-Wentrup et al., 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., 2008) 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. (2008) suggested that higher scores in mastery confidence, ie, 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 et al., 2010; Witte et al., 2013). In the same vein, control beliefs (Witte et al., 2013), ie, 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 of confidence, control beliefs, and self-efficacy can be classed as context-specific states, ie, states triggered each time a person faces a specific situation.

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. In addition, active learners seem to perform better than reflective learners (Jeunet et al., 2015a) in a context of MI-BCI control. This dimension, active vs reflective, is one of the four dimensions of the Learning Style that can be assessed using the Index of Learning Style test (Felder and Spurlin, 2005). Abstractness, ie, imagination abilities, has also been shown to correlate with classification accuracy in an MI-BCI experiment (Jeunet et al., 2015a). Furthermore, Hammer et al. (2012) have proposed a model for predicting SMR-BCI performance—which includes visuomotor 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 four session experiment (one calibration and three training sessions) within a neurofeedback-based SMR-BCI context (ie, 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, ie, visual–motor coordination, failed significance. With this model, the average prediction error was less than 10%. Moreover, kinesthetic imagination and visual–motor imagination scores have both been shown to be related to BCI performance by Vuckovic and Osuagwu (2013). Finally, a strong correlation [$r = 0.696$] between mental rotation scores and MI-based BCI performance has been reported (Jeunet et al., 2015a) in a six session experiment, during which participants had to learn to perform three MI tasks (motor imagery of the left hand, mental subtraction, and mental rotation of a 3D shape). This finding has recently been replicated in an experiment based purely on motor imagery (imagination of left- and right-hand movements) in which mental rotation scores correlated with participants' peak performance [$r=0.464$] (Jeunet et al., 2016).

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. More recently, tension and self-reliance (ie, autonomy toward the group) were related to MI-BCI performance (measured in terms of classification accuracy) in a model also including abstractness abilities and the active/reflective dimension of the learning style (Jeunet et al., 2015a). This model enabled prediction of more than 80% of the between-participant variance in terms of performance with an average prediction error of less than 3%.

2.3 OTHER FACTORS IMPACTING MI-BCI PERFORMANCE: DEMOGRAPHIC CHARACTERISTICS, EXPERIENCE, AND 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-olds 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, 2012; Randolph et al., 2010). 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 et al., 2010) positively impact SMR-BCI performance. However, the consumption of affective drugs seems to have the opposite effect (Randolph et al., 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).

2.4 TO SUMMARIZE: MI-BCI PERFORMANCE IS AFFECTED BY THE USERS' (1) RELATIONSHIP WITH TECHNOLOGY, (2) ATTENTION, AND (3) SPATIAL ABILITIES

To summarize, the predictors of MI-BCI performance can be gathered into the three following categories, as depicted in Table 1:

- Category 1—*The user–technology relationship and the notion of control* (spades, see Table 1): indeed, based on 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.

Table 1 This Table Summarizes the Different Predictors (State, Trait, and Others) That Have Been Related to MI-BCI Performance in the Literature

States	Emotional state	♣	Mood (Nijboer et al., 2008)
	Cognitive state	♣	Attention level (Grosse-Wentrup and Schölkopf, 2012; Grosse-Wentrup et al., 2011)
		♣	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)
		♠	Tension (Jeunet et al., 2015a)
		♠	Self-reliance (Jeunet et al., 2015a)
	Cognitive profile	♣	Attention span (Hammer et al., 2012)
		♣	Attentional abilities (Daum et al., 1993)
		♣	Attitude toward work (Hammer et al., 2012)
		♣	Memory span (Daum et al., 1993)
		◆	Visual–motor coordination (Hammer et al., 2012, 2014)
		◆	Learning style: active vs reflective learners (Jeunet et al., 2015a)
		◆	Kinesthetic imagination score (Vuckovic and Osuagwu, 2013)
		◆	Visual–motor imagination score (Vuckovic and Osuagwu, 2013)
		◆	Mental rotation scores (Jeunet et al., 2015a)
		◆	Abstractness (Jeunet et al., 2015a)
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 and 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)

The predictors related to the user–technology relationship are associated to spades, while those related to attention are associated to clubs and those related to spatial abilities are associated to diamonds.

- Category 2—*Attention* (clubs, see Table 1): 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* (diamonds, see Table 1): many predictors depicted in the previous brief review are related to motor abilities (eg, two-hand coordination, sports, or music practice) or to the ability to produce mental images (eg, kinesthetic imagination scores or abstractness abilities). 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 et al., 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, ie, *the User–Technology Relationship and the Notion of Control*, can be explained by the fact that users were BCI-naïve while the involvement of the predictors in Categories 2 and 3, ie, *Attention and 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 (ie, 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 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 interindividual differences during skill acquisition (Ackerman, 1988). In his model, Ackerman argues that skill acquisition is divided into three phases and that interindividual 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, interindividual 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 interindividual differences.

- Phase #3: Automatic phase—During this third phase, noncognitive psychomotor abilities are mostly responsible for interindividual differences (Wander et al., 2013).

As stated earlier, BCI users were in an early stage of learning, ie, 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 interindividual 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, ie, relationship with technology, attention, and spatial abilities are introduced, and their neural correlates are described in the following sections.

3 THE USER–TECHNOLOGY RELATIONSHIP: INTRODUCING THE CONCEPTS OF COMPUTER ANXIETY AND SENSE OF AGENCY—*DEFINITION AND 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 two 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 et al., 2010; Witte et al., 2013), the fear of incompetence (Kleih et al., 2013; Nijboer et al., 2008), and tension (Jeunet et al., 2015a), all having been shown to negatively impact MI-BCI performance, reflect a certain apprehension of the user toward BCI use. This apprehension can be defined as *computer anxiety* (CA).

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 high a 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 toward 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 conceptualized 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 CA). We will notably see that the *sense of agency* (ie, the feeling of being in control) actually mediates CA (ie, the apprehension of the technology).

3.1 APPREHENSION OF TECHNOLOGY: THE CONCEPT OF CA—*DEFINITION*

Computer Anxiety (CA), also called "Tech-Stress" (Achim and Al Kassim, 2015), can be classed as a *context-specific anxiety*, ie, 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, ie, high CA 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 summarize, 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).

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 toward 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), ie, 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 MI 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 et al., 2008) which explains why MI, under certain conditions, can be associated with a sense of agency (Peres-Marcos et al., 2009).

The sense of agency can be divided into two components (Farrer and Frith, 2002; Gallagher, 2012; Synofzik et al., 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 nonconceptual 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 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 et al. (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., 2013).

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 (ie, one must not believe there to be an outside influence). Moreover, several indicators influencing the judgement of agency have been proposed (Wegner, 2003; Wegner et al., 2004): bodily and environmental cues (Where am I?), bodily feedback (proprioceptive and kinesthetic information), bodily feedforward (ie, 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, 2003), 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, 2003): agents who are "feeling without doing," and thus think they are in control although they are not.

3.3 "I DID THAT!": THE CONCEPT OF SENSE OF AGENCY—*NEURAL CORRELATES*

As stated by Ehrsson et al. (2004), 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, ie, 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 et al., 2008).

Self-agency has been shown to be underlain by an increased activity in the PMC (Ehrsson et al., 2004; Farrer and Frith, 2002) and more specifically in its ventral part, the SMA (Farrer and Frith, 2002; Kühn et al., 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 et al., 2004). Thus, it is thought that the PMC enables a multisensory integration and thus provides a mechanism for bodily attribution (Ehrsson et al., 2004). 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 multimodal 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 et al., 2008).

Contrariwise, the activation of the 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., 2013). Indeed, PPC activation is linked to the processing of visual–motor incongruence during self-generated actions (David et al., 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 et al., 2008). But it seems that the AG also monitors the signals linked to action selection in the dorsolateral prefrontal cortex to prospectively provide information about the subjective feeling of control over action outcomes (Chambon et al., 2013). 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., 2013). While consistent, these correlates are still discussed. For instance, Kühn et al. (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 et al., 2008).

To summarize, 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 et al., 2008).

4 ATTENTION—*DEFINITION AND NEURAL CORRELATES*

The second category of factors that have been found to correlate with BCI performances contains attention-related predictors. Indeed, both attentional traits, ie, the BCI user's intrinsic attentional capacities, and attentional states, ie, the amount of the user's attentional resources dedicated to the BCI task, were found to be correlated to BCI performances. To summarize (see Table 1), the attentional traits predicting BCI performances include attention span (Hammer et al., 2012), attentional abilities (Daum et al., 1993), attitude toward 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 et al., 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 (Bamdadian et al., 2014; Grosse-Wentrup and Schölkopf, 2012; Grosse-Wentrup et al., 2011) (see Section 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, 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 et al., 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.

4.1 ATTENTION—*DEFINITION*

Attention could be defined as the "the ability to focus cognitive resources on a particular stimulus" (Frey et al., 2014b). According to Posner and Petersen (1990), the attention system can be divided into three main subsystems, each of which corresponds to a major attentional function. These three subsystems 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, ie, 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 Petersen and Posner (2012), Posner and Boies (1971), and Posner and Petersen (1990). 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, eg, because they have to perform dual-attentional tasks (ie, 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 altogether (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, 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 distractors), 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 subsystems of attention (sustained attention, selective attention, and focal attention) are therefore involved in the learning process. Since 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 BCI performance.

4.2 ATTENTION—*NEURAL CORRELATES*

Interestingly enough, the attention system corresponds to specific anatomical structures in the brain that are different than those dedicated to information processing (Posner and Petersen, 1990). Each of the three attention subsystems (alerting, orienting, and executive control) corresponds to a specific brain network (Petersen and Posner, 2012; Posner and Petersen, 1990). 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 AG and thalamic areas (Petersen and Posner, 2012; Seghier, 2013). The orienting network notably involves the frontal eye fields, the intraparietal sulcus and the superior parietal lobe, the temporoparietal junction, the AG, and the ventral frontal cortex (Petersen and Posner, 2012; Seghier, 2013). Finally, the Executive Network involves multiple brain areas, including the medial frontal cortex, the anterior cingulate cortex, 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 interindividual variability in the efficiency of these networks which explains, at least in part, the interindividual variations in attentional abilities, ie, 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, ie, in an increased power for low frequency EEG rhythms (delta ~1–4 Hz, theta ~4–7 Hz, low alpha ~7–10 Hz), and a decreased power for higher frequency EEG rhythms (Frey et al., 2014a,b; 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 (~8–12 Hz) 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,b). A delta (3–8 Hz) over beta (16–24 Hz) power ratio has also been used as a marker of sustained attention (Bamdadian et al., 2014).

Finally, it seems that the Gamma (55–85 Hz) power in attentional networks related to the executive control system also correlates with the attentional level (Grosse-Wentrup et al., 2011).

Consistent with the cognitive literature 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, has 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 and Schölkopf, 2012; Grosse-Wentrup et al., 2011) and for general MI-BCI (Schumacher et al., 2015). Moreover, the extent of activation of the dorsolateral prefrontal cortex (involved in executive control as seen earlier), 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).

5 SPATIAL ABILITIES—*DEFINITION AND 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 kinesthetic and visual–motor imagery questionnaires to performances obtained with a BCI based on object-oriented motor imagery. They show that the kinesthetic 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 vs poor imagers. They used functional magnetic resonance imaging (fMRI) to compare the pattern of cerebral activations in able and poor imagers during both the physical execution and MI 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.

Another spatial skill that has been shown to be related to MI-BCI performance is mental rotation ability. Mental rotation scores (measured using a mental rotation test) are a robust measure of spatial abilities, particularly for mental representation and manipulation of objects (Borst et al., 2011; Poltrock and Brown, 1984). Mental rotation scores have been shown to be correlated with scores obtained with other tests of spatial abilities such as space relation tests or spatial working memory (Just and

Carpenter, 1985; Kaufman, 2007), suggesting that they may be related to more general spatial skills (Thompson et al., 2013). Jeunet et al. (2015a) have explored the relationships between MI-BCI performance and the personality and cognitive profile of the user. The main result is a strong correlation between MI-BCI performances and mental rotation scores.

In the same vein, 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 et al. (2007) observe that performances in a mental rotation test are enhanced after only 10 h 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 et al., 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 performances. 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 chase and an equivalent straight distance sprint. Data revealed that the time taken to complete the chase was influenced by speed and sex, but also by the individual mental rotation ability. 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 (eg, 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.

5.1 SPATIAL ABILITIES—*DEFINITION*

As mentioned earlier, spatial abilities embody the ability to produce, transform, and interpret mental images (Poltrock and Brown, 1984). Lohman (1993) greatly highlighted the pivotal role of spatial abilities and particularly MI 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 (such as James Clerk Maxwell, Michael Faraday, and

Herman von Helmholtz) and inventors, 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 et al. (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 et al., 1993; Shea et al., 2001).

The key role of MI in human cognition has also been highlighted by the fact that it is involved in certain pathological situations such as Posttraumatic Stress Disorders (Brewin et al., 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 a review, see Pearson et al., 2013). 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 wayfinding (or spatial navigation) defined as "the process of determining and following a path or route between origin and destination" (Golledge, 1999). Wayfinding 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 (VR) simulations (Wiener et al., 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 MI consisting of several component processes. For example, the classical model of Kosslyn (1980, 1994) 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 et al., 2006).

5.2 SPATIAL ABILITIES—*NEURAL CORRELATES*

The neural correlates of visual MI are subject to much debate. Some authors claim a functional equivalence between visual perception and visual MI, 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 frontoparietal network involving the superior parietal lobule and frontal eye field bilaterally.

Motor imagery is a particular case of MI 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/kinesthetic (first person) motor imagery recruit distinct neural networks. Guillot et al. (2004) showed that visual imagery predominantly activated the occipital regions and the superior parietal lobules, whereas kinesthetic imagery preferentially activated the motor-associated structures and the inferior parietal lobule. Finally, Ridderinkhof and Brass (2015) specify that activation during kinesthetic MI is not just a subliminal activation of the same brain areas involved in the real action. For these authors the activation during kinesthetic 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 kinesthetic motor imagery leads to better MI-BCI performances than visual–motor imagery (Neuper et al., 2005). Nevertheless, the distinction between these different forms of MI, 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. Jeunet et al. (2015a) demonstrated that spatial skills and particularly mental rotation scores are a relevant predictor of BCI efficiency. Moreover, many skills related to spatial abilities (such as playing sports, musical instruments, and action video games) 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.

6 PERSPECTIVES: THE USER–TECHNOLOGY RELATIONSHIP, ATTENTION, AND SPATIAL ABILITIES AS THREE LEVERS TO IMPROVE MI-BCI USER-TRAINING

6.1 DEMONSTRATING THE IMPACT OF THE PROTOCOL ON CA AND SENSE OF AGENCY

In Section 3, we stressed the impact of the notion of control on performance, notably through its mediating role on CA. The notion of control can be conceptualized as a *Sense of Agency*, ie, "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 (Coyle et al., 2015; McFarland et al., 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 CA 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) 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, ie, 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, ie, the sensory outcome must fit the predicted outcome. And third, the exclusivity principle, ie, 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 hypothesized 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 nontransparent. 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 recognized, respectively. In the nontransparent 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's (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. In a recent study (Jeunet et al., 2015b), we showed that an equivalent tactile feedback provided on users' hands was more efficient. 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 summarize, 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, ie, 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.

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 toward 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 nonmeditators in the frontoparietal and the default mode networks, in fMRI studies (Braboszcz et al., 2010). The Gamma EEG power in these areas also differs between expert meditators and nonmeditators (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 (eg, Eskandari and Erfanian, 2008; He et al., 2015). In other words, meditation improves attentional abilities, which in turn improves BCI performances.

Attentional capabilities can also be improved using neurofeedback training, eg, by providing users with games in which they have to increase an EEG measure of their attentional level to win (Lim et al., 2010, 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, 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 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 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., 2013b) 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 visualization 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 visualization techniques such as Teegi (Frey et al., 2014a,b). 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, ie, requiring users to divide their attentional resources between two different subtasks, especially if these tasks involve the same modality, eg, 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 et al., 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, eg, to control a game or a visual speller. Interestingly enough, it has been shown that providing tactile instead of visual feedback in such a split-attentional task leads to improved BCI performance (Jeunet et al., 2015b). Thus, it would be worth studying as well auditory feedback, see, eg, (McCreadie et al., 2014), in similar contexts. 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 et al. (2015).

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's, 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, other studies have shown greater performance improvement in women than in men (Okagaki and Frensch, 1994), or a waning of gender differences (Kass et al., 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 et al. (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, surgical performances, and music. However, very few studies have focused on BCI practice.

Erfanian and Mahmoudi (2013) have investigated the role of mental practice and concentration on a natural EEG-based BCI 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.

In the study of Jeunet et al. (2015a), participants followed a standard training protocol composed of six identical sessions during which they had to learn to perform three MI tasks: mental rotation, mental subtraction, and left-hand motor imagery. On the one hand, no improvement in performance was noticed between the 1st and 6th session on average, suggesting that participants did not learn despite the large number of sessions. On the other hand, the BCI performance appeared to be strongly correlated to participants' mental rotation scores. In the near future, the authors propose to test the impact of spatial training and particularly mental rotation training on BCI efficiency. The authors also considered applications in the context of patients suffering from motor impairments, since MI abilities can be preserved after brain injury. In any case, it is a challenging project to study the impact of spatial training on reducing the "BCI illiteracy" phenomenon, and thus enabling BCI to be more systematically used outside laboratories.

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, ie, 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, ie, 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 interuser 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*), ie, 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 interuser 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, a discussion about how these factors could be taken into account when designing future protocols in order to optimize user-training. More specifically, the impact of the training protocol on users' CA 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 emphasized. 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 toward 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 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. Finally, the user's mental rotation ability seems to be a very good candidate to be trained, since this ability has been identified as a relevant predictor of BCI performance and since the consequences of mental rotation training on spatial and more general skills have been clearly identified.

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. Nevertheless, it is important to note that improving training protocols is not enough. The roles of the researcher and experimenter are also of utmost importance, notably concerning: (1) the demystification of the BCI technology to reduce a priori CA, through scientific mediation and communication with the media; (2) the writing of informed-consent forms and explanations, which should be clear and informative, and provide an objective estimation of the benefit on risk balance and enable to regulate any form of hope that may be generated (Nijboer et al., 2013); and (3) the social presence and trust relationship with the user, which are essential in facilitating the learning process (Kleih et al., 2013).

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RESEARCH ARTICLE

Predicting Mental Imagery-Based BCI Performance from Personality, Cognitive Profile and Neurophysiological Patterns

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Abstract

Mental-Imagery based Brain-Computer Interfaces (MI-BCIs) allow their users to send commands to a computer using their brain-activity alone (typically measured by ElectroEncephaloGraphy—EEG), which is processed while they perform specific mental tasks. While very promising, MI-BCIs remain barely used outside laboratories because of the difficulty encountered by users to control them. Indeed, although some users obtain good control performances after training, a substantial proportion remains unable to reliably control an MI-BCI. This huge variability in user-performance led the community to look for predictors of MI-BCI control ability. However, these predictors were only explored for motor-imagery based BCIs, and mostly for a single training session per subject. In this study, 18 participants were instructed to learn to control an EEG-based MI-BCI by performing 3 MI-tasks, 2 of which were non-motor tasks, across 6 training sessions, on 6 different days. Relationships between the participants' BCI control performances and their personality, cognitive profile and neurophysiological markers were explored. While no relevant relationships with neurophysiological markers were found, strong correlations between MI-BCI performances and mental-rotation scores (reflecting spatial abilities) were revealed. Also, a predictive model of MI-BCI performance based on psychometric questionnaire scores was proposed. A leave-one-subject-out cross validation process revealed the stability and reliability of this model: it enabled to predict participants' performance with a mean error of less than 3 points. This study determined how users' profiles impact their MI-BCI control ability and thus clears the way for designing novel MI-BCI training protocols, adapted to the profile of each user.

Introduction

A brain computer interface (BCI) is a hardware and software communication system that enables humans to interact with their surroundings without the involvement of peripheral

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nerves and muscles, i.e., by using control signals generated from electroencephalographic (EEG) activity [1]. More specifically, this paper focuses on BCIs for which these control signals are sent via the execution of *mental tasks*: so-called Mental-Imagery based BCIs (MI-BCIs). MI-BCIs represent a new, non-muscular channel for relaying users' intentions to external devices such as computers, assistive appliances, or neural prostheses (for a review, see [2]).

Since the 1990's, many different kinds of MI-BCI have been developped [3]. Mostly, MI-BCIs have been designed for the purpose of improving living standards of severely motor-impaired patients (e.g. those with locked-in syndrome or spinal cord injuries) by enhancing their mobility autonomy and communication possibilities [1, 4, 5]. In addition to these applications, one should also note the emerging fields of BCI-based rehabilitation, e.g., for stroke rehabilitation [6, 7], and multimedia and virtual reality [8–10] for which MI-BCIs—notably those based on motor imagery—bring innovative perspectives.

Unfortunately, most of these promising technologies based on MI-BCIs cannot yet be offered on the public market since a notable portion of users, estimated at between 15 and 30%, does not seem to be able to control an MI-BCI based system [11]: this phenomenon is often called "BCI illiteracy" or "BCI deficiency". Even for MI-BCI users who are not "illiterate", the average performance they reach is most of the time rather low [12, 13], i.e., around 75% of classification accuracy for 2 class MI-BCIs. Nonetheless, it is important to note that around 20% of users obtain performances between 80% and 100% of classification accuracy [14] after training for two mental tasks.

It is now known that the control of an MI-BCI requires the aquisition of specific skills, and particularly the ability to generate stable and distinct brain activity patterns while performing the different Mental-Imagery (MI) tasks [1, 15]. Appropriate training is required to acquire these skills [15]. Yet, Lotte et al. [16] suggested that current standard training protocols, which do not take into account the recommendations from psychology (such as proposing adaptive and progressive tasks or explanatory, supportive and multimodal feedback), are not appropriate, and thus might be partly responsible for BCI illiteracy and poor user performance. This hypothesis was strengthened in a recent study [17] in which a standard MI-BCI protocol [4] was tested in a BCI-free context: participants were asked to learn to do simple motor tasks (draw circles and triangles with a pen on a graphic tablet) using this standard MI-BCI training protocol. As would have been the case with MI tasks, participants had to find the right strategy (e.g., finding the right size and drawing speed) so that the motor task they were performing (i.e., drawing circles or triangles) was recognised by the system. Results showed that 15% of the participants did not manage to learn to perform these simple motor tasks (i.e. they did not find out how to adapt their strategy) using the standard training protocol, which is close to BCI-illiteracy rates. This result reinforced the idea that current standard MI-BCI protocols are not suitable for skill-learning, and emphasised the importance of working on improving them.

However, the fact that training protocols are not adapted does not explain the huge between-subject variability. Thus, this variability in MI-BCI control performance over subjects has raised questions about which parameters could help to predict users' ability to control such a system. The training process to learn to control an MI-BCI being time- and resource-consuming, being able to predict users' success (or failure) could avoid important loss of time and energy for both users and experimenters. From another perspective, knowing these predictors could also help understand why some people cannot learn to control an MI-BCI using standard protocols, and then guide the design of new training protocols that would be adapted to users' relevant characteristics. So far, two kinds of predictors have been explored: neurophysiological and psychological predictors. A brief state of the art of these predictors is proposed in the following paragraphs.

Neurophysiological Predictors: Recently, evidence was presented that the amplitude of sensorimotor-rhythms (SMRs) at rest is a good predictor of subsequent BCI-performance in motor-imagery paradigms [13]. The authors proposed a new neurophysiological predictor based on the μ (about 9–14 Hz) rhythm over sensorimotor areas: referred to as "Blankertz's SMR predictor" in this paper. This predictor was determined from a two minute-long recording in a "relax with eyes open" condition, using two Laplacian EEG channels. Results showed a correlation of r = 0.53 between the proposed predictor and BCI performance on a large subject data base (N = 80) which makes this neurophysiological predictor the most reliable so far. Moreover, Grosse-Wentrup et al. [18] demonstrated that the modulation of SMRs, induced by motor-imagery of either the left- or right-hand, was positively correlated with the power of frontal and occipital γ-oscillations, and negatively correlated with the power of centro-parietal γ-oscillations. Besides, Grosse-Wentrup and Schölkopf [19] showed that the power of high-frequency γ-oscillations originating in fronto-parietal networks predicted variations in performance on a trial-to-trial basis. As γ-oscillations are often associated with shifts in attention [19], the authors interpreted this finding as empirical support for an influence of attentional networks on BCI performance via the modulation of SMRs [19]. Furthermore, Ahn et al. [20] investigated the difference between BCI-literate and BCI-illiterate groups in terms of spectral band powers by comparing non-task related state (NTS) during the eyes-open state, resting but ready state (before motor imagery) and during motor imagery. They found that the BCI-illiterate group showed high θ- and low α-power levels in comparison with the BCI-literate group. Statistically significant areas were frontal and posterior-parietal regions for the θ-band and the whole cortex area for the α-band. A high positive correlation between γ-activity and motor-imagery performance was also shown by [21] in the prefrontal area. Finally, [22] proposed a novel predictor computed from the spectral power of pre-cue EEG data for specific rhythms over different regions of the brain. The authors argue that this predictor reflects the attentional level. Results showed that there is a significant correlation (r = 0.53) between the predictor and the cross-validation accuracies of subjects performing motor-imagery. They also found that having higher frontal θ and lower posterior α prior to performing motor-imagery, which reflects a high attentional level, may enhance the BCI classification performance. This last result seems to be in contradiction with [20]. However, the brain areas considered in these two studies are different. Ahn et al. [20] used sensori-motor areas while Bamdadian et al. [22] considered frontal theta and lower posterior alpha. Furthermore, the statistical analyses used by the authors in [20] have recently been criticised in [23]: the discrepancies in the analyses could also explain this contradiction. While the search for neurophysiological predictors seems to be a promising approach, some studies showed that the user's psychological profile could also be an important factor influencing BCI-control performance.

Psychological Predictors: Memory span and attention were correlated to the ability to regulate slow cortical potentials (SCP) in patients with epilepsy [24]. Besides, Neumann and Birbaumer [25] found that mood together with certain predictors which were neither psychological nor neurophysiological, such as quality of caregiving, headache, sleep, and even room temperature were related to BCI performance in some patients. Nijboer et al. [26] correlated mood and motivation with SMR-BCI performance. The authors showed that higher scores of mood and mastery confidence were related to better SMR regulation abilities, whereas higher rates of fear of incompetence were correlated to lower SMR regulation abilities. Furthermore, [27] obtained a positive correlation between a Locus of control score related to dealing with technology and the accuracy of BCI control. Fear of the BCI system was also shown to affect performance [27–29]. Finally, Hammer et al. [30] showed that the psychological parameters they investigated (attention span, personality and motivation) play only a moderate role in one-session SMR-BCI control performance. However, their findings support the validity of the

"Blankertz's SMR predictor" [13] mentioned earlier (μ peak during relaxation) and they proposed a model for predicting SMR-BCI performance—including visuo-motor coordination (assessed with the Two-Hand Coordination Test) and the degree of concentration (assessed with the Attitudes Towards Work)—that reached significance. In a recent study, Hammer et al. [14] 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 the SMR-BCI performance in a linear regression. However, the first predictor, i.e., visuo-motor coordination, failed significance. With this model, the average prediction error was less than 10%.

To summarise, all the studies concerning BCI-performance predictors considered either Band Power values for SMR-BCIs, or Slow Cortical Potentials (SCP). As stated by [18], "it remains to be seen if similar results can be obtained for BCI systems not [only] based on motor paradigms". Furthermore, most of the previous studies were based on a few runs, most of the time recorded during a one-session experiment. Yet, except for SCP-BCI [25], it has not been shown that first session performance was 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 trained during the first session, (2) the fact that the cap position can change, (3) the EEG-signal non-stationnarity or (4) the novelty effect. Finally, there is only one study, by Hammer et al. [30], in which psychological factors were combined with a neurophysiological predictor [13] to determine a predictive-model of motor-imagery based BCI performance.

The main contribution of this paper is to propose a predictive model 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. Their average performance over the six sessions they attended was then set as the variable to explain in a step-wise linear regression. The scores obtained at the different psychometric tests as well as neurophysiological predictors were used as explanative factors.

Materials and Methods

Participants

18 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 [31]).

Variables and Factors

The aim of this study was to evaluate the impact of different psychological and neurophysiological parameters 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 and of the values of neurophysiological markers on the variable "MI-BCI classification performance" was evaluated.

Experimental Paradigm

Each participant took part in 6 sessions, on 6 different days spread out over several weeks. Each session lasted around 2 hours and was organised as follows: (1) completion of psychometric questionnaires, which are described in the next section (around 30 min), (2) installation of the EEG cap (around 20 min), (3) five 7-minute runs during which participants had to learn to perform three MI-tasks (around 60 min, including breaks between the runs) and (4) uninstallation and debriefing (around 10 min). The MI-tasks (i.e., left-hand motor imagery, mental rotation and mental subtraction) were chosen according to Friedrich et al. [32], who showed that these tasks were associated with the best performance. "Left-hand motor imagery" (*L-HAND*) refers to the kinesthetic continuous imagination of a left-hand movement, chosen by the participant, without any actual movement [32]. "Mental rotation" (*ROTATION*) and "mental subtraction" (*SUBTRACTION*) correspond respectively to the mental visualisation of a 3 Dimensional shape rotating in a 3 Dimensional space [32] 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 [32].

During each run, participants had to perform 45 trials (15 trials per task x 3 MI-tasks, presented in a random order), each trial lasting 8s (see Fig 1). At t = 0s, an arrow was displayed with a left hand pictogram on its left (*L-HAND* task), the subtraction to be performed on top (*SUBTRACTION* task) and a 3D shape on its right (*ROTATION* task). At t = 2s, a "beep" announced the coming instruction and one second later, at t = 3s, a red arrow was displayed for 1.250s. The direction of the arrow informed the participant which task to perform, e.g., an arrow pointing to the left meant the user had to perform a *L-HAND* task. In order to stress this information, the pictogram representing the task to perform was also framed with a white square until the end of the trial. Finally, at t = 4.250s, a visual feedback was provided in the shape of a blue bar, the length of which varied according to the classifier output. Only positive feedback was displayed, i.e., the feedback was provided only when there was a match between the instruction and the recognised task. The feedback lasted 4s and was updated at 16Hz, using a 1s sliding window. During the first run of the first session (i.e., the calibration run, see next Section), as the classifier was not yet trained to recognise the mental tasks being performed by the user, it could not provide a consistent feedback. In order to limit biases with the other runs, e.g., EEG changes due to different visual processing between runs, the user was provided with an equivalent sham feedback, i.e., a blue bar randomly appearing and varying in length, and not updated according to the classifier output as in [32]. A gap lasting between 1.500s and

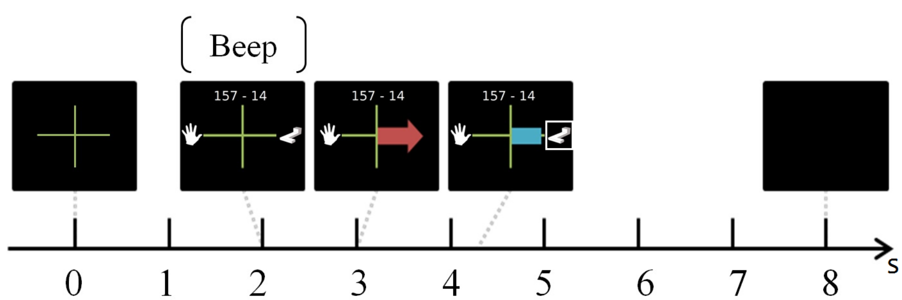

Fig 1. Timing of the protocol.

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3.500s separated each trial. At the end of the 5 runs, participants were asked to rate their arousal on the Self-Assessment Manikin scale [33] and to rate their invested mental effort on the Rating Scale Mental Effort [34].

EEG Recordings & Signal Processing

The EEG signals were recorded from a g.USBamp amplifier (g.tec, Graz, Austria), 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) [32], referenced to the left ear and grounded to AFz. EEG data were sampled at 256 Hz.

In order to classify the 3 mental imagery tasks on which our BCI is based, the following EEG signal processing pipeline was used. First, EEG signals were band-pass filtered in 8–30Hz, using a Butterworth filter of order 4. Then EEG signals were spatially filtered using 3 sets of Common Spatial Pattern (CSP) filters [35]. The CSP algorithm aims at finding spatial filters whose resulting EEG band power is maximally different between two classes. Each set of CSP filters was optimised on the calibration run of each user (i.e., the first run of the first session) to discriminate EEG signals for a given class from those for the other two classes. We optimised 2 pairs of spatial filters 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 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 overlap between consecutive time windows) and log-transformed. These resulted in 12 band-power features that were fed to a multi-class shrinkage Linear Discriminant Analysis (sLDA) [36], 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 left-hand motor imagery, mental rotation and mental subtraction during the 6 user-training sessions. The sLDA classifier output (i.e., the distance of the feature vector from the LDA separating hyperplane) for the mental imagery task to be performed was used as feedback provided to the user. In particular, if the required mental task was performed correctly (i.e., correctly classified), a blue bar with a length proportional to the LDA output and extending towards the required task picture was displayed on screen and updated continuously. If the required mental task was not correctly classified, no feedback was provided, i.e., we provided positive feedback only, as in the study of Friedrich et al. [32]. To reduce between session variability, the LDA classifiers' biases were re-calculated after the first run of the sessions 2 to 6, based on the data from this first run, as in [32]. EEG signals were recorded, processed and visually inspected with OpenViBE [37].

Personality and Cognitive Profile Assessment using Psychometric Questionnaires

At the beginning of each of the 6 sessions, participants were asked to complete different validated psychometric questionnaires, to assess different aspects of their personality and cognitive profile, that have been related to learning in the literature. During the first session all the participants completed the same questionnaires: the information form, the *Harris Lateralisation test* and the *State Trait Anxiety Inventory*. During the other sessions (2 to 6) the administration order of the remaining questionnaires was counterbalanced for all the participants, in the aim of avoiding order effects. Thus, we ensured that the administration time of the tests did not exceed 45min per session: it lasted 30min on average. The following questionnaires were used:

- 6 subscales of the *Wechsler Adult Intelligence Scale* (WAIS-IV) [38], 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* [39] focuses on visuo-spatial short term and working memory abilities.
- the *Revised Visual retention test* [40] quantifies visual retention abilities as well as perceptive organisation.
- the *Learning Style Inventory* (LSI) [41] 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) [42] 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) [43] is a multi-dimensional locus of control assessment.
- the *State Trait Anxiety Inventory* (STAI) [44] is composed of two subscales, STAI Y-A and STAI Y-B, which respectively measure anxiety as a state and anxiety as a trait. Thus, participants were asked to complete STAI Y-B at the first session only, while they were asked to complete the STAI Y-A at the beginning of each session.
- the *Bruininks-Oseretsky Test of Motor Proficiency* (BOT-2) [45] evaluates motor abilities; based on Hammer et al. [30]. We considered only some subtests evaluating bilateral and upper limb coordination as well as fine motor skills.
- the *Mental Rotation test* [46] measures spatial abilities.
- the *Arithmetic test* [38] is one of the WAIS-IV sub scales, measuring working memory abilities and more specifically the ability to concentrate while manipulating mental mathematical problems.

Neurophysiological Predictors of BCI Performance

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 (2500ms to 500ms before the instruction) and in-trial (500ms to 3500ms after the feedback start). Low α-power in fronto-parietal networks has been shown to be associated to a high attentional level [22, 47].
- β-power [16–24Hz] over each electrode, measured pre-trial and in-trial. In the paper of Ahn et al. [20], 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 [48]. High θ-power has also been shown to be related to cognitive, and more specifically to memory performance, when combined with high α power [47].

- γ-power over each electrode, measured pre-trial and in-trial. High pre-trial fronto-parietal γ-power has been associated with attentional processes [19]. Also, the ability to modulate SMR has been shown to be negatively correlated to γ power in occipital areas [18]. It has to be noted that muscular activity can represent a confounding factor as it is also correlated with γ power [18].
- the predictor proposed by Bambadian et al. [22] was calculated on pre-trial (2500ms to 500ms before the instruction). It is claimed to reflect the participant's attentional level as the latest is, 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 $C_\theta = [F_3, F_z, F_4]$, $C_\alpha = [P_7, P_3, P_Z, P_4, P_8]$ and $C_\beta = [C_Z, Cp_Z]$.

- the predictor proposed by Ahn et al. [20] was computed on electrodes C_3 and C_4 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 [13] 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 SMR-predictor were computed for each trial, then averaged over all trials, runs and sessions for each subject. The Blankertz 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.

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 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.

Results

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 $\alpha = 5\%$ [49]. 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 [50]. Moreover, no gender effect [$t_{15} = -1.733$, $p = 0.104$] was noticed.

Correlations between performance and neurophysiological predictors

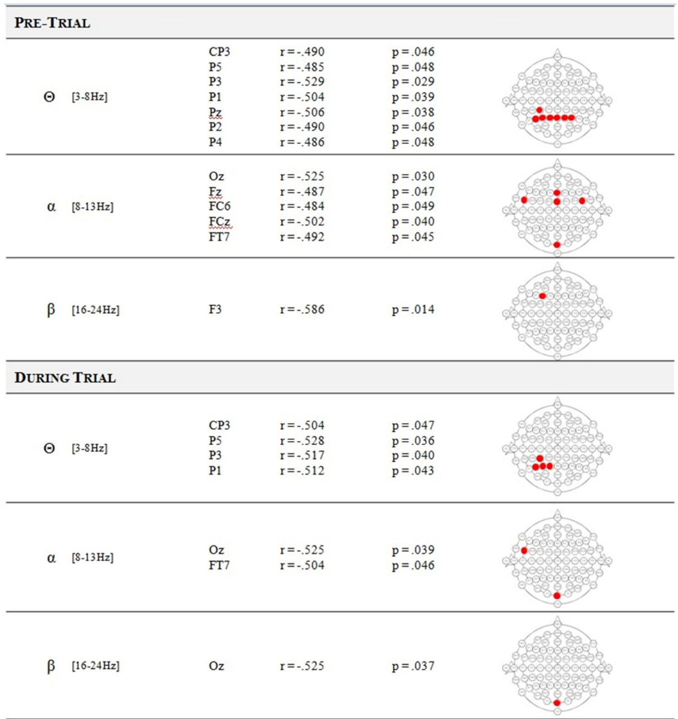
Bivariate Pearson correlation analyses between MI-BCI performance and different neurophysiological patterns (i.e., α-power, β-power, θ-power, γ-power, Bamdadian, Ahn and Blankertz predictors) were performed. First, results showed no correlations between MI-BCI performance and the Bamdadian predictor, 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 in-trial measurements and (3) β-power: FT7 in pre-trial and Oz in in-trial measurements. These results are depicted in Fig 2. However, all these correlations failed to reach significance after a Positive False Discovery Rate (pFDR) correction for multiple comparisons [51].

Correlations between performance and psychometric tests

Bivariate Pearson correlation analyses revealed correlations between MI-BCI performance and (1) Mental Rotation scores [$r = 0.696$, $p < 0.005$], (2) Tension [$r = -0.569$, $p < 0.05$], (3) Abstractness ability [$r = 0.526$, $p < 0.05$] and (4) Self-Reliance [$r = 0.514$, $p < 0.05$] (see Fig 3). Tension, abstractness 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, abstractness 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 [$p < 0.05$] [51].

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



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

Fig 2. Correlations between MI-BCI performance and neurophysiological markers. Statistically 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.

doi:10.1371/journal.pone.0143962.g002

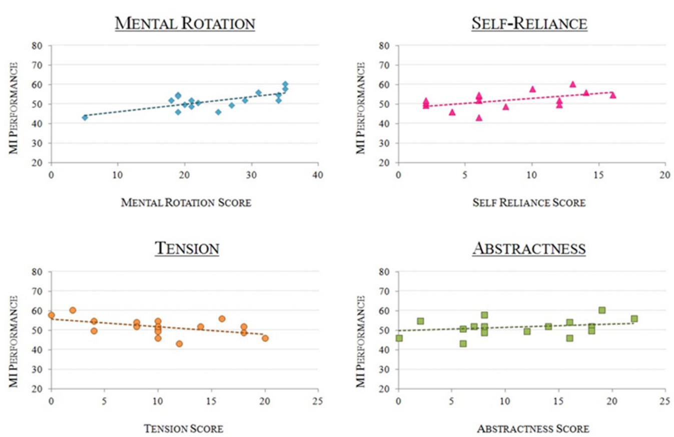


Fig 3. MI-BCI Performance as a function of personality profile. Graphs representing the participants' MI-BCI performances as a function of (1) Mental Rotation scores -top left-, r = 0.696; (2) Self-Reliance -top right-, r = 0.514; (3) Tension -bottom left-, r = -0.569; (4) Abstractness -bottom right-, r = 0.526.

doi:10.1371/journal.pone.0143962.g003

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

Fig 4. 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 [$R^2_{adj} = 0.962$, $p < 0.001$].

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the dimensionality of the problem (and thus avoid the Curse-of-Dimensionality [52]), while all the psychometric test scores were used (43), only the neurophysiological predictors 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 4): 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.

The first step of the 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]).

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 [53, 54]. Moreover, the mental rotation score is most probably mainly related to the performance at the mental rotation imagery task, and therefore not independent of the mental tasks used in this specific BCI. 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 5 and including 4 parameters: Tension, Abstractness, the Learning Style "Active/Reflective" subscale and Self-Reliance. Tension, Abstractness 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 6 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, Abstractness, 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, Abstractness and the Digit Span subscale of the WAIS-IV were included.

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 7. 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)

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

Fig 5. Characteristics of Model ♯2. This model included 4 factors: Tension, Abstractness, the "Visual/Verbal" dimension of the Learning Style and Self-Reliance. Abstractness, 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].

doi:10.1371/journal.pone.0143962.g005

Training DataSet	Step-Wise Linear Regression Model								$R^2_{adjusted}$
	Constant	Tension	Abstracteness	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

Fig 6. 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.

doi:10.1371/journal.pone.0143962.g006

	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

Fig 7. 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.

doi:10.1371/journal.pone.0143962.g007

the error of the model, i.e., $Perf_{predicted}$—$Perf_{real}$. 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 (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 generalize to new subjects and predict their MI-BCI performances from their personnality and cognitive profile. More precisely, the chance level model (obtained with the permutation test) predicted an average accuracy of 51.6331 ± 0.8620%, which corresponds to an absolute average error of 4.6859 ± 0.8752%. The chance-level predictions for each subject are displayed on Fig 7.

Relationship between Model ♯2 and Mental Rotation Scores

Fig 8 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 corresponding 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 [46]. 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

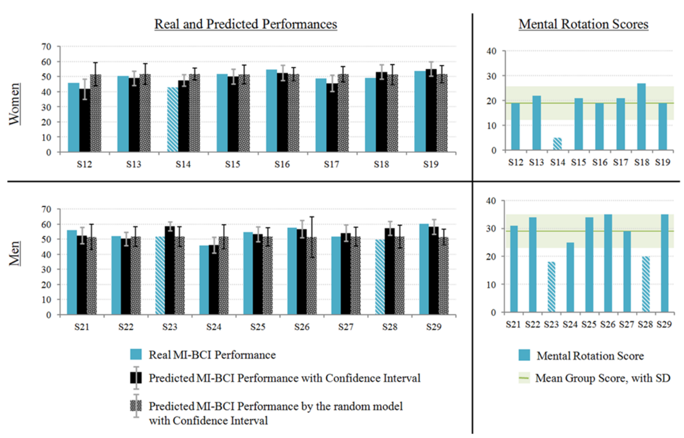

Fig 8. Real and predicted BCI performance as well as Mental Rotation scores according to the gender. Women's results are shown at the top, men's results on bottom. On the left, the graphical representation of the real (left) and predicted (right) BCI-performance of each participant, with the corresponding 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).

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on the graphs on the right of Fig 8. The rectangle surrounding this line represents the mean ± 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.

Discussion

In this paper, we proposed a predictive model 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, e.g., 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-.

Five 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 and these predictors were not selected in the regression. Thus, 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. The third result is the definition of Model ♯1 which 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, the fourth major result is 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, abstractness, 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. It should be noted that since we averaged the BCI performances over the 6 sessions, the performance variance across subjects was rather low. As such, although our model predicted the performance significantly better than chance, the obtained error rate was not that low as compared to that obtained by a random model. Nonetheless it was still better, and, more importantly, it enabled us to identify the relevant factors (cognitive profile and personality) linked to BCI performances. Finally, the fifth and very interesting result is the complementarity between MODEL ♯2 and mental rotation scores. Indeed, the only participants for whom MODEL ♯2 failed, by overrating their performances, were the participants with a very low mental rotation score. These results are discussed in the following paragraphs.

A first very interesting result is the prominent role of mental rotation scores: this factor is highly correlated with MI-BCI performance, is the first one to be selected in MODEL ♯1 and brings relevant additional information to MODEL ♯2 to predict MI-BCI performance. Mental rotation scores reflect spatial abilities [55], i.e., the capacity to understand 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, it is obviously related with the mental rotation task. Second, [56] 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 [57]. The close relationship between mental rotation and the three MI tasks 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.

Two other personality factors were strongly 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 occuring in a context free of social interaction (the learner interacts with a computer, there are no teachers or students). Indeed, on the one hand, [58] 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 distance education such as the one presented in this study. On the other hand, in [59], autonomy is presented as being of utmost importance in independant learning, and thus in distance 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. An alternative hypothesis could also be that users that are more self-reliant may comply better with the BCI tasks, i.e., they really and conscientiously perform the required tasks—which other users might not do as well—which in turns leads to higher classification accuracy. However, since we do not have the ground truth of whether users did comply with the required tasks, we cannot verify this hypothesis. This seems nonetheless a less likely hypothesis than the ones related to distant learning, which are more theoretically solid.

The *abstractness* dimension of the 16 PF-5 was also correlated with MI-BCI performance and included in Model ♯2. Abstractness refers to creativity and imagination abilities. It has been reported that creative people frequently use mental imagery for scientific and artistic productions [60] which could explain why participants with high abstractness abilities are more used to 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 [61]. While active learners like testing and discussing the information, reflective learners need more time to think and examine it introspectively. As stated in [61], 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, [62] showed that motor-imagery performances are higher when the subjects use active kinesthetic 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 overrating 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, abstractness 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 influencial, it has the upper hand and decreases MI-BCI performance. In this case, the model's overrating 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.

This model should now be tested on larger and more heterogenous 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.

This study has highlighted the huge impact of spatial abilities on MI-BCI performance. Future work will consist in designing new kinds of MI-BCI training protocols aiming at improving users' spatial abilities, prior to MI-BCI use. Concretely, based on his/her basic spatial abilities, the user will be provided with specific exercices. The difficulty of these exercices will increase gradually, according to the user's results, to end with complex MI tasks allowing to control an MI-BCI. It would also be interesting to adapt the MI-tasks to each user so that they are optimal for each of them.

Furthermore, in order to take into account the personality factors related to MI-BCI performance, a virtual learning companion will be developped. It will be able to provide the user with (1) cognitive support (e.g., by proposing examples) in the case of students with low abstractness abilities, (2) emotional and social support, notably social presence by giving advice and collaborating during the training procedure, for users with high "tension" and low "self-reliance" scores.

We hypothesise that by combining tindividualised training to improve the users' spatial abilities with a virtual learning companion providing a user-specific support in an intelligent tutoring system [63], MI-BCI training will be more user friendly.

This improved training protocol could potentially increase acceptability and accessibility of MI-BCI based technologies, which are extremely promising for improving living standards of severly motor disabled patients and their families, for stroke rehabilitation, for leisure (e.g., video games) or for education.

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Author Contributions

Conceived and designed the experiments: CJ BN SS MH FL. Performed the experiments: CJ. Analyzed the data: CJ BN FL. Contributed reagents/materials/analysis tools: CJ BN FL. Wrote the paper: CJ BN SS MH FL.

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EEG-based workload estimation across affective contexts

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Workload estimation from electroencephalographic signals (EEG) offers a highly sensitive tool to adapt the human–computer interaction to the user state. To create systems that reliably work in the complexity of the real world, a robustness against contextual changes (e.g., mood), has to be achieved. To study the resilience of state-of-the-art EEG-based workload classification against stress we devise a novel experimental protocol, in which we manipulated the affective context (stressful/non-stressful) while the participant solved a task with two workload levels. We recorded self-ratings, behavior, and physiology from 24 participants to validate the protocol. We test the capability of different, subject-specific workload classifiers using either frequency-domain, time-domain, or both feature varieties to generalize across contexts. We show that the classifiers are able to transfer between affective contexts, though performance suffers independent of the used feature domain. However, cross-context training is a simple and powerful remedy allowing the extraction of features in all studied feature varieties that are more resilient to task-unrelated variations in signal characteristics. Especially for frequency-domain features, across-context training is leading to a performance comparable to within-context training and testing. We discuss the significance of the result for neurophysiology-based workload detection in particular and for the construction of reliable passive brain–computer interfaces in general.

Keywords: workload, stress, brain–computer interface, classification, electroencephalography, passive brain computer interface

INTRODUCTION

The increasing complexity and autonomy of information systems rapidly approaches the limits of human capability. To avoid overload of the users in highly demanding situations, a dynamic and automatic adaptation of the system to the user state is necessary. Reliable knowledge about the user state, especially his workload, is a key requirement for a timely and adequate system adaptation (Erp et al., 2010). Examples are systems supporting air traffic control, pilots, as well as medical and emergency applications.

Conventional means of workload assessment, such as self-assessment and behavior, are intrusive or limited in their sensitivity, respectively (Erp et al., 2010). Physiological sensors, assessing for example the galvanic skin response (GSR) or elecrocardiographic activity (ECG), offer an unobtrusive and continuous measure that has been found sensitive to workload (Verwey and Veltman, 1984; Boucsein, 1992). In the last two decades, neurophysiological activity became popular as a modality for the measurement of mental states in general and of workload in specific. So-called "passive brain-computer interfaces" (pBCI, Zander and Kothe, 2011) are able to measure neuronal activity in terms of the electrophysiological activity of neuron populations as in the case of EEG or the oxygination of the cerebral blood flow as for functional near-infrared spectroscopy (fNIRS). Both approaches have been found informative regarding the detection of cognitive load (Brouwer et al., 2012; Solovey et al., 2012), and there is evidence for a partially superior sensitivity of neural measurements compared to other physiological sensors (Mathan et al., 2007) or self-report (Peck et al., 2013).

Most experiments on passive BCI use a very controlled approach, which naturally limits the range of real-world conditions they reflect. While this control is necessary to ensure the psychophysiological validity of the mental state detection, their results lack a certain ecological validity, they can not be generalized to other contexts. This might be one of the most impeding problems for the creations of passive BCI systems that work in the real world, since daily life is characterized by the variability of the conditions we function under. A prominent example are changes of affect while working, for example working under the pressure of an impending evaluation vs. work without pressure. A system that is supposed to work in such contexts needs to be calibrated and tested in them. Previous research in the domain of pBCI largely ignored the problem. To shed light on the interaction of mental state classification and change of affective context, we devised a protocol that recreates conditions of work, requiring different effort, during relaxed conditions and under psychosocial stress in a controlled environment. To study the resilience of a state-of-the art workload detection system to changes in affective context, we train subject-specific classifiers in either stressed or non-stressed context and test their performance within the same and in the other context.

In summary, the contributions of this paper for the study of the effect of affective context on workload classification are:

1. The creation and validation of a novel protocol to test interactions of workload classifier performance and affect[1].
2. The design and evaluation of a workload classifier generalizing across affective contexts.
3. Quantifying the impact across affective context generalization on classification performance, with and without across context-training.

Below, we will give the reader some background to neurophysiology-based detection of workload under varying (affective) user states and its potential interactions with stress responses. Then, we will introduce the employed approaches to manipulate the user's mental state, the used devices, and the applied signal processing and classification algorithms. We will then report the nature of the found effects, discuss their relevance, and conclude with the general consequences and limitations of the presented findings.

RELATED WORK

DETECTION OF WORKLOAD FROM NEUROPHYSIOLOGY

Mental workload can be defined as (perceived) relationship between the amount of mental processing capability and the amount required by the task (Hart and Staveland, 1988). The closer the requirements are to the actual capabilities, the higher is the (perceived) workload. Therefore, a general strategy for workload manipulation is the manipulation of task demand or difficulty (Gevins et al., 1998; Grimes et al., 2008; Brouwer et al., 2012), though alternative strategies, such as the manipulation of feedback or participant motivation (Fairclough and Roberts, 2011), exist.

Already in 1998, Gevins et al. (1998) showed that EEG is a viable source of information regarding the workload of a person, enabling 95% accuracy when using about 30 s of signal. However, there are many factors that can affect the performance of classification algorithms, such as the number of training data available, their distribution, their separability between classes, the data signal-to-noise ratio, the similarity (in terms of data distribution) of the training data and testing data, etc. (Duda et al., 2001). The estimation of these performances also depends on the number of testing data available (Müller-Putz et al., 2008), and the way they are estimated (cross-validation, independent test set). Finally, more BCI-specific factors affect the performances, such as whether the classification is subject-specific or subject-independent (see, e.g., Lotte et al., 2009), which subjects are used (there is a huge between-subject variability), whether the training and testing data are from the same session (e.g., same day) or not, etc. (Lotte et al., 2007). In this regard, Grimes et al. (2008) showed that a number of factors, such as the numbers of channels, amount of training data, or length of trials, have a strong influence on classification performance of workload classifiers. For example, reducing the length of the signal from 30 to 2 s reduces the classification performance on two workload levels from almost 92% to about 75%. Similar tradeoffs between optimal and practical signal processing settings are reported for channel number and training time. Another work, by Brouwer et al. (2012), studied in a similar setup the feasibility of different types of features (i.e., from the time- and frequency-domain, and combined) to differentiate workload levels, finding that the different feature types work comparably well with accuracies of about 85% after 30 s. Reducing the signal length to 2 s reduced the accuracy to about 65%. Zarjam et al. (2013) showed that workload manipulated by an arithmetic task can be classified with a performance of 83% for seven workload levels. Walter et al. (2013) tested the generalization of workload classifier from simple tasks, such as go/no-go, reading span, n-back tasks, to complex tasks involving diagram and algebra problems. While they were able to train well-performing classifiers for the simple tasks, reaching performances of about 96% for two classes on signals of a few seconds length, a cross-testing of a workload classifier trained on a simple task to a complex task did not succeed. However, since in both studies the order of workload levels was not randomized, a temporal trend present in the features could have biased the results toward a higher accuracy. Overall, these studies show that the workload level can be classified from neurophysiological activity. Indeed, it has also been suggested that neurophysiological information is more sensitive than information from other physiological signals (Mathan et al., 2007). Most importantly, these studies show that different factors, mainly methodological differences in workload induction, signal acquisition and processing, can have significant influences on the classification results.

However, to date there have only been few studies regarding the influence of the mental state changes during training and testing on the classifier performance. For active BCI, Reuderink and colleagues studied the influence of frustration on left and right hand movement classification during a computer game, using freezing screens and button malfunctions as induction tools (see Reuderink et al., 2013). The resulting loss of control (LOC) during "frustrating" episodes, surprisingly led to higher classification performance than during normal, relaxed game play (Reuderink et al., 2011). Zander and Jatzev (2012) induced LOC in a similar way during a simple behavioral task, the RLR paradigm, which resulted in lower classification performance. For passive BCI and specifically for workload level detection, only Roy et al. (2012) tested the impact of fatigue on EEG signal characteristics and workload classification performance. With increasing fatigue, the differentiating signal characteristics diminished and, consequently, the classification performance declined. This lack of research on interactions between passive BCI and changes in user state is problematic, since BCIs in general have been found susceptible to changes in task-unrelated mental states during classification, such as attention, fatigue or mood. Specifically, it is believed that variations in task-unrelated mental states are partially responsible for what is called non-stationarities of the signal, the change of its statistical properties over time, and thereby the source of one of the most notorious problems for BCI (Krusienski et al., 2011; van Erp et al., 2012).

In the next section, we will briefly introduce the concept of stress, which is another possible contextual factor influencing workload estimation that is occurring during daily life and work, and thus might be a relevant source of variance for workload detection devices.

[1]The validation of the administered stress-induction protocol was presented at the PhyCS 2014 conference (see Jeunet et al., 2014 for more details).

STRESS RESPONSES AND WORKLOAD

The psychophysiological concept of "stress," was introduced in 1936 by Selye (1936) to describe "the non-specific response of the body to any demand for change." In that sense, it is an organism's response to an environmental situation or stimulus perceived negatively—called a "stressor"—which can be real or imagined, that taxes the capacities of the subject, and thus has an impact on the body's homeostasis (that is to say that the constants of the internal environment are modified). To face the demand (i.e., to restore homeostasis), two brain circuitries can be activated during a "stress response cascade" (Sinha et al., 2003; Dickerson and Kemeny, 2004; Taniguchi et al., 2009): the sympatho-adrenomedullary axis (SAMa, also called the noradenergic circuitry) and the hypothalamus-pituitary gland-adrenal cortex axis (HPAa). On the one hand, the SAMa induces the release of noradrenaline which allows immediate physical reactions (such as increased heart rate and skin conductance, or auditory and visual exclusion phenomena) associated with a preparation for violent muscular action (Dickerson and Kemeny, 2004). On the other hand, the HPAa activation (which is lower) results in the releasing of cortisol the purpose of which is to redistribute energy in order to face the threat. Thus, more energy is allocated to the organs that need it most (brain and heart), while non-necessary organs for immediate survival (reproductive, immune and digestive systems) are inhibited. This stress response cascade ends when homeostasis is restored.

However, stress can be of different types, such as physical, psychological or psychosocial (Dickerson and Kemeny, 2004), each kind of stress being associated with a specific response. Indeed, physical stress, induced by extreme temperatures or physical pain for example, is associated with an increase of heart rate (Loggia et al., 2011), skin conductance (Boucsein, 1992; Buchanan et al., 2006) and subjective stress ratings but with only a weak cortisol response (Dickerson and Kemeny, 2004). These results suggest that this kind of stress induces an activation of the SAMa but only a weak activation of the HPAa. Psychological or mental stress, associated with difficult cognitive tasks, uncontrollability or negative emotions is associated with a weak release of cortisol (weak HPAa activation), but strong effects on heart rate and skin conductance (strong SAMa activation) (Boucsein, 1992; Reinhardt et al., 2012). Finally, psychosocial stress, triggered by a social evaluation threat (that is to say a situation in which the person's own estimated social value is likely to be degraded), and added to by a feeling of uncontrollability (in particular during the Trier Social Stress Task (TSST) Kirschbaum et al., 1993), has been shown to induce a strong activation of both the SAMa (Hellhammer and Schubert, 2012) and the HPAa (Dickerson and Kemeny, 2004).

Psychosocial stress and workload potentially can interact on physiological, neurophysiological and behavioral levels. Since workload can also be understood as the response to a particular type of psychological stressor, such as increased task demand, both concepts are associated with the activation of the sympathetic nervous system (see SAMa above). Furthermore, psychosocial stress and workload share also neurophysiological responses. From research in the neurosciences, and consistent with the notion of neural response systems, we know that stress has strong correlates in the EEG as well. One of the most prominent correlates of anxiety, as induced by psychosocial stress, is found in the alpha band, and specifically in brain asymmetry. Tops et al. (2006) proposed that cortisol administration (which simulates a stress situation) leads to a global decrease of cortical activity (except for the left frontal cortex in which activity is increased). However, other studies (Lewis et al., 2007; Hewig et al., 2008) showed that stress was associated with a higher activity in the right hemisphere, and that the right hemisphere activation was correlated with negative affect. For Crost et al. (2008), the explanation of these conflicting results would be that an association between EEG-asymmetry and personality characteristics, such as anxiousness, may only be observed in relevant situations to the personality dimensions of interest. For workload, on the other hand, we know that the alpha band plays a role in terms of increased sensory processing leading to decreased occipito-parietal alpha power (Gevins et al., 1998; Brouwer et al., 2012), as well as for frontal alpha asymmetry covarying with changes in engagement (Fairclough and Roberts, 2011). From a theoretical point of view, Eysenck and Derakshan (2011) suggested that increasing anxiety, for example due to psychosocial stress, has effects on different cognitive processes, leading to impaired processing efficiency and performance effectiveness. Specifically for workload-related processes, their "attentional control theory" suggests that anxiety impairs efficient function of inhibition and shifting mechanisms of the central executive, subsequently decreasing attentional control and increasing distraction effects of irrelevant stimuli. However, these deficits might not necessarily lead to decreases of performance if they are compensated by alternative strategies, such as enhanced effort.

Summarizing, increases in workload, as induced by higher task demand, can be subsumed under the concept of psychological stress and have been found to lead to increasing physiological and neurophysiological activity that has also been found responsive to anxiety as induced by psychosocial stress. Furthermore, cognitive theories propose links between anxiety and pre-attentional and attentional cognitive processes, which are expressed in behavior and physiology. Due to these possible interactions of workload and stress, it seems relevant to experimentally study the effect of stress on workload detection.

RESEARCH QUESTIONS

The work on the effects of potential contextual factors, such as moods or fatigue, on the stability of BCI performance, and the physiological and psychological links between stress and cognitive processes suggests that stress can be a relevant factor influencing the classification of workload levels. In more general, the findings of context-dependency of BCI performance make it seem imperative to explore the effect of factors, such as mood, on brain signals and classifier performance, to gain insight into the relevance of task-unrelated mental states on classifier performance, and to find ways to render classifiers robust against such changes. Specifically, for the development of reliable passive BCIs in the wild, those functioning robustly in private or work environments, the influence of contextual changes of mental states that are predominant in the context of application have to be explored. That is why we test the robustness of three workload classifiers, using features from either frequency-, time-, or both domains, to the influence of (psychosocial) stress. We let participants work under different levels of workload, while either under the impression of being observed and validated, or while being relaxed and free from this kind of pressure. We are interested in the effect of the contextual manipulation of stress on the classifier performance and in testing cross-context training as a simple and straightforward remedy to the problem. Thus, we address the following questions:

Q1: Can we induce stress and workload in a controlled manner? We validated stress and workload manipulation of our experimental protocol using participants' self-assessments, behavioral performance, and physiological indicators of sympathetic nervous system (SNS) activation (i.e., GSR, ECG). Stress is expected to increase perceived anxiety and SNS activity, while workload increase should be reflected in increased perceived arousal and mental effort, decreased performance, as well as increased SNS activity (Verwey and Veltman, 1984; Boucsein, 1992).

Q2: Can we train a workload classifier based on the data collected via this protocol? To ensure that we are using a state-of-the-art workload classifier, we trained the classifier on all data, irrespective of context, as done in conventional studies. We expect a performance of about 70% as shown by Grimes et al. (2008) and Brouwer et al. (2012) under similar conditions.

Q3: Does the classifier generalize across affective contexts, and if so, how well? To study the effect of different affective contexts on the classification performance, we compared the results from classifiers trained in either stressful or non-stressful context and applied it then to test data from the same ("within") or the other context ("across"). We expect a higher "within" compared to "across" performance to indicate the difficulty of the classifier to generalize.

Q4: Does training based on multiple context render the classifier resistant against changes in affective context,and if so, how resistant? To test if the training with combined data from both affective contexts is effecting the classifier's capability to generalize, we compare the performance depending on the training context ("single," that is training on only stress or non-stress context, or "combined," that is training over contexts) and expect higher performance for a classifier trained on data from the combined contexts.

MATERIALS AND METHODS

As mentioned before, we designed a protocol in which subjects had to do cognitive tasks involving two levels of mental workload, manipulated via task difficulty, while being exposed to two levels of psychosocial stress. We used the EEG signals collected with this protocol to design and assess a workload classifier across different stress conditions. This section describes in details the subjects involved, the protocol and the method to validate it, the EEG-based workload classifier used and the evaluations performed with it.

PARTICIPANTS

Twelve female and twelve male participants were recruited for our experiment. The participants were between 18 and 54 years old, with a mean age of 24.7 ± 7.9, and except four all were right-handed. Educations varied between high school degree and Ph.D., with a mean education of 3.1 ± 2.4 years after high school. To be admitted, people had to be at least 18 years, to speak the local language and to sign an informed consent. Furthermore, non-inclusion criteria were applied: bad vision, heart condition, neurological or psychological diseases, and affective troubles. Moreover, people were asked to select a time for the experiment in which they would feel alert. Finally, we asked them not to drink coffee and tea less than 2 h before the experiment.

MATERIAL

For our recordings, we used the following sensors: ElectroEncephaloGram (EEG, 28 active electrodes in a 10/20 system without T7, T8, Fp1, and Fp2), ElectroCardioGram (ECG, two active electrodes), facial ElectroMyoGram (EMG, two active electrodes), ElectroOculoGram (EOG, four active electrodes), breath belt (SleepSense), pulse (g.PULSEsensor), and a galvanic skin response sensor (g.GSRsensor). All sensors were connected and amplified with three synchronized g.USBAmp amplifiers (g.tec, Austria). The workload task was designed in the Presentation software (Neurobehavioral Systems, www.neurobs.com/presentation) and EEG signals were recorded and visually inspected with Open ViBE (Renard et al., 2010). **Figure 1** shows a participant sitting fully-wired in the experimental environment.

Subjects were first asked to sign an informed consent and to fill out three questionnaires: one assessing personal characteristics (such as gender, age and education) and form Y-A (anxiety state) and Y-B (anxiety trait) of the State-Trait Anxiety Inventory (STAI) (Spielberger et al., 1970) (see below for details). Then, all the sensors were installed and a 3 min baseline recorded. To avoid order effects, we counterbalanced the order of stress and relax condition (affective context) and 0-back and 2-back task (workload blocks), resulting in four scenarios (see **Figure 2A**). Each scenario was composed of 12 workload blocks in the stressful and 12 workload blocks in the relaxed context. The scenarios therefore begin with either relaxation or stress induction, and the workload blocks either start with the low workload (0-back) or high workload (2-back) condition. In each affective context, the subject performs, in alternating order, six times each workload condition (low/high) ($6 \times 2 \times 2 = 24$ min per block), with a short break after six tasks (i.e., after about 12 min). After each context was absolved, that is

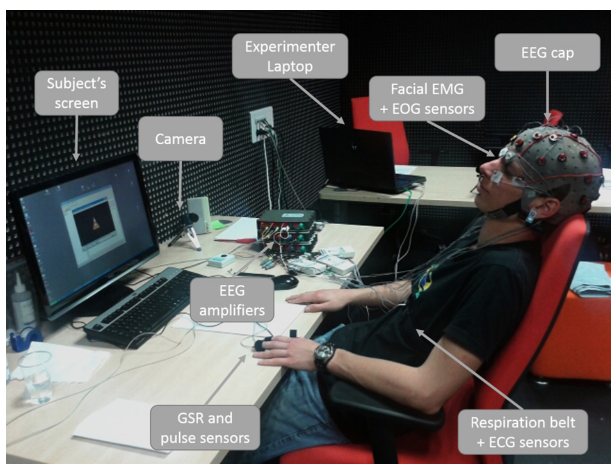

FIGURE 1 | A fully wired participant in the experimental environment during the relaxation induction period.

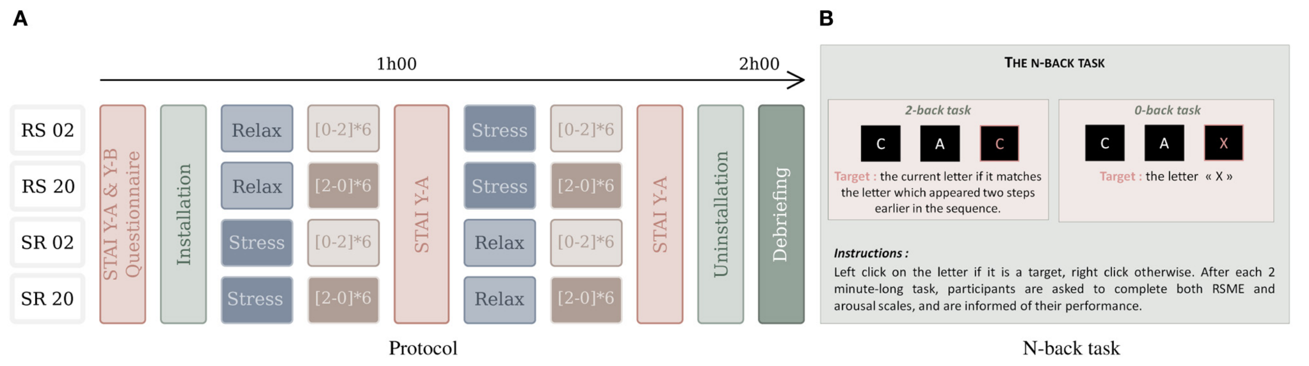

FIGURE 2 | The experimental protocol (A) with four scenarios, used for counterbalancing the order of conditions: the easy (0-back task) and difficult (2-back) workload tasks that follow the (R)elax and (S)tress induction procedures. "RS02" means that relaxation context is followed by stress context and that the interleaved workload blocks start with the 0-back condition. The N-back task **(B)** requires responses to target and non-target characters.

after the induction phase and the 12 workload blocks, the STAI form Y-A questionnaire was administered again to assess the anxiety state. Finally, the sensors were removed and the participant was debriefed about the aim of the experiment.

Stress and relaxation inductions

In order to manipulate stress, we used a stress-induction protocol based on the Trier Social Stress Task (TSST) (Kirschbaum et al., 1993) and a relaxation condition using a resting phase, music and/or videos. The stress-induction protocol is composed of three parts lasting together about 15 min and it requires the participation of three people, "the committee," who are presented as being body language experts. In the first part, a member of the committee asks the subject to prepare, during 5 min, a fake job interview for a position fitting the professional profile of the subject. During the second part, the committee asks the person to do this job interview and to speak about himself for 5 min. They tell the subject that he is filmed for a future behavioral analysis and take notes during the whole interview. The committee acts as being serious and neutral/unresponsive toward the subject. The third part is a 3 min long arithmetic task (the subject has to count from 2083 to 0 by steps of 13) and to begin again at any mistake or hesitation. At the end of this protocol, in order to keep the stress level high, the committee tells the subject he will be filmed during the workload tasks and that he will have to do another interview, which will be longer, and a self-evaluation based on the recorded film material after it. Furthermore, during the experiment, participants are receiving visual feedback about their performance in the workload tasks. During the stress condition, these feedbacks have been modified to display a performance 5–10% below their actual performance. Thereby, this protocol includes psychosocial stress and uncontrollability in order to maximize the chance to trigger a stress response for all the participants (Dickerson and Kemeny, 2004). On the other hand, the goal of the relaxation induction was to create a condition (referred to as "relax" condition) in which participants would be able to relax and thus execute the workload task without the influence of additional psychosocial and psychological stressors. To allow for an effective relaxation, participants were allowed to choose between resting in silence or select music/videos that would help them to feel calm (Krout, 2007). In order to measure the level of anxiety of the subjects and thereby to validate the stress/relax manipulation, the "State Trait Anxiety Inventory" (Spielberger et al., 1970) is used. It is composed of two scales of 20 propositions each: STAI form Y-A and STAI form Y-B. STAI form Y-A score measures anxiety state and is increased when the person currently experiences psychological stress. A college student (female/male) has a mean state anxiety index of 35/36, while values higher than 39/40 have been suggested to detect clinically significant symptoms (see Julian, 2011).

Workload tasks

We used the n-back task (Kirchner, 1958) as workload task (see **Figure 2B**), as it is easy to modify workload while keeping visual stimulation and behavioral motor requirements the same. Similar to Grimes et al. (2008) and Brouwer et al. (2012), we decided for a manipulation of task-difficulty to manipulate workload. Specifically, we used 0-back (low workload) and 2-back (high workload) varieties of the n-back task, which were presented in blocks of 2 min each. In both tasks, a stream of 60 white letters appears on a black background on the screen. Each letter is presented for 500 ms, followed by an inter-stimulus interval of 1500 ms. Among these letters, 25% are targets. In both tasks, when a letter appears, the subject is asked to perform a left mouse click if this is a target letter, and a right mouse click otherwise. For the 0-back task, the low workload condition, the target is the letter "X": each time an "X" appears, the subject has to do a left click, and in all the other cases he has to do a right click. For the 2-back task, the high workload condition, the subject has to do a left click if the letter that appears is the same as the one preceding the last letter. For example, if the sequence "C A C" appeared, the second "C" would be a target. At the end of each 2-min block, the subject has to report his level of arousal (on a scale from 1 to 9) (Bradley and Lang, 1994) and the perceived effort necessary to perform the task (Rating Scale of Mental Effort—RSME, Zijlstra, 1993). Finally, a screen with his performance during the block (see section 4.3.2) appears. As mentioned before, during the stressful condition, this displayed performance is lower than the actual performance to induce additional uncertainty.

PROTOCOL VALIDATION METHODS

Self-assessment data

To investigate the effect of the psychosocial stress induction on the STAI score, we computed an ANOVA with this score in the three factor-levels "baseline," "after relaxation," and "after stress induction." To assess the effect of both stress and workload manipulation, we conducted 2 (stress) × 2 (workload) ANOVAs for the averaged-over-blocks ratings on the arousal scale of the SAM and on the RMSE.

Behavioral data

To investigate the effects of the experimental manipulations on behavior, we calculated the performance per block based on the number of true positive (TP), true negative (TN), false negative (FN), and false positive (FP) responses resulting from the button presses within the n-back task (left click for targets, right click for non-targets) using the following equation: $Perf = \frac{(TP+TN)}{(TP+TN+FP+FN)}$. As for ratings, we analyzed the data in a 2 (stress) × 2 (workload) ANOVA.

Physiological data

Physiological responses were analyzed with respect to heart rate (HR) and galvanic skin response (GSR). Before applying statistical methods, the GSR data was pre-processed by extracting the mean GSR value (μS) for each block and then averaging these values over blocks as described above. The ECG signal was band-pass filtered between 5 and 200 Hz, applying a notch-filter 48–52 Hz to reduce power line noise, before mean HR for each of the blocks was extracted. As for the former analyses, we analyzed the data with a 2 (stress) × 2 (workload) ANOVA. We are reporting data as significant if $p < 0.05$ and as trend if $p < 0.1$. For all ANOVAs partial eta squared values ($\eta_p{}^2$) are calculated as a measure of effect size.

EEG SIGNAL PROCESSING

Our system aims at estimating the level of mental workload of the user from its EEG signals. To do so, we employed a machine learning approach based on state-of-the-art algorithms developed for Brain-Computer Interfaces (BCI) technologies (Lotte et al., 2007; Blankertz et al., 2008; Ang et al., 2012). This section describes the way EEG signals were preprocessed and segmented into trials, the machine learning algorithms used as well as the approach followed for the evaluating our method (see **Figure 3** for a schematic overview of these procedures).

EEG preprocessing and segmentation

We first cleaned signals from eye movements (EOG) contamination using the automatic method proposed in Schlögl et al. (2007). The EEG signals from each 2 min n-back task were

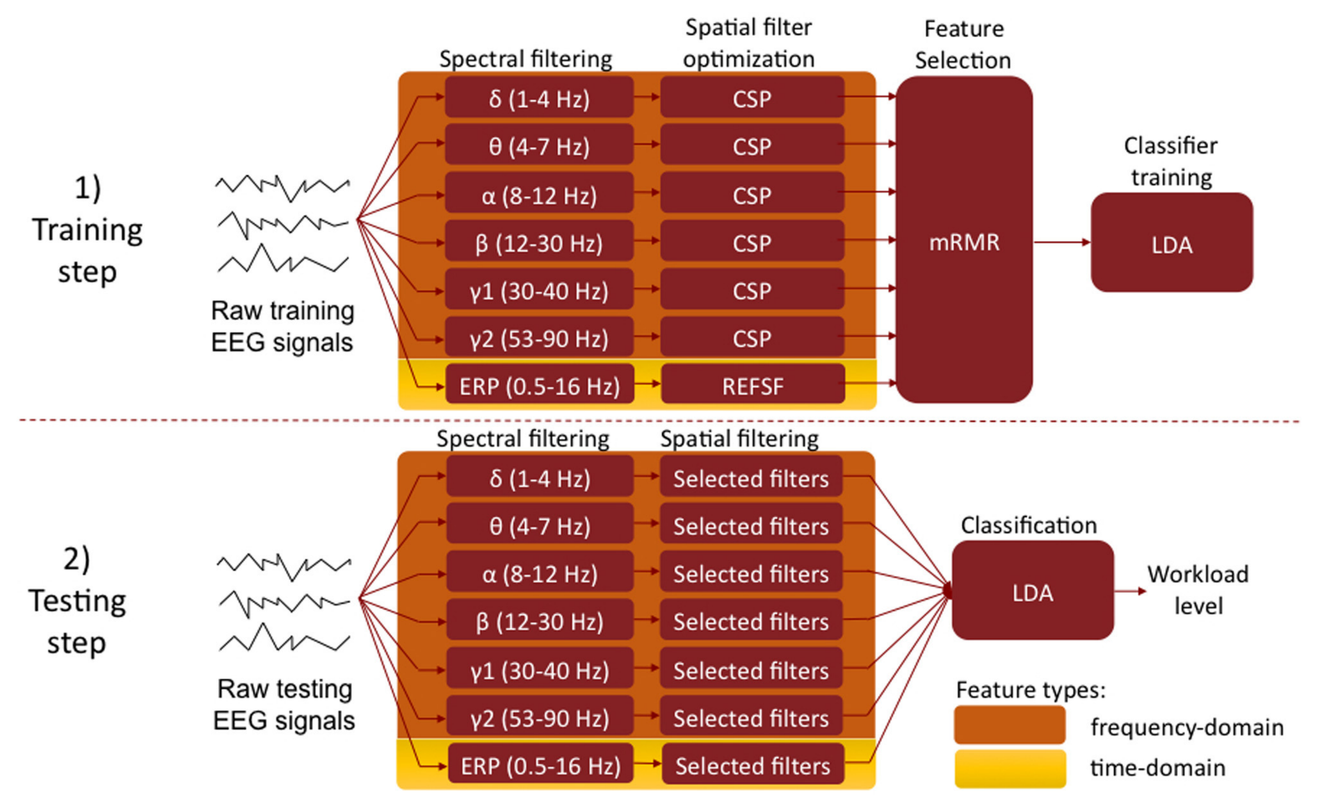

FIGURE 3 | Machine learning approach to workload level classification from EEG signals. Top: training set, aiming at identifying the relevant frequency bands (i.e., spectral filters) and channels (i.e., spatial filters), using the Filter Bank CSP and REFSF approach. **Bottom:** testing set, using the optimized spectral and spatial filter to estimate the workload level from an unknown EEG trial. (CSP, Common Spatial Patterns; REFSF, regularized Fisher spatial filter; mRMR, maximum Relevance Minimum Redundancy; LDA, Linear Discriminant Analysis).

then divided into 60 EEG trials, i.e., one EEG trial per letter appearance. More precisely, each EEG trial was defined as starting at a letter appearance onset and ending 2 s later, i.e., just before the next letter appearance. This resulted in 60 EEG trials per task, i.e., 720 trials per workload level (360 trials in the stressful condition, 360 in the non-stressful condition). Among them, trials corresponding to target letters were discarded in order to avoid confounding and interfering effects that may result from Event Related Potentials (ERP—notably a P300) likely to be triggered by target identification. This left 540 trials per workload levels (270 trials per psychosocial stress condition).

Machine Learning algorithms

In order to estimate workload levels from EEG signals, we investigated two different types of neurophysiological information: (1) oscillatory activity and (2) Event Related Potentials (ERP), both of which having been shown to be useful for such a task (Brouwer et al., 2012). We set up state-of-the-art signal processing pipelines in order to estimate workload using these two types of information, both individually and in combination (see **Figure 3**). They are described below:

Oscillatory activity. To classify low mental workload vs. high mental workload in EEG signals based on oscillatory activity, we used a variant of the Filter Bank Common Spatial Patterns (FBCSP) algorithm (Ang et al., 2012) in order to learn optimal spatial and spectral features, i.e., EEG frequency bands and channels. The FBCSP is one of the most efficient algorithms to extract spatio-spectral features from EEG signals. It was indeed the algorithm used by the winners of the last BCI competition on all EEG data sets (Ang et al., 2012; Tangermann et al., 2012), showing the superiority of this method over other approaches. The FBCSP-based approach we employed works as follows. The first step—the training step—consists in identifying the most relevant frequency bands (i.e., spectral filters) and EEG channels (i.e., spatial filters), using examples of EEG signals from the high and low workload conditions (see below for details on the definition of the training sets). To do so, we first filter each training EEG trial into multiple frequency bands using a bank of band-pass filters. Here we used band-pass filters in the following frequency bands, which correspond to classical EEG rhythms: δ (1–4 Hz), θ (4–8 Hz), α (8–12 Hz), β (12–30 Hz), γ (30–47 Hz), and high γ (53–90 Hz). Then for each of these bands, the band-pass filtered EEG trials are used to optimize spatial filters, i.e., linear combinations of the original EEG channels. These spatial filters are optimized using the Common Spatial Pattern (CSP) algorithm (Blankertz et al., 2008), which finds the optimal channel combination such that the power of the resulting spatially filtered signals is maximally discriminant between the two conditions (here, low and high workload). We optimize 12 (6 pairs) such CSP filters for each frequency band. Then, the power of the spectrally and spatially filtered EEG signals is used as features, resulting in each EEG trial being described by 72 features (12 CSP filters × 6 frequency bands). From these 72 features, the 18 most relevant ones are selected using the maximum Relevance Minimum Redundancy (mRMR) feature selection algorithm (Peng et al., 2005). This amounts to selecting the 18 most relevant pairs of spectral and spatial filters. Finally, the 18 selected power features are used to train a shrinkage Linear Discriminant Analysis (LDA) classifier (Blankertz et al., 2010; Lotte and Guan, 2010) to discriminate low workload EEG trials from high workload ones. This concludes the training step. For testing, i.e., to predict the workload level of a given EEG trial, the EEG signals are first filtered using the 18 selected pairs of spectral and spatial filters, then the power of the resulting signals is computing and given as input to the previously trained LDA classifier whose output indicates the workload level (high or low).

Event related potentials. To classifiy low mental workload vs. high mental workload in EEG signals based on ERP, we first band-pass filtered the signals between 0.5 and 16 Hz, and downsampled them to 36 Hz, to reduce the signal dimensionality. We only used the first second of EEG signals from each trial (i.e., the first second after letter presentation in the N-back task) to analyse ERP, i.e., 36 samples per channels. Then, based on these 1-second of EEG signals from the training set, we learned optimal spatial filters for the discrimination of ERP based on EEG samples, by using the Fisher Spatial Filters (FSF) proposed by Hoffmann et al. (2006). We extracted 6 such spatial filters, which resulted in 216 features (6 filters × 36 EEG samples per filter), using a regularization parameter $\lambda = 0.4$ for optimizing the FSF for all subjects. We finally selected 18 features (i.e., 18 EEG samples) out of these 216 initial ones, using mRMR feature selection. These 18 selected features were used to train a shrinkage LDA. For testing, the EEG signals were preprocessed in the same way (i.e., band-pass filtered in 0.5–16 Hz and downsampled to 36 Hz), spatially filtered using the 6 Fisher Spatial Filters optimized during training, and the 18 resulting selected features were used as input to the previously trained LDA classifier whose output indicates the workload level (high or low).

Combination of oscillatory activity and ERP. In order to combine both oscillatory activity and ERP information, we extracted 18 FBCSP features as described above and 18 ERP features, as described above as well, from each trial. These 36 features were concatenated into a single feature vector, which was used as input to a shrinkage LDA classifier.

Evaluation scheme

The performance of our workload-level estimator was assessed using sixfold stratified Cross-Validation (CV), separately for each subject. This means the data from each subject was divided into six parts, each part containing the same number of trials from each class (high/low workload). Five of these parts were used for training, i.e., to identify the relevant spectral and spatial filters, as well as to train the LDA classifier. The 6th part was used for testing the resulting workload-level estimator for that subject. This process was repeated six times, with each part used exactly once as the testing set. For three subjects we used only three- and fourfold CV due to missing blocks in the end of the recording. The performance, here the classification accuracy (i.e., rate of trials with correctly estimated workload-level), hence obtained on each testing part are then averaged to give a final performance of the workload-level estimator for that subject.

The goal of our work is to design a generic workload-level estimator, usable in practice, i.e., that can work across different affective contexts (here, different psychosocial stress levels). To do so, we performed different evaluations to estimate (1) the general performance of our system, independently of the affective context; (2) how it behaves *within* a given affective context; (3) how it behaves *across* different affective contexts, i.e., can a workload-level estimator calibrated on data from a given affective context (e.g., a relaxed condition) be used to estimate workload in another affective context (e.g., a stressful condition), (4) if effects of time can explain across-context classification performance loss, and (5) whether calibrating our system with data from different affective contexts makes the system better or worse, even if used in a single affective context. Different sub-parts of the data were thus used for training and testing within our CV scheme, in particular:

1. **General performance estimation:** This is the overall evaluation, in which we used all the data, from both affective contexts, i.e., with EEG trials from both the relaxed and the stressful conditions. Therefore, within each fold of the CV, 20 blocks (i.e., 900 trials) were available for training, and 4 blocks (i.e., 180 trials) were available for testing. The number of trials from each workload-level (high/low) and each psychosocial stress (relaxed/stressful) was balanced in both the training and testing set.
2. **Within affective context performance estimation:** This evaluation assessed the performance of our system when calibrated on a single affective context and tested on the same affective context. This is the evaluation generally performed in previous works, in which a single affective context is considered. Therefore, in each fold of the cross-validation, 10 blocks (i.e., 450 trials) were available for training, all coming from the relaxed (resp. stressful) condition, and 2 blocks (i.e., 90 trials) were available for testing, all coming as well from the relaxed (resp. stressful) condition. The number of trials from each workload-level was balanced in both the training and testing set.
3. **Across affective context performance estimation:** This evaluation assessed the performance of our system when calibrated on a given affective context and tested on a different affective context. This evaluation is usually ignored in current workload-level estimation works. Previous works indeed implicitly considered that the user was always in the same affective state, which is very unlikely in practice and can thus compromise the usability of the system. Therefore, in each fold of the cross-validation, 10 blocks (i.e., 450 trials) were available for training, all coming from the relaxed (resp. stressful) condition, and 2 blocks (i.e., 90 trials) were available for testing, all coming from the other affective context i.e., the stressful (resp. relaxed) condition. The number of trials from each workload-level was balanced in both the training and testing set.
4. **Investigation of time effects on classifier performance:** To rule out that a difference between within-context and across-context training is merely caused by the time passing between affective contexts, we devised an analysis similar to the above two analyses, but with first and second half of each context instead of relax and stress context. Therefore, we trained our classifiers on the data of 4 blocks and tested them on 2 blocks from either the same or the other half of the context. This was done in a threefold cross-validation scheme and resulted in two within and two across classification performance values (one from 1st half to second half, and one backwards) for each affective context. These were averaged over the affective contexts and yielded one value for the workload classification accuracy for within- and across-context (i.e., "half") per participant per half[2]. For a genuine effect of affective context instead of an effect of simply the time passing between both contexts, the "within vs. across halfs" performance loss for a classifier that was only trained on one half should be smaller compared to the loss between "within vs. across affective context" performance loss for a classifier that was only trained on one affective context.
5. **Calibration across affective context performance estimation:** When considering different affective contexts, an interesting question is whether using data from different contexts to calibrate the workload-level estimator will make it better or worse, notably as compared to the within affective context evaluation. Indeed, on the one hand, using data from different contexts can force the machine learning approach to identify workload indices that are invariant to the affective context, thus improving the system, but on the other hand it adds more noise and variability to the data, which can impede the machine learning process. Therefore, with this evaluation, in each fold of the cross-validation, 20 blocks were available for training, coming from both the relaxed and stressful condition, and 2 blocks were available for testing, coming from either the stressful or the relaxed condition (but not both). To ensure that the comparison of this approach with the within-context approach is fair, we had to use the same number of training trials for each approach. Indeed, using all the trials available in the 20 training blocks would mean using more training trials than in the within-context evaluation, which could result in higher performance simply due to a larger number of training trials. Therefore, for this last evaluation, we randomly selected 6 blocks from each context for training, from 4 of which all trials were used, while we selected every other trial from the remaining 2 blocks to keep the workload classes balanced within context. Further two blocks were selected from each context for testing. This procedure was repeated six times for a cross-validation comparable to the within-/across context evaluation.

RESULTS

In this section, we first present the validation analysis, suggesting that our protocol indeed induced different levels of workload and stress (Q1). Then the results of the EEG-based workload classification over, within, and across affective contexts are presented, showing that a state-of-the-art subject-specific workload

[2] For three subjects, the averaging only contained data from the stress context due to missing blocks in the 2nd half of the relax context.

classifier (Q2) has difficulty generalizing over affective contexts (Q3), but can be rendered less context-sensitive by calibration across affective contexts (Q4).

VALIDATION OF THE PROTOCOL

Subjective indicators

Each subject filled in three "STAI form Y-A" (state) questionnaires: one at the beginning ($STAI_{BL}$) of the experiment and one in the end of each affective context, that is after performing the n-back tasks under stress or relax condition (stress: $STAI_S$; relax: $STAI_R$) (see **Figure 4A**). Three data sets were excluded due to incompleteness. A repeated-measures ANOVA ($N = 21$) with the factor levels "baseline," "stress," and "relax" showed a significant difference of perceived anxiety between the conditions [$F_{(2,\ 20)} = 3.6225$, $p < 0.05$, ${\eta_p}^2 = 0.108$]. We conducted a *post hoc* analyses using paired t-tests with the hypothesis that subjectively perceived anxiety increases due to the stress induction procedure relative to baseline and relaxation condition. The results suggest that the stress-induction protocol indeed increases anxiety compared to baseline and relaxation condition, and keeps it significantly higher until measured in the end of the affective context (see **Figure 4A**): $STAI_S$ scores (mean $= 37.5 \pm 12.6$) are significantly higher [$t_{(20)} = 2.87$, $p = 0.01$] than $STAI_{BL}$ scores (mean $= 30.1 \pm 4.6$) and they are significantly higher [$t_{(20)} = 2.37$, $p = 0.028$] than $STAI_R$ scores (mean $= 32.2 \pm 8.6$). This increased anxiety seems mainly due to the interview and the apprehension of a final evaluation, rather than due to the n-back task as such: we found no difference between $STAI_R$ and $STAI_{BL}$ [$t_{(20)} = 1.27$, $p = 0.22$], that is when they performed the n-back tasks knowing that there would be no evaluation.

We furthermore asked the subjects after each block to rate their arousal on the respective scale of the Self-Assessment Maneken (see **Figure 4B**) and to rate the mental effort on the Rating Scale Mental Effort (see **Figure 4C**). Two data sets were excluded due to incompleteness. We submitted the data of each scale to a 2 (stress) $\times$ 2 (workload) repeated-measures ANOVA. Regarding the subjectively perceived arousal, we only found a main effect of the workload manipulation [$F_{(1,\ 21)} = 4.444$, $p = 0.047$, ${\eta_p}^2 = 0.175$] with higher perceived arousal for the 2-back task (mean $= 4.7 \pm 1.4$) compared to the 0-back task (mean $= 4.3 \pm 1.7$). Regarding the subjectively perceived workload, we only found a main effect of the workload manipulation [$F_{(1,\ 21)} = 63.216$, $p < 0.0001$, ${\eta_p}^2 = 0.751$] with higher perceived effort for the 2-back task (mean $= 48.1 \pm 11.5$) compared to the 0-back task (mean $= 28.6 \pm 12.9$).

Objective indicators

For the analysis of the objective indicator of behavioral performance, we logged all responses and computed the task accuracy for each task block (see **Figure 5A**). Two data sets were excluded due to incompleteness. We submitted the accuracy to a 2 (stress) $\times$ 2 (workload) repeated-measures ANOVA. As for the subjective indicators of perceived arousal and effort, we found a main effect of the workload manipulation [$F_{(1,\ 21)} = 65.251$, $p < 0.0001$, ${\eta_p}^2 = 0.757$] with higher accuracy for the simple 0-back task (mean $= 97.3 \pm 2.0$) compared to the hard 2-back task (mean $= 91.1 \pm 4.8$).

As a further objective indicator, we computed skin conductance level and heart rate. Four data sets were excluded due to incompleteness. For heart rate analysis a further data set was excluded due to malfunctioning sensors. We submitted the data of the physiological signals to a 2 (stress) $\times$ 2 (workload) repeated-measures ANOVA. For GSR (see **Figure 5B**), we found an increase of the skin conductance level [$F_{(1,\ 19)} = 4.4806$, $p = 0.048$, ${\eta_p}^2 = 0.191$], indicating higher sympathetic arousal during the stress condition (mean $= 3.83 \pm 2.05$) compared to the relax condition (mean $= 3.52 \pm 2.07$). Skin conductance level increased for high compared to low workload condition as well, however, not significantly. For HR (see **Figure 5C**), we found a trend toward an increase of the heart rate [$F_{(1,\ 18)} = 3.2123$, $p = 0.089$, ${\eta_p}^2 = 0.151$], indicating higher sympathetic arousal during the stress condition (mean $= 79.41 \pm 10.23$) compared to the relax condition (mean $= 78.30 \pm 10.08$). More importantly, we found a highly significant effect of the workload manipulation on

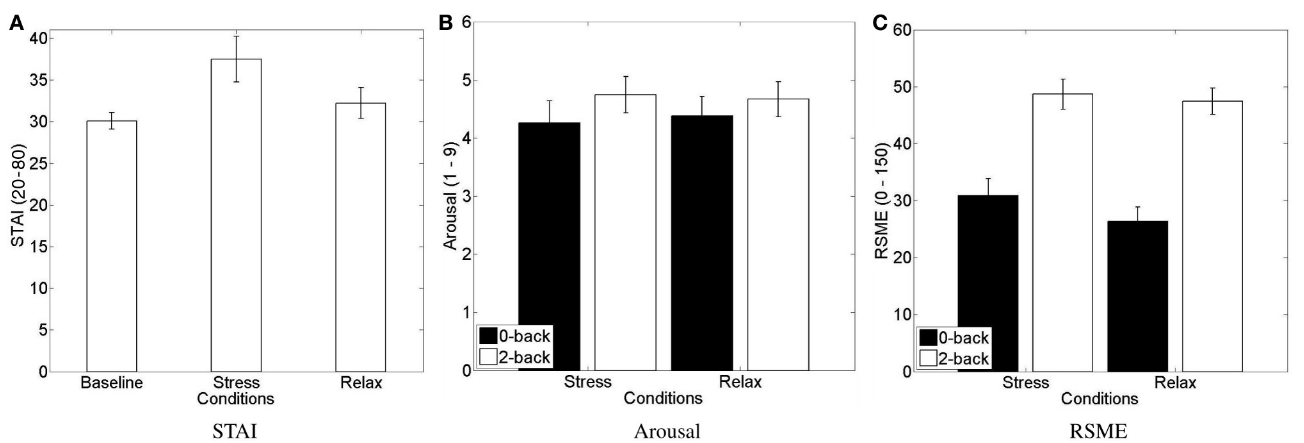

FIGURE 4 | Mean and standard error of mean of subjective stress level assessments. (A) STAI form Y-A scores, **(B)** SAM arousal scale, and **(C)** RSME. **(A)** Shows significant increase of perceived stress during the stressful condition compared to the baseline and the relax condition. **(B,C)** Show an increase of perceived arousal and mental effort for the 2-back compared to 0-back task.

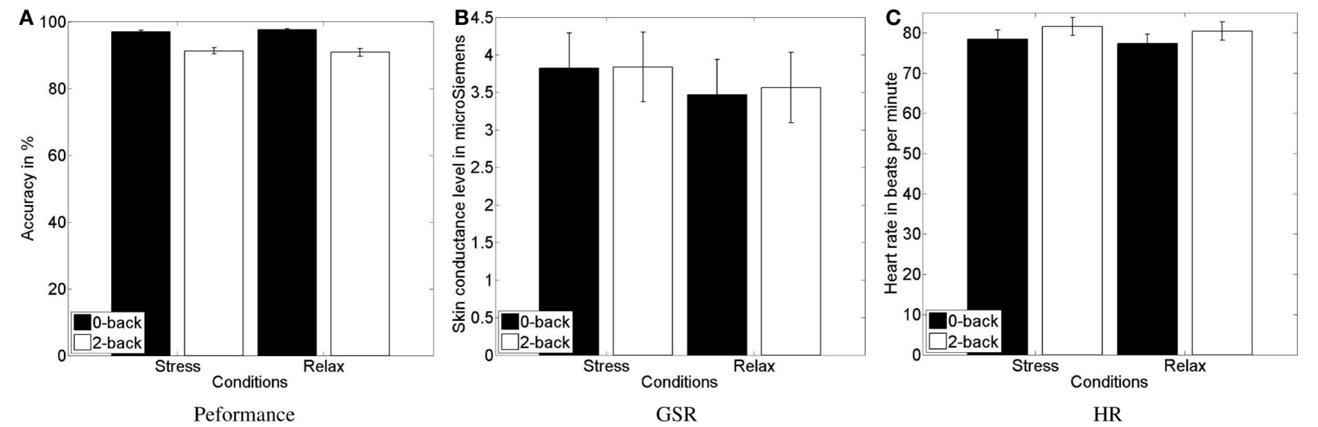

FIGURE 5 | Mean and standard error of the task performance (A), showing the decreased performance in high vs. low workload conditions, and of GSR response (B) and heart rate (C), indicating higher physiological activity in response to the psychosocial stress and workload manipulation, respectively.

HR [$F_{(1,\,18)} = 36.1431$, $p < 0.0001$, ${\eta_p}^2 = 0.667$], with a higher HR for the more challenging 2-back task (mean $= 80.4 \pm 9.89$) compared with the relatively easy 0-back task (mean $= 77.27 \pm 10.19$).

In summary, we found evidence for the validity of the stress and workload induction (Q1) in both, the subjective (questionnaires) and objective (performance and physiological sensors) measures. This ensures that calibrating and evaluating a workload classifier on the EEG recorded with this protocol is meaningful.

CLASSIFICATION OF EEG

General performance estimation

In this section we report the general classification performance for a training on the whole data set, showing that our setup is state-of-the-art compared to similar studies hence positively answering question Q2. Specifically, we obtained performances similar to the best performances that were presented more recently with the n-back task paradigm and with 2 s short trials by Grimes et al. (2008) and Brouwer et al. (2012). The data of two participants was excluded due to incompleteness and of another one due to malfunctioning EEG sensors.

For the training and testing on the basis of all available data, those trials recorded during stress *and* relax context, we achieved an average classification accuracy of 76.1% when using only frequency-domain features, with performances between 58.7% and 95.4% (see **Figure 6**). According to Müller-Putz et al. (2008), we determined the above chance-level performance via a binomial test. For a two-class problem and given the number of 1080 trials used in our sixfold cross-validation scheme, the chance-level is at 53.1% for $p = 0.05$. Consequently, the classification performance was above chance for each subject, with a highly significant better-than-random performance for the average result over all subjects ($p \ll 0.0001$).

Subsequently, we tested the previously observed increase of performance for increasing decision intervals, that is when more data is available for testing (Grimes et al., 2008; Brouwer et al., 2012). A majority vote over the classifier decisions for all 45 relevant trials of a given block, using only frequency-domain features, leads to an accuracy of 96%, well over the 71% chance-level resulting from a binomial test on the basis of 24 decisions (one per block). For time-domain features, we observed an average accuracy of 74% for 2 s trials (of which only the first was used), and 96% for the judgement after 45 trials. For both feature varieties in combination, the 2-second accuracy was the highest with 80.4%, though the block-wise accuracy was only 94.4%. Since all accuracies are well over chance level the used classification schemes enable for a solid classification performance for all feature varieties with the combined frequency- and time-domain features performing best for short estimation intervals and separate feature varieties performing best for the long decision intervals.

From a scientific point of view it is necessary to know about the source of the classification performance: is the information of neural origin or is it derived from muscular activity that is known to contaminate higher frequency bands of the EEG (Goncharova et al., 2003)? Although this question is often eluded in previous works (Grimes et al., 2008), we tried to answer it by first computing the percentage of the features selected from each frequency band in the FBCSP algorithm. As **Figure 6** indicates, the majority (about 65%) of features selected with the mRMR feature selection algorithm employed came from lower frequency bands (i.e., delta, theta, alpha). However, the remaining 35% originated in high frequency bands, those over 12 Hz (beta, gamma, gamma2). To ensure that the classifier performance does rely on neuronal sources and not on muscle activity, we repeated the workload classifier evaluation excluding these potentially contaminated high frequency bands, both for training and testing. We achieved a somewhat lower, but again much better-than-random ($p \ll 0.0001$) classifier performance of 74.2%, with accuracies between 53.9% and 88.2%. This suggests that our workload classifier does rely mostly on neural information from low frequency bands.

Within- vs. across-context estimation

In this section we tested the generalization of the classifier to a different affective context (question Q3). To evaluate the effects of testing in dependence of training context, we conducted a 2 (training context: relax, stress) × 2 (testing context: same-as-training, different-from-training) repeated-measures ANOVA for each feature type. **Figures 7**, **8** depict the average classifier performance when tested within and across affective context and the average loss of performance for the three used feature varieties (and the loss for the specific frequency bands), respectively.

The main effect found for the testing context when using frequency-domain features alone [$F_{(1,\ 20)} = 5.610$, $p = 0.028$, $\eta_p{}^2 = 0.219$] shows that the transfer from one context to another is problematic and results in a decrease of classifier performance (mean $= 69.4 \pm 9.7\%$) compared to testing on the same context as for the training (mean $= 72.4 \pm 9.4\%$). An exploratory analysis of the effect of context change on classifiers using only specific frequency bands revealed a significant contribution of the low frequency bands to the performance decline, while the less relevant high frequency bands were not or only minimally contributing (see **Figure 8**).

For time-domain features alone, the decrease of classifier performance for across context is as well significant, though stronger [$F_{(1,\ 20)} = 21.002$, $p < 0.001$, $\eta_p{}^2 = 0.512$], with a lower across-context classification performance (mean $= 69.1 \pm 5.5\%$) compared to within-context classification performance (mean $= 73.3 \pm 5.1\%$).

For frequency- and time-domain features combined, the decrease of classifier performance across-context (mean $= 73.2 \pm 8.8\%$) compared within-context (mean $= 77.3 \pm 7.9\%$) is as well marked [$F_{(1,\ 20)} = 12.104$, $p = 0.002$, $\eta_p{}^2 = 0.377$].

To rule out that the differences between within-context and across-context training were caused by the time passing between affective contexts, we divided each context into two parts (1st half,

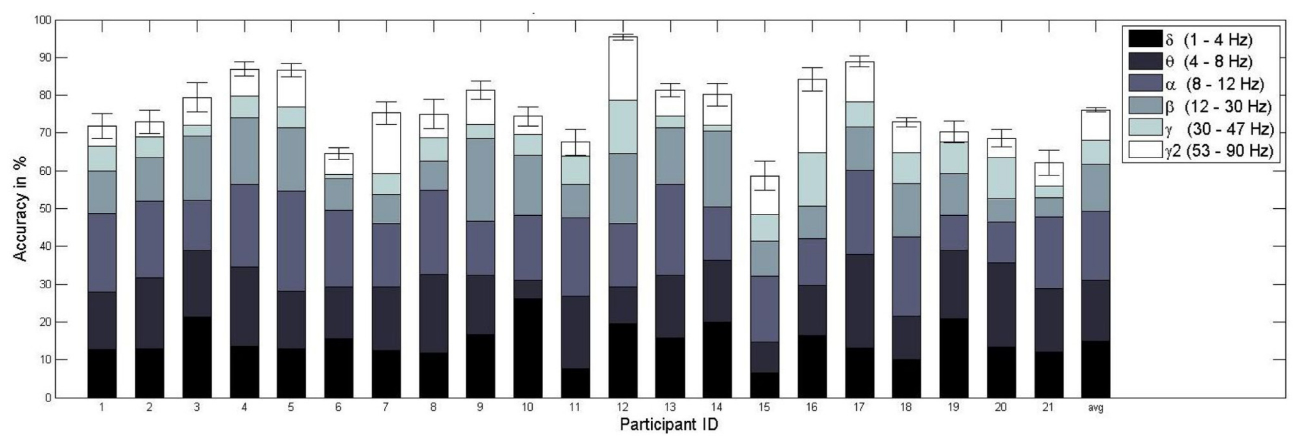

FIGURE 6 | Mean and standard error of the workload classification performance (sixfold cross-validation) per subject. The different colored subdivisions within each bar represent the percentage (total bar height = 100%) of features selected from a specific frequency band (delta, theta, alpha, beta, gamma, gamma2). For example, for subject 1 on average 9% of the features were chosen from the delta range. The last bar represents the mean classification accuracy over subjects and the average contribution from the frequency bands over subjects.

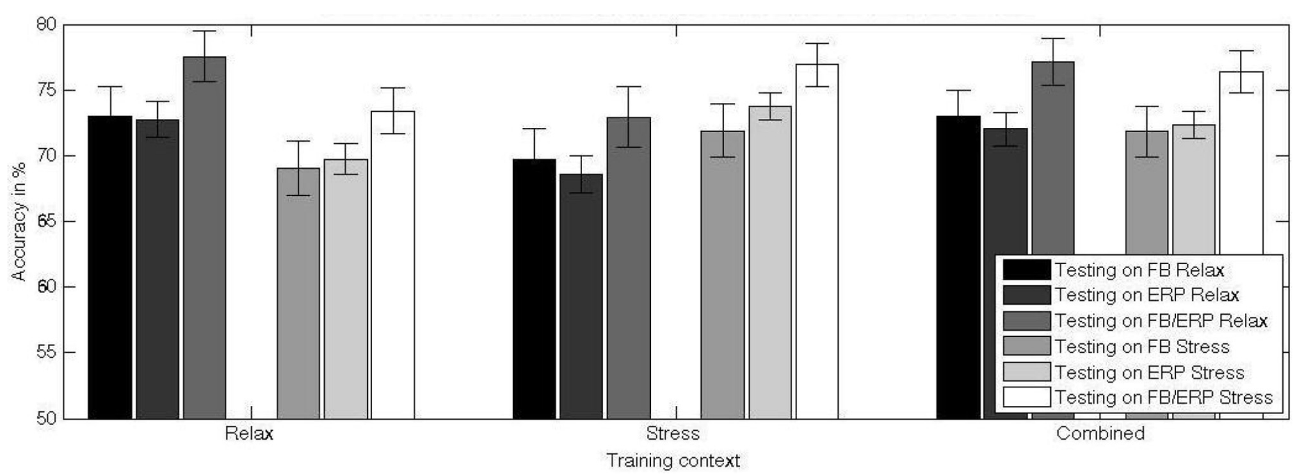

FIGURE 7 | Mean and standard error of the mean of the classification performance of a classifier trained in different training contexts (relax, stress, combined) and tested on data from relax and stress context. The differences between the testing performance for stress and relax context show an interaction between training and test factor: the difficulty of the classifier to generalize to another context. The higher performance for the combined training set relative to the training on data from a single context indicates a gain of the classifier in invariance and hence a protection against over-fitting.

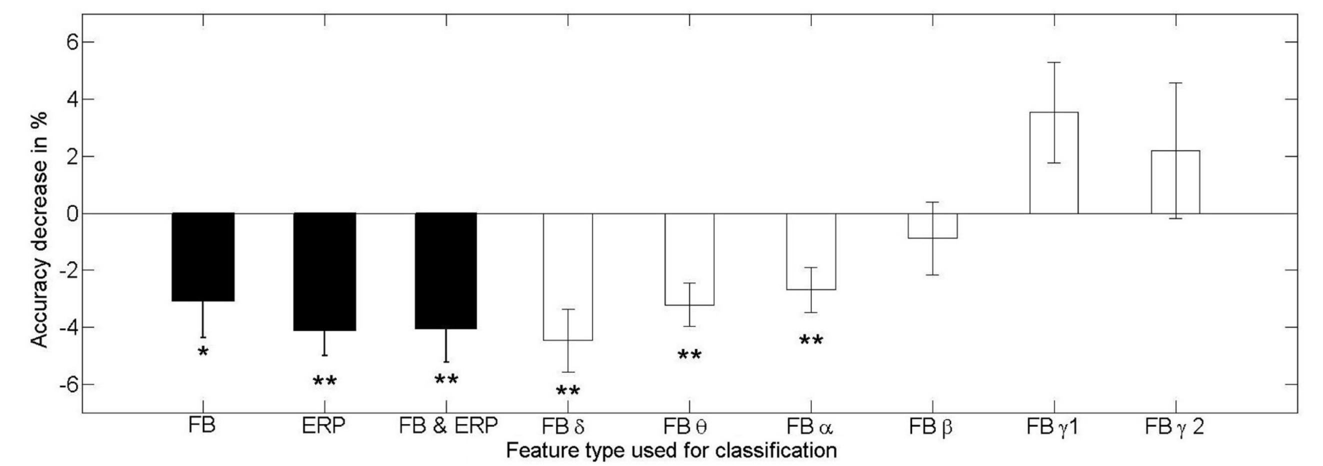

FIGURE 8 | Mean and standard error of the mean loss of the classification performance of a classifier trained and tested in different training contexts for the feature types from frequency-domain (FB), time-domain (ERP), both (FB and ERP), and for the individual frequency bands (FB $\alpha - \gamma 2$). The stars indicate the significance testing with the respective methods mentioned in the text ($^*p < 0.05$, $^{**}p < 0.01$). Only the low frequency bands show significant effects of performance detoriation in the phase of changing affective context, while the high frequency bands seem relatively stable against changes in context.

2nd half) and trained and tested the classifiers in the same manner as done for the within (e.g., training and test on 1st half) and across affective context (e.g., training on 1st half and test on 2nd half) tests. With the data averaged over affective contexts, we conducted a 2 (training context: 1st half, 2nd half) × 2 (testing context: same-as-training, different-from-training) repeated-measures ANOVA for each feature type. We did not find the pattern of performance loss that we observed for within vs. across affective context testing. Surprisingly, the only effect we found was a increase of performance for across vs. within context (half) testing for the frequency-domain only feature variety [$F_{(1,\ 20)} = 5.142, p < 0.04, \eta_p{}^2 = 0.204$] from 61.1% to 63.7%.

Summarizing, all feature varieties have been found susceptible to changes in affective context. For the frequency-domain features, only classifiers using the low frequency bands of delta, theta and alpha are significantly declining in performance when tested in an affective context different from the training context (see **Figure 8**). However, as we showed, these frequency bands are the most informative regarding the workload level. An additional test of the within vs. across effects between the 1st and 2nd half of the affective contexts on classifier performance showed that the time effect alone does not lead to a consistent decrease of performance.

Across-context calibration

To evaluate the use of a combined training context to increase the capability of the classifier to generalize over affective contexts (question Q4), we conducted a 2 (training context: average single, combined) × 2 (testing context: stress, relax) repeated-measures ANOVA for each feature type. The specific effects of across-context calibration in comparison to single context (stress and relax) calibration are depicted in **Figure 7**.

The main effect of the training context for frequency-domain features alone [$F_{(1,\ 20)} = 6.816,\ p = 0.017,\ \eta_p{}^2 = 0.254$] indicates a higher performance for training with combined (mean $= 72.4 \pm 9.5\%$) vs. with single affective context (mean $= 70.9 \pm 9.3\%$). There is no significant difference between testing on the (optimal) same context vs. combined testing.

For time-domain features the increase of classifier performance between single (mean $= 71.2 \pm 5.2\%$) and combined context (mean $= 72.1 \pm 4.9\%$) training is as well significant [$F_{(1,\ 20)} = 6.703,\ p = 0.017,\ \eta_p{}^2 = 0.251$]. Despite the observed increase due to training with combined data from both contexts, there is still a significant decrease of performance of about 1.2% relative to training and testing on the same context [$t_{(20)} = -3.526, p < 0.01$].

For frequency- and time-domain features combined, we observed an increase of classifier performance between single (mean $= 76.7 \pm 7.6\%$) and combined context training (mean $= 75.2 \pm 8.1\%$) with [$F_{(1,\ 20)} = 6.306,\ p = 0.021,\ \eta_p{}^2 = 0.240$]. There is no difference between testing on the (optimal) same context vs. combined testing.

Summarizing, for those classifiers trained with frequency-domain and combined frequency- and time-domain features, training on combined contexts leads to an increase of performance comparable with (optimal) same context training and testing. For classifiers trained with time-domain features only, we observe a significant increase of classification performance when training on combined context, but there is still a loss of performance compared to the (optimal) same context training and testing. Since the number of trials for both conditions are kept equal, this is evidence for a gain in resilience of the workload classifier against contextual changes, especially for classifiers based on frequency-domain features.

DISCUSSION

If we want to create passive brain-computer interfaces that work in the wild, we need to take the variability of such environments into account. To test how well a workload classifier would be able to cope with variability due to changes in affective context, we trained it on the data from a subject performing a task under the evaluative pressure of an impending interview, the same subject in a non-stressful setting, and from both contexts.

We validated the experimental protocol using subjective and objective indicators of the psychophysiological activation expected due to stress/relaxation induction and different workload levels. Though we did not see a significant difference in the perceived arousal measure (SAM), higher values for the STAI and increased sympathetic nervous system activity (as indicated by significant differences for GSR and a trend for HR) support a successful induction of anxiety in the stressful compared to the non-stressful condition. Higher perceived arousal and mental demand, higher sympathetic nervous system activity (as indexed by HR) as well as lower behavioral performance for high compared to low workload levels support the efficacy of the workload induction paradigm.

We showed that workload can be classified on the basis of 2 s of neurophysiological signals with an accuracy of 76.1%. This is comparable to previously reported results for such short intervals of data (Grimes et al., 2008; Brouwer et al., 2012). It was shown that the accuracy can be increased using decision-level fusion over the results of several trials (Brouwer et al., 2012) or simply by using longer signal epochs (Grimes et al., 2008), however, with the tradeoff of a less fine-grained, more discrete, and lagging measure of workload. We observed a similar increase of classifier performance to between 94.4% and 96% using a majority vote based on the classifier outcome of the relevant 45 trials of a given block.

While the source of information measured via EEG, neuronal or myographical, might seem of no immediate significance for an application on able-bodied users, it seems relevant to us to ensure that we indeed measure the neural activity implied by pBCI. In this regard, it is noteworthy that the distribution of relevant frequencies vary between subjects. While in general the majority of features (65%) is selected from low frequency bands (delta, theta, alpha), some subjects have a strong contribution of high frequencies (beta, gamma, gamma2) up to 50%. Since these higher frequency bands are notorious for their response to muscle activity in addition to neuronal information (Goncharova et al., 2003), we tested if the workload classification would suffer considerably when excluding them from the feature pool. The average performance did indeed decrease slightly to 74.2%. However, the highly significant above-chance performance over all subjects indicates an only marginal role of muscular activity in workload estimation[3]. This is in line with other studies that suggest a relevance of low frequency bands for workload (Jensen et al., 2002; Jensen and Tesche, 2002) and its estimation (Zarjam et al., 2013). Consequently, we showed that the trained classifier uses the neural correlates of workload to discern two workload levels with a performance equaling that reported in similar studies.

Regarding the classifier generalization to different affective contexts, we show that a classifier created in a non-stressful context can generalize to a stressful context and vice versa. However, the training context has a significant influence on the classification performance, with decreasing performance for cross-context classification (i.e., from 72.4% to 69.4% for frequency-domain features, from 73.3% to 69.1% for time-domain features, and from 77.3% to 73.2% for features from both domains). Interestingly, we found that a training which takes several relevant contexts into account enables the generalization of the classifier to a certain degree. Classifiers based on frequency-domain and on combined frequency- and time-domain features perform comparably well after training with data from both affective context (72.4% and 76.7%, respectively) as after being trained and tested within a specific context. Classifiers based on time-domain features profit as well from a training with data from both affective contexts (72.1%), but still show a declined performance relative to optimal, within-context training and testing.

The current study is limited in its generality by the use of a stress induction paradigm which manipulates affective context only once. We chose the TSST because it is a recognized standard of social stress induction and a powerful elicitor that allows to keep stimuli and task comparable during the workload session of stressful and non-stressful condition. However, since we have only two stress conditions and not several interleaved stress conditions, the stress manipulation is synonymous with a change in time, though with a counter-balanced order. Both affective contexts are separated by at least 10 min and we can not exclude that signal changes with time played a role for classifier performance. The analysis of effects of time within the affective contexts, however, did not reveal general performance decreases due to time passing and thus adds to the evidence of context-related performance loss. Similarly, the spread of training blocks over a larger time in combined compared to single testing contexts limits comparability of both performance measures. To ensure that our results hold for stress in specific, interleaved stress induction methods can be used, though a viable experiment length, reliability of stress induction, and comparability of stimuli and task need to be guaranteed.

Another limitation of the paradigm can result from a potential interaction of (psychosocial) stress and workload. For example, impaired cognitive processes or increased engagement in the face of evaluative pressure, could lead to differences in participant performance between affective contexts (Eysenck and Derakshan, 2011). Despite the lack of such interaction effects in our analysis, the possibility of participant's performance-related differences being reflected in brain activity is a general issue that needs to be considered, since such changes in brain activity would be only indirectly related to stress. Therefore, future research needs to identify the processes that are responsible for the signal variability in the face of psychosocial stress. On a related note, other stressors could be manipulated to identify the source of the performance decrease, for example in terms of impaired cognitive processes.

The result of our study suggests that classification performance for passive BCIs can be increased using not only a larger quantity of training data, but by introducing qualitative variations. Here, we varied the stress level of our participants during the task performance. This manipulation is comparable to the variation of the affective context of a task in real-world scenarios, for example task performance under pressure vs. normal task performance. Consequently, to create more reliable BCIs for

[3]Alternatively, the decrease might be due to the removal of relevant neural information represented in beta or gamma bands.

workload detection, robust against alterations in contextual conditions, such as affective factors (emotions, moods), the training data should include data collected under the relevant contextual conditions.

Zander and Jatzev (2012) found that certain metrics might enable the identification of phases of changed contexts and therefore identify phases were additional calibration might be necessary. One could then use transfer learning (Pan and Yang, 2010) or other re-calibration strategies to enable an adaptation of the transfer algorithm to the new context. However, the suggested metric specifically enables the detection of LOC, which is useful for the detection of perceived LOC and subsequent reliability decrease of active BCIs when environmental and internal factors of the user change. Passive BCIs are not directly related to a feeling of control since they do not enable nor aim at the intentional control of machines. Therefore, for passive BCI one needs other indicators of reliability.

Currently, several groups are investigating the cognitive, affective, and demographic factors that influence active BCI performance (see Lotte et al., 2013). We argue that a similar research program would allow to build more robust passive BCIs by (1) taking into account changes in relevant contextual factors (e.g., stress), (2) by exploring indicators of such changes or the subsequent loss of reliability, and (3) by the exploration of strategies to update the classifier in face of the loss of reliability due to contextual changes.

CONCLUSION

The current work has relevance for the development of passive brain-computer interfaces that are able to specifically classify one psychophysiological construct (e.g., workload), while being invariant to others (e.g., stress). We devised and validated a protocol to test the effect of stress on pBCI approaches. We showed that a classifier has trouble transfering from stressful training data to non-stressful test data and vice versa, indicating an influence of affective task context on the performance of a workload classifier. Moreover, we found that the classification profits from the training on a mix of the varied affective task contexts. Such classifiers perform comparably well to those trained and tested on the same affective context. More generally spoken, the results suggest that the classification performance is not only dependent on quantitative factors, such as the numbers of channels, amount of training data, or length of trials, but also on qualitative factors, such as the affective context. This underlines the need for studies that identify such contextual factors and that elucidate ways to deal with detrimental effects related to their influence. Future research and development of workload classification systems using physiological sensors needs to take the contextual factors into account to increase the generality and ecological validity of the system.

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Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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RAPPORT de PRESENTATION de la THESE

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Nom du candidat *Candidate (Last Name, First Name):* JEUNET Camille

Titre de la thèse *Thesis title: "Understanding and improving mental-imagery based brain-computer interface (MI-BCI) user-training : towards a new generation of reliable, efficient and accessible brain-computer interfaces »*

1. Evaluation générale *General assessment :*

Digne d'être soutenue, en l'état, en vue du Doctorat ?
Can the thesis dissertation be defended in its current state? ☒ OUI *YES* ☐ NON *NO*

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If not, are any changes recommended prior to the defense? ☐ OUI *YES* ☐ NON *NO*

2. Evaluation en vue de la soutenance *Evaluation in view of the thesis defense*

Nom, Prénom *Last Name, First Name: Dr. Kübler, Andrea*

Grade/établissement *Title/institution: Prof. Dr./University of Würzburg*

Date: 18.11.2016

Signature :

Andrea Kübler

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2. Rapport (2/3 pages maximum) commentant les raisons pour lesquelles vous êtes favorable à la soutenance de cette thèse ou au contraire pour lesquelles vous êtes défavorable à la soutenance en l'état actuel du manuscrit
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17. November 2016

PhD thesis by Camille Jeunet for the degree of "Doctor of Philosophy"
"Understanding and improving mental-imagery based Brain-Computer interface (MI-BCI) user-training: towards a new generation of reliable, efficient and accessible brain-computer interfaces"

Appraisal

Background

In the past 20 years research into the development of brain-computer interfaces (BCI) has almost exponentially increased. BCI connect the human brain via a computer with a device to fulfil specific purposes such as communication, or – more generally speaking – to replace lost function. Practical BCI measure the electrical activity of the brain with electroencephalography (EEG) which has been shown to be applicable at the patients' bedside. BCI often suffer from too low an accuracy and information transfer rates (ITR), albeit tremendous progress has been made toward reliable and fast communication.

The intense research effort into BCI still lacks a close interaction with the end-user of this technology, i.e. the human factor of this interaction is hardly ever systematically taken into account. Quite some knowledge about human influencing factors exists in the neurofeedback literature of the 70ies of the last century, which seems to be forgotten. BCI which depend on regulation of specific components of the EEG such as frequencies of the alpha band require a close neurofeedback loop such that the end-user is constantly informed about his or her brain activity in relation to the current thoughts. Little systematic research has been done in the BCI community into the human factors component of the BCI. The research results that exist are lacking integration and acknowledgment. The current thesis sets out to remedy some of these aspects.

Aims and Questions

The overall aim of the thesis was to provide a theoretical framework that integrates cognitive and psychological factors and the user-technology relationship into the approach to BCI user training that use mental imagery dependent changes in the EEG frequency spectrum as input signal. Based on this framework several assumptions were derived to test the framework and to elucidate the influence of the proposed components.

More specifically, the following goals and questions were formulated:

1. To investigate the effect of cognitive factors, specifically spatial abilities on MI-BCI performance.
2. Do personality factors influence MI-BCI performance.
3. How does the presentation and type of feedback affect BCI performance.

Altogether 9 studies were carried out to address these questions and aims.

Performance

The thesis is surrounded by a thorough theoretical framework. At least parts of the theoretical background are thoroughly reviewed and the derived research questions clearly follow from this background. The integration of the results is remarkable.

In more detail, the thesis comprises the following aspects and achievements:

- Providing a theoretical background and delineating three research topics from it
- Investigating the influence of cognitive aspects, namely spatial (mental rotation) abilities and attention, on BCI performance
- Identifying and replicating cognitive predictors (mental rotation) of MI-BCI performance
- Identifying personality factors (e.g., tension) influencing BCI performance
- Based on the finding about personality factors, introducing a companion that my relieve tension and computer anxiety
- Thorough elaboration of the “character” of the companion
- Introducing the companion into BCI training
- Testing the appropriateness of the often used “extending bar” feedback for learning
- Introducing another feedback modality, namely tactile stimulation, into the MI-BCI approach
- Theoretical and future considerations that follow from each of the three experimental parts
- Summary and critical discussion of the results

Evaluation

<u>Strengths:</u> Altogether, the thesis is embedded in a thoroughly outlined theoretical framework. The approach of investigating the influence of several human factors on BCI performance is worthwhile and urgently needed in the field of BCI. The systematic comparison of different training protocols is well implemented and thought through; the theoretical background is in its great part well elaborated. The systematic approach within all three experimental parts of the theses is mostly well done (see limits). To address whether a previously identified predictor of MI-BCI performance can be trained to improve such performance contributes to the research effort of identifying correlates of BCI-control. Also the effort to replicate the previously found predictor constitutes an important piece of research as the aspect of replication and confirmation is often neglected. Taking into account human factors is – generally speaking – far too often ignored in the BCI field and the way social interaction may support learning has not been systematically investigated. In this respect the thesis is truly outstanding. The introduction of a companion to assist BCI training is an interesting and appealing new idea and feedback on the appearance of the companion was considered in the companion's development. The investigation of the efficiency of feedback for motor learning was also nicely delineated from existing work and very well implemented into an experiment on motor learning. Consequently the feedback was changed such that another modality was introduced and investigated. Taken together, the aim of the thesis to put the user of BCI in the centre of investigation is an important step in BCI development which only few investigators take and the implementation is in its most parts outstandingly well done.

<u>Limits:</u> The most striking limit of the thesis is that recent research and progress toward integrating the end-user into the BCI research and development are not at all acknowledged. The user-centered design (UCD) focuses on usability, i.e. how well a specific technology suits its purpose and meets the needs and

requirements of the targeted users and was standardized in the ISO 9241–210. The three aspects of usability – effectiveness, efficiency, and satisfaction – were adapted to BCI and metrics were suggested for each of these aspects and moreover, the framework is open to specific adaptation dependent on the application. The herein defined metrics are not taken into account, it is even stated that no standardized metrics exist, and thus, custom made questionnaires are used instead of validated existing ones; effectiveness and efficiency are equalised although they are two different aspects of usability. This is all the more striking as in other aspects of the thesis quite an immense number of literature is reviewed and integrated.

With respect to the experiments, the lack of specific and clearly formulated hypotheses renders the evaluation of the results difficult including the statistical approaches. It often remains unclear what exactly are the independent and dependent variables and how many factors enter the analysis and the descriptive data, e.g. performance, are often not reported.

The performance of the subjects throughout the experiments is low and mainly in the range of 50 to 60%, and no learning occurs in the experiments in which several sessions of BCI training are conducted. Such a lack of learning does happen, the problem here is that it is not appropriately addressed in the discussion. If no learning occurs it is somewhat difficult to discuss how the defined end-user/human factors influence learning.

Despite some shortcomings, the thesis constitutes a well elaborated, valuable piece of work which substantially contributes to the BCI field.

I recommend accepting the thesis “in partial fulfilment of the requirements for the degree of Doctor of Philosophy”.

Andrea Kübler

Dr. Andrea Kübler

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Digne d'être soutenue, en l'état, en vue du Doctorat ?
Can the thesis dissertation be defended in its current state? ☒ OUI *YES* ☐ NON *NO*

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Nom, Prénom *Last Name, First Name: Reinhold, Scherer*

Grade/établissement *Title/institution: Associate Professor, Graz University of Technology, Austria*

Date: 14.11.2016

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2. Rapport (2/3 pages maximum) commentant les raisons pour lesquelles vous êtes favorable à la soutenance de cette thèse ou au contraire pour lesquelles vous êtes défavorable à la soutenance en l'état actuel du manuscrit
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I would like to start by congratulating the PhD candidate, Camille Jeunet, on her achievements: First, the research questions are very innovative and by querying current state-of-the-art approaches they encourage scientific discussion. Second, an extensive amount of work was performed. Several pre-studies and studies have been carried out to support and adjust research questions and hypotheses. Not everyone is willing and able to invest the required time. Moreover, work was performed in an interdisciplinary team involving neuroscientists, human-computer interaction, computer scientists and medical doctors. From personal experience I know that this requires great power of endurance and excellent communication skills in order to progress and move forward. Third, the quality and the amount of dissemination of the results are most remarkable. I was impressed by the large number of peer-reviewed articles in international journal and conference proceedings that were published within the three year time period. That speaks for itself!

The thesis is clear, well organized, comprehensive, and most importantly addresses several crucial aspects related to mental-imagery brain-computer interface (BCI) end-user training protocols. End-user training is of utmost importance for practical BCI applications, however, not well researched in the community. Most research focuses on decoding and machine learning aspects for improving performance. As such, the topic and the results presented in this thesis are highly relevant.

The thesis studies the impact of cognitive, personal and feedback factors on BCI training. Supporting studies are well designed and build upon each other. To study the impact of the above factors on BCI performance, standard state-of-the-art methods were used to process brain signals. The selected method are well established and commonly in use today. This provides a sound basis and helps to compare some of the obtained results – especially the performance of the control groups – with results reported in the literature.

The first main contribution of the thesis is the finding that the spatial abilities correlate with mental imagery BCI performance. This finding is in agreement with the literature. Based on this a specific training protocol was developed and evaluated. The results of a supporting training study did not show significant differences in BCI performance between groups with different training protocols. I found the hypothesis triggered by these results, i.e., the idea to setup spatial training protocols to enhance motor rehabilitation after stroke, very intriguing and interesting.

The second main contribution is a predictive model of BCI performance based on personality traits. This model again led to the development of a learning companion. Social presence and emotional support is essential for learning for some class of people. A supporting feedback study with the learning companion confirmed that the user motivation and engagement in the task increased when the learning companion was adapted to provide user-specific support and feedback. This study is a wonderful example of how integrating concepts from human learning and educational psychology enrich BCI training protocol user experience.

The third and in my point of view the most relevant contribution of this thesis is the proof that current BCI training protocols are suboptimal for the human trainee. A clever experimental design was used to demonstrate this fact. Standard (visual) feedback requires a substantial amount of cognitive resources. This was identified as one factor that hampers learning. Since motor imagery was used to encode BCI messages, as next consequent step haptic vibrotactile feedback was presented to the hand. This mapping is more intuitive and direct, and uses less cognitive resources.

Results of a supporting study confirmed higher performances and less cognitive demands when compared to standard visual feedback.

In summary, the thesis addresses very important topics in the field, is timely, innovative and will have an impact in the BCI community. I like the fact that the work tackles open issues from a human factors point of view and not, as most researchers do, from a machine learning perspective. I cannot find systematic errors, errors in reasoning or other major flaws. The work is sound and thoughtful and provides a sound basis for future research. I think that the thesis makes a significant original contribution to the subject area and I am pleased to recommend that it be approved for award the Ph.D. degree.

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Nom, Prénom *Last Name, First Name:* Guehl Dominique

Grade/établissement *Title/institution:* PUPH CHU Bordeaux - Université de Bordeaux

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Rapport de thèse de Camille Jeunet portant sur la compréhension et l'amélioration de l'entrainement à l'imagerie mentale dans le cadre des interfaces cerveau-machine. Ce travail s'inscrit dans le cadre de l'école doctorale sociétés, politique et santé publique, spécialité sciences cognitives.

Généralités

Cette thèse est écrite en anglais dans un style très fluide et très didactique. Elle se présente comme un manuel d'utilisation avec une structure qui permet au lecteur, même naïf, de se faire une idée sur les données de la littérature scientifique en lien avec chaque question posée. Vient ensuite la problématique puis les méthodes utilisées pour tenter de répondre aux questions posées. Les résultats sont clairement exposés dans chacune des parties expérimentales puis discutés à la lumière des études antérieures publiées par d'autres équipes travaillant sur le sujet. La critique de ces études est toujours bien faite et les questionnements qui découlent de leur discussions ouvrent des perspectives pertinentes. On voit à travers ce manuscrit que Camille Jeunet maîtrise parfaitement son sujet. Elle manipule les concepts avec beaucoup d'aisance ce qui lui permet de prendre du recul sur les questions abordées, d'en faire les critiques appropriées qui débouchent sur des problématiques fondamentales du domaine des interfaces cerveau-machine (ICM). Cette bonne maîtrise du sujet se traduit d'ailleurs par un niveau de publications dans des revues internationales à comité de lecture rarement atteint au stade du doctorat (3 articles en premier auteur, 1 article en 2° auteur, 1 article en 2° auteur soumis et un chapitre de livre).

Ce travail de thèse met l'accent sur le fait que l'apprentissage d'une tâche d'imagerie mentale ne permet pas de générer un signal pertinent (pour l'ordinateur) par notre cerveau dans près de 30% des sujets. Or, un signal électrique pertinent doit pouvoir être obtenu de façon fiable et reproductible si l'on veut que des ordinateurs puissent le détecter et, grâce à un algorithme, l'utiliser pour commander un robot par exemple. Ainsi, le niveau de performance qui n'est pas atteint par tous les sujets sains représente un challenge si l'on veut « démocratiser » ce système et donc le rendre accessible à tous et notamment aux patients. Le travail de Camille Jeunet s'est donc focalisé sur les moyens qui pouvaient être mis en œuvre pour tenter d'améliorer ces performances d'apprentissage.

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Aspects méthodologiques généraux

Parmi les tests neuropsychologiques utilisés pour évaluer les fonction cognitives (page 65), le STAI Y-B paraît être davantage une échelle d'évaluation de l'anxiété qu'une échelle visant à évaluer une fonction cognitive. Elle devrait donc être déplacée dans la rubrique suivante (emotional state measures).

Pour qu'une ICM fonctionne il est nécessaire que les activités cérébrales générées par le cerveau lors de la réalisation d'une tâche soient reconnues par l'ordinateur pour être ensuite utilisées correctement. Ceci est basé sur une méthode appelée « précision de classification ». Cette terminologie reste un peu flou pour le lecteur non familiarisé avec cette littérature. En effet, cette partie pourrait être un peu plus développée car on ne voit pas d'emblé à quoi elle correspond. On en devinera le principe plus tardivement dans la suite du manuscrit mais une précision sur cet élément fondamental aurait pu apparaître plus tôt dans l'introduction.

Dans les pages 14, 66 et 72, il est fait référence à l'acquisition du signal électrique généré par le cerveau. Dans ce travail de thèse, on a bien compris que l'objectif n'était pas d'insister sur les différentes techniques utilisées (invasives versus non invasives) pour enregistrer les signaux électriques mais il aurait été intéressant d'avoir un rappel bibliographique rapide sur cette question. Dans le travail de thèse, l'EEG est enregistré en surface et une analyse du signal est ensuite faite dans le domaine fréquentiel. Ainsi, on essaie de déterminer parmi les différentes bandes de fréquences celle(s) qui est (sont) le plus liée(s) à la tâche effectuée. Les bandes alpha, béta et gamma semblent intéressantes. Pourquoi filtrer le signal à 30 Hz ce qui va gêner l'acquisition du signal dans la bande gamma impliquée dans l'attention ? Page 74, la partie sur le « common spatial pattern » est difficile à suivre pour un naïf.

Cette partie amène à un questionnement plus général. En effet, si le fait de visualiser les mouvements d'une main droite ou gauche semble comme cela une tâche triviale, il n'en demeure pas moins que les réseaux qui sous tendent cette action, le niveau attentionnel requis pour l'accomplir et la motivation mise en place pour la finaliser peuvent varier d'un sujet à l'autre. Ainsi, la réduction de ce type d'activité cérébrale à l'amplitude d'une bande de fréquence donnée sous un nombre limité d'électrodes ne nous prive t'elle pas de l'essentiel de la pertinence du signal électrique généré par le cerveau dans ces conditions ?

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Ainsi, n'y aurait-il pas moyen (mais peut-être que cela a déjà été fait ?) d'utiliser d'autres paramètres pertinents tels que le niveau de synchronisation au sein du réseau impliqué dans la tâche. En effet, chaque tâche cognitive active plusieurs régions cérébrales d'intérêt et se limiter à une de ces régions explique peut être la variabilité du signal (en fréquence et en amplitude) d'un sujet à l'autre. Etudier la dynamique du réseau (entre cortex frontal et lobe pariétal inférieur par exemple ?) pourrait être un point intéressant pour contourner cet écueil ?

Que penser de l'utilisation de la NIRS dans le cadre des interfaces cerveau-machine. En effet, cette technique enregistre de façon non invasive les modifications métaboliques du cerveau en lien avec les régions activées. Est ce que le signal ne serait pas plus stable, plus simple à analyser et plus reproductible que le signal EEG ?

2°/ Les études

Les différentes études effectuées chez le sujet sain visent successivement à déterminer :
- l'existence de facteurs cognitifs prédictifs d'une performance optimale lors de la réalisation d'une tâche d'imagerie mentale.
- si les compétences spatiales des individus peuvent influencer leurs performances dans une tâche qui vise à imaginer un mouvement.
- s'il est possible de proposer un protocole visant à améliorer les compétences visuo-spatiales des sujets.
- si le niveau de stress du sujet et sa capacité à reconnaître qu'il peut directement interagir avec un ordinateur par l'intermédiaire d'une modulation de son activité cérébrale (*self-reliance*), influencent les performances au cours d'une tâche d'imagerie mentale.
- si une présence non humaine (robot) peut combler le « vide » social des sujets ayant un certain niveau d'anxiété et une *self-reliance* faible lorsqu'ils sont face à un ordinateur afin d'apprendre une tâche qui vise à moduler leur activité cérébrale de façon spécifique (conditions expérimentales très particulières). Tout ceci avec l'idée que ce compagnon pourrait aider à l'apprentissage (amélioration des performances dans le cadre d'une interaction ICM).
- si une modification de la nature du feedback (tactile versus visuel) peut influencer l'apprentissage du sujet.

On se perd parfois un peu dans cette présentation des études et de leurs résultats avec des retours en arrière, même si l'on comprend que l'étudiante souhaite aborder les questions par thème.

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Dans ces différentes études, il ne ressort pas clairement de caractéristique EEG en lien avec la tâche et qui pourrait être utilisée ou détecter par l'ordinateur comme signal pertinent. Cet aspect pourra être discuté à l'oral. Je me pose une question par rapport au feedback car je n'ai pas bien compris en quoi les modifications plus franches de la synchronisation EEG par stimulation tactile pourrait aider l'ordinateur à reconnaître un signal EEG pertinent au cours de la tâche (l'activité en lien avec le feedback arrive trop tard par rapport à l'activité pertinente qui est sensée être détectable par la machine juste avant). Une discussion durant la soutenance me permettra sans doute de mieux comprendre cette partie ?

Au total, on mesure à travers ces multiples études la quantité de travail accompli au cours de cette thèse par Camille Jeunet. On touche également du doigt certaines limites qui d'ailleurs sont abordées ensuite dans la discussion finale. A travers les discussions de chaque étude et à travers la discussion finale, on peut noter de la maîtrise du sujet par l'étudiante qui se positionne à la fois comme actrice de sa recherche mais également comme « philosophe » de son sujet en posant les bonnes questions et en proposant des pistes de recherche pertinentes.

3°/ Concernant les perspectives

L'étude des capacités d'apprentissage des interactions ICM chez le sujet cérébro-lésé est importante. Combien de patients seront-ils en mesure de mobiliser suffisamment de motivation et d'attention pour apprendre à piloter un ordinateur ou un robot à partir de leur activité cérébrale ? D'autres part, ces patients sont souvent sous psychotropes (anxiolytiques, antidépresseurs ...) qui peuvent modifier l'activité cérébrale et complexifier le signal EEG. Les lésions cérébrales peuvent également modifier la topographie des régions d'intérêt et les régions d'intérêt utiles à contrôler ces interfaces peuvent aussi être affectées par les lésions. Autant de questions qui restent donc ouvertes à ce jour. Etre capable d'adapter ces systèmes aux patients demeure donc un challenge incontournable si l'on veut un jour transférer ces systèmes d'ICM dans la domaine de la santé.

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<u>En conclusion</u>

Il s'agit donc d'un travail de thèse de grande qualité avec une démarche scientifique et expérimentale qui s'inscrit dans la lignée de celle de Claude Bernard. Il s'agit d'une recherche appliquée avec élaboration d'outils pouvant être testés directement, ce qui n'est pas si courant dans le domaine des sciences cognitives. Les résultats présentés dans cette thèse sont très encourageants par rapport aux applications possibles dans le domaine de la santé. En effet, l'optimisation des protocoles d'apprentissage des ICM devrait permettre un transfert de ces systèmes mieux adaptés aux malades, c'est-à-dire qui tiennent compte des contraintes liées à la pathologie (cas des cérébro-lésés par exemple). Ce sujet passionnant mais complexe est présenté avec beaucoup de clarté, de rigueur et en anglais, ce qui témoigne de l'ouverture d'esprit de cette étudiante qui possède à mon sens toutes les compétences d'un chercheur de haut niveau qui sera tout à fait en mesure de poursuivre des travaux de recherche dans cette voie et d'encadrer de jeunes chercheurs en formation. Je donne un avis très favorable à la soutenance de cette thèse par Camille Jeunet en vu de l'obtention du doctorat de philosophie de l'Université de Bordeaux.

Bordeaux, le 15 Novembre 2016

Dr dominique guehl

Professeur Dominique GUEHL
Neurologue
Service des explorations fonctionnelles
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UNIVERSITÉ DE BORDEAUX

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RAPPORT DE SOUTENANCE DE THESE

Signé par le président et contresigné par tous les membres du jury
(to be signed by the President of the jury and all the members)

Nom du candidat *Candidate (Last Name, First Name):* JEUNET Camille

Titre de la thèse *Thesis title: « Understanding and improving mental-imagery based brain-computer interface (MI-BCI) user-training : towards a new generation of reliable, efficient and accessible brain-computer interfaces »*

Date de la soutenance *date of the defense :* Vendredi 2 décembre 2016

Spécialité *Speciality :* Sciences Cognitives et Ergonomie, option Sciences Cognitives

Jury de soutenance *Defense jury*:

- M. GUEHL Dominique, Professeur PH, Université de Bordeaux, *Rapporteur*
- M. HACHET Martin, Chargé de Recherche, INRIA Bordeaux Sud-Ouest, *Co-directeur de thèse*
- M. KUBLER Andrea, Professeur, Université de Würzburg, Allemagne, *Rapporteur* (visioconférence)
- M. LOTTE Fabien, Chargé de Recherche, INRIA Bordeaux Sud-Ouest, *Co-directeur de thèse*
- M. MATTOUT Jérémie, Chargé de Recherche, INSERM, Bron
- M. N'KAOUA Bernard, Professeur, Université de Bordeaux, *Directeur de thèse*
- M. SCHERER Reinhold, Assistant Professeur, TU Graz, Autriche, *Rapporteur*
- M. SUBRAMANIAN Sriram, Professeur, University of Sussex, United Kingdom, *Co-directeur de thèse*

Nom du Président du jury *President of the jury (Last Name, First Name):* SCHERER Reinhold

Nom du rapporteur de soutenance (si différent du Président du jury) *Reviewer of the defense if isn't the president (Last Name, First Name):* ....

Evaluation générale de la thèse *General assessment of the thesis*:

EXCELLENT THESIS BASED ON AN EXCEPTIONAL AMOUT OF WORK ADRESSING VERY IMPORTANT AND NOT WELL RESEARCHED ASPECTS ON USER TRAINING. SIGNIFICANT WORK IN THE FIELD FROM A MOTIVATED AND PASSIONATE PhD CANDIDATE. DOCTORAL THESIS WITH HIGH HONORS.

Talence, le 02/12/2016

Signatures des membres du jury présents. Si membre du jury en visioconférence, l'indiquer sous le nom.

Un membre invité n'a pas voix délibérative et ne signe pas les documents relatifs à la soutenance. Il n'est pas comptabilisé comme membre du jury.

Jérémie MATTOUT

université de BORDEAUX

M. GUEHL Dominique	M. HACHET Martin	M. KUBLER Andrea (visioconférence)
M. LOTTE Fabien	M. MATTOUT Jérémie	M. N'KAOUA Bernard
M. SCHERER Reinhold	M. SUBRAMANIAN Sriram	

RAPPORT DE SOUTENANCE *Report of the defense :*

PhD defence Report for Camille Jeunet, December 2, 2016

The thesis is original and tackles several open issues in an interdisciplinary research area. The work is well structured, detailed and puts some very interesting ideas forward. Relevant literature is cited and discussed. Finding answers to the research questions required the candidate to perform a substantial amount of experimental work. Several studies were conducted with, compared to other studies in the field, large amount of subjects. Results of the individual studies were integrated into an extensive model characterizing factors that impact on user training. Developed model and its complexity are quite impressive. The questions asked covered a broad area, which required expertise from different fields. The candidate managed to handle four supervisors from different areas in an enriching way. These achievements clearly demonstrate that the candidate can work autonomously, is a team player and has leadership qualities. It should also be noted that the quality and the amount of dissemination in form of peer-reviewed articles in international journals and conference proceedings are most remarkable.

The presentation was very well prepared and done. The interaction and scientific discussion with the panel was professional, and the answers provided were qualified and honest.

Overall the PhD candidate is very mature, highly motivated and very passionate about her research. The committee in unison agrees that this is an excellent thesis.

REINHOLD SCHERER
DIRECTOR

Sriram Subramanian

Fabien LOTTE,
co-director

Martin Hachet
co-director

Bernard N'Kaoua
Co-director

ANDREA KÜBLER

Jérémie MATTOUT

Guehl Dominique

université de BORDEAUX

ATTESTATION DE REUSSITE AU DIPLOME DE DOCTEUR

VU les titres initiaux produits par **Madame Camille JEUNET**
Né(e) le 11 octobre 1990 à Pessac (Gironde)

VU les rapports rédigés par :

- M. GUEHL Dominique, Professeur PH, Université de Bordeaux
- Mme. KUBLER Andrea, Professeur, Université de Wurzburg, Allemagne
- M. SCHERER Reinhold, Assistant Professeur, TU Graz, Autriche

VU les pièces constatant que l'intéressé(e) a présenté en soutenance, conformément aux règlements, à la date du **2 décembre 2016**

Une thèse portant sur le sujet suivant :

« Understanding and improving mental-imagery based brain-computer interface (MI-BCI) user-training : towards a new generation of reliable, efficient and accessible brain-computer interfaces »

devant un jury constitué au sein de l'Université de Bordeaux, composé de :

- M. GUEHL Dominique, Professeur PH, Université de Bordeaux, *Rapporteur*
- M. HACHET Martin, Chargé de Recherche, INRIA Bordeaux Sud-Ouest, *Co-directeur de thèse*
- M. KUBLER Andrea, Professeur, Université de Würzburg, Allemagne, *Rapporteur*
- M. LOTTE Fabien, Chargé de Recherche, INRIA Bordeaux Sud-Ouest, *Co-directeur de thèse*
- M. MATTOUT Jérémie, Chargé de Recherche, INSERM, Bron
- M. N'KAOUA Bernard, Professeur, Université de Bordeaux, *Directeur de thèse*
- M. SCHERER Reinhold, Assistant Professeur, TU Graz, Autriche, *Rapporteur, **Président du jury***
- M. SUBRAMANIAN Sriram, Professeur, University of Sussex, United Kingdom, *Co-directeur de thèse*

VU la décision dudit jury prononçant l'admission de l'intéressé(e),

La Directrice Générale des Services Adjointe, certifie que le diplôme de

DOCTEUR en Sciences Cognitives et Ergonomie, option Sciences Cognitives

est conféré à **Madame Camille JEUNET** pour en jouir avec les droits et prérogatives qui y sont attachés.

Fait à Talence, le 12 décembre 2016

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P/O Hélène JACQUET
Directrice générale des services adjointe
Directrice du Pôle Recherche, International, Partenariats et Innovation

Cécile GIRARD
Responsable administratif et financier du Collège des Ecoles doctorales

AVIS TRES IMPORTANT
L'intéressé(e) ne devra en aucun cas se dessaisir de la présente attestation car il ne lui en sera pas délivré un second exemplaire.

UF Mathématique et
Interactions
Master SHS Sciences
Cognitives et Ergonomie

Responsable Pédagogique :
Pr Bernard N'Kaoua

Bordeaux, le 19/12/2016

Objet : soutien à la candidature de Camille Jeunet au prix de thèse IFRATH-KAELIS 2016

Madame, Monsieur

Camille Jeunet a obtenu à l'Université de Bordeaux, sa Licence en Mathématiques Appliquées aux Sciences Sociales avec mention bien (classée $3^{ème}$) et son Master en Sciences Cognitives avec mention très bien (classée $1^{ère}$). Durant son Master, elle a effectué une mobilité d'un semestre au Québec (note : A+). Elle s'est passionnée pour les interfaces cerveau-ordinateur dès son projet de fin de licence et a effectué plusieurs stages sur le sujet en cherchant à se familiariser avec différents points de vue, puisqu'elle a su alterner entre le milieu des sciences humaines, le milieu des neurosciences et le milieu informatique/interaction homme-machine. De 2013 à 2016, Camille a été doctorante au sein de l'Equipe Handicap Activité Cognition Santé (Université de Bordeaux) et de l'équipe Potioc (Inria Bordeaux Sud-Ouest). Camille a obtenu une allocation de recherche Idex, allocation réservée aux meilleurs étudiants, après s'être classée seconde au concours de l'Ecole Doctorale Sociétés, Politique et Santé Publique. Elle a réalisé une thèse internationale en collaboration avec le « Interact Lab » (Université du Sussex, UK).

Camille a mené son travail de thèse avec un dynamisme, une motivation et des compétences qui font d'elle une étudiante extrêmement brillante. Elle a soutenu sa thèse le 2 Décembre 2016 et le jury a reconnu les très grandes qualités scientifiques de Camille et le caractère novateur du travail qu'elle a réalisé dans le champ de la prise en compte du facteur humain dans les interfaces cerveau-ordinateur. Elle a déjà pu valoriser ses recherches par la rédaction d'articles scientifiques publiés dans des revues de très haut niveau international (PLoS Pne, Progress in Brain Research, Journal of Neural Engineering ou encore Frontiers in Neurosciences). Elle a également participé à de très nombreux congrès nationaux et internationaux, dont l'un (CJCSC 2015) qui lui a valu le Best Paper Award.

Camille a également une expérience conséquente d'enseignement (en tant que monitrice durant deux années) dispensée au sein de la licence MIASHS et du master en Sciences Cognitives et Ergonomie de l'Université de Bordeaux. Elle a également participé à l'organisation de 3 Workshops, expertisé des articles pour de nombreuses revues internationales (PLoS One, International Journal of Psychophysiology, etc.), et contribué à l'encadrement de nombreux étudiants de master.

Enfin, en plus de son impressionnante activité scientifique, Camille s'est également impliquée dans des activités collectives en étant membre du comité des doctorants de l'école doctorale Sociétés, Politique, Santé Publique, ou encore Membre fondateur de l'Association des doctorants de l'EDSP2 et Trésorière de cette association pendant deux ans.

Pour conclure, j'ai côtoyé Camille lors de sa licence (en tant qu'enseignant), de son master (en tant que responsable du master) et de son doctorat (en tant que co-encadrant de sa thèse). Il s'agit d'une étudiante que l'on peut qualifier d'exceptionnelle tant par son dynamisme et ses compétences (comme en témoigne son impressionnante épreuve de titre) que par ses qualités humaines qui en font une collaboratrice appréciée de tous.

Pour toutes ces raisons, je soutiens sans réserve la candidature de Camille Jeunet au prix de thèse IFRATH-KAELIS 2016.

Bien cordialement

Bernard N'Kaoua
Laboratoire Handicap Activité Cognition Santé
Equipe Phoenix Inria Bordeaux Sud-Ouest
Co-Responsable du Master Sciences Cognitives et Ergonomie
Directeur de l'école doctorale sociétés, Politique et Santé Publique

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INVENTORS FOR THE DIGITAL WORLD

Recommendation letter for Camille Jeunet

To whom it may concern,

I had the opportunity to start working with Camille Jeunet in February 2013, when I co-supervised her Master Thesis with Dr. Christian Mühl. She was working on stress monitoring in brain signals with us. I have been working with her since then. Indeed, after her Master Thesis, Camille started a PhD with me (that I co-directed with Dr. Martin Hachet, Pr. Bernard N'Kaoua, Pr. Sriram Subramanian) in October 2013. The domain of her PhD was Brain-Computer Interfaces (BCIs), which are communication and control tools that enable people to send commands to a computer by using brain activity only. For instance, a BCI can enable a user to move a cursor on a computer screen towards the left or right, by imagining left or right hand movements, respectively. As such, BCIs are very promising technologies for severely motor impaired users, as they can be used to controlled assistive devices such as wheelchairs, prostheses and spellers without any physical activity. Unfortunately, BCIs are still barely used outside laboratories, because they are not yet reliable: they often erroneously recognize the mental commands sent by the user. Bringing BCIs to motor impaired users thus requires to improve their reliability. Camille's PhD address this issue in a very original way: rather than focusing on brain signals decoding, which most of the BCI community is doing, she studied the user in the loop and how to efficiently train BCI users to gain control of the BCI, to produce reliable mental commands. Her PhD aimed at understanding BCI control skill acquisition and at proposing new training approaches for BCI, in order to improve their reliability, which is needed to make them usable by motor impaired users.

Overall, I consider myself very fortunate to have had the chance to work with Camille, as she is really an exceptional scientist and collaborator. Camille is very hard working, organized, autonomous, rigorous and with a high sense of integrity. She is also scientifically curious and willing to learn new things, and she does not hesitate to seek by herself relevant help and collaborators to complement her own skills and perform even higher quality research. This results in a very impressive scientific productivity, with Camille having already published, 4 journal publications in high quality journals (PLOS One, Frontiers in Neurosciences, Progress in Brain Research, Journal of Neural Engineering, all with impact factors higher than 3), 1 book chapter and 9 peer-reviewed international conference papers (including a best-paper award). More importantly than this important quantity of research, the quality of the research produced by Camille is to be noted, as her work revealed some very important links between BCI users profile and cognitive abilities, and their skills at BCI control. Her work also contributed a first model of BCI control performance, and thus a clearer and theoretically grounded understanding of BCI skills. Based on this understanding, she also proposed, implemented and evaluated several new methods, feedback and training tasks that actually improved BCI user training and/or user experience during training. Her exceptional work opened the door to many new research directions and applications of BCIs. In particular, based on her results, Camille and I started to work with Bordeaux hospital, to use BCI with motor impaired users, for post-stroke rehabilitation. The results obtained from her PhD also form an excellent basis to further improve BCIs and make them finally reliable. I notably recently obtained an ERC starting grant for the project BrainConquest (2017-2021), which is a direct follow-up on Camille thesis. This project indeed aims at developing models and tools to understand and drastically improve BCI user training, to make them finally efficient and usable in everyday life by motor impaired users.

In addition to scientific works, Camille is also very active in scientific animation, including teaching, scientific mediation and outreach as well as workshops organization. She notably teaches in cognitive sciences and mathematics and computer sciences applied to social sciences, for instance classes in Human-Computer Interaction and Human Factors. Her dedication to teaching and her original approach enabled her to won the "best teacher award" from Bachelor students. She is also regularly giving popularization talks on BCI, for which she even won an audience prize and a jury prize for the French "3 minutes thesis" competition. Finally, she is also very active in organizing scientific events and workshops, such as popularization events, scientific workshops and debates within the lab, and she even co-organizes scientific special sessions in international conferences. She notably co-organized two special sessions on BCIs as part of the IEEE System Man and Cybernetics international conference series.

Finally, as a person, Camille is extremely enjoyable to work with. She very friendly, easy to talk to, funny and kind. She is also very rational, and has an objective view of her strengths and weaknesses, which makes debates and work discussions with her constructive and efficient.

For all these reasons, I am therefore very happy to recommend Camille Jeunet for a PhD thesis award from the IFRATH, as her PhD work is clearly an important landmark in the research and development of BCIs and their future use by motor impaired people. Such a prize would also certainly contribute to make Camille able to pursue her work in the field, as it will certainly help her to obtain an associate-professor or research scientist position on BCI, which she is very passionate about. I am actually confident that Camille will become a major scientific actor in the field of Brain-Computer Interfaces research and assistive technologies in the future.

Please don't hesitate to contact me if you need any additional information.

Best regards,

Fabien LOTTE