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Evaluation report for the PhD manuscript of Mr. Jimmy Petit, entitled “Somatosensory Gating for Brain-Computer Interfaces using Vibro-Tactile Stimulation”

This PhD manuscript by Mr. Jimmy Petit, which is 198 pages long including appendixes, describes the work he performed on the design of ElectroEncephaloGraphy (EEG)-based Brain-Computer Interfaces (BCI) exploiting both Steady State Somatosensory Evoked Potentials (SSSEP) and Motor Imagery (MI) tasks. The general idea is the exploit the somatosensory gating phenomenon, which is expected to reduce the amplitude of SSSEP during vibro-tactile stimulation when the user is performing MI, thus possibly generating a clearer EEG pattern to decode with a multi-class BCI based on the SSSEP amplitude. This thesis comprises 7 chapters, including a general introduction, a state-of-the-art survey chapter, 4 experimental and methodological chapters and a conclusion chapter. I comment each of them separately below.

The first introductory chapter presents a general introduction to the thesis, presenting the different types of BCIs, the main BCI challenges, and then the motivation of the thesis, which is to combine active and reactive BCI, to design a new BCI that could be used without sight control. This led to the proposal of combining SSSEP with MI to benefit from a synergetic effect of both BCI types. While I was not fully convinced by the argument that using MI could increase the number of commands – indeed it was shown than only very few classes of MI (typically around only 3) could be used together without degrading the information transfer rate (Kronegg 2007), the argument that MI could act as a gating mechanism to affect SSSEP amplitude and thus lead to clearer patterns for each class, was a strong and valid argument. This chapter then presents the main research questions of this thesis – all very relevant – and gave an overview of the associated contributions.

The following chapter, chapter 2, presents a state-of-the-art survey on SSSEP characterization and their use for BCI. This chapter presents a systematic review of the literature, and describes the various characteristics of SSSEP (e.g., spatial or spectral ones), an overview of studies dedicated to this phenomenon, e.g., on how to trigger such SSSEP, or about the optimal frequencies of stimulation for the maximum SSSEP responses. It also presents an overview of the studies using SSSEP to design BCIs, including about which tasks the users had to do or how the EEG were processed and classified to identify SSSEP. This state-of-the-art is very well written, clearly organized and comprehensive, giving a very nice overview. It should also be stressed that it was published in Journal of Neural Engineering, one of the most prestigious journal in the BCI field.

Chapter 3 presents a signal processing contribution on the estimation of the amplitude of sinusoidal components, here for SSSEP estimation. It proposes a nice theoretical model to represent such SSSEP signals, and generate them, as well as a theoretical estimation of their amplitude. Such estimated amplitudes seem correct, although one derivation mentioned that the average of squared cosine terms converges to zero and can be negligible. It does not, it actually converges to 0.5, but the

provided final result seem correct (hence the “divided by 2” in equation 3.6), so it is probably just a writing error, not a mathematical error. Regarding the assumption that the signal of interest is the same in all measurement channels and that the noises are mutually independent, I am not sure that this assumption is too reasonable. Indeed, typical noises such as EMG or EOG affect multiple channels simultaneously, thus making their noise not mutually independent. It may be true for other types of noise though. Otherwise, it would be nice to mention the order and low-pass frequency cutoff for the LiA.
The proposed model, used to provide a ground truth, is then used to generate artificial data and compare different signal processing algorithms, including LiA (with various spatial filters), CCA and PLS. Simulations show that LiA, notably with a Laplacian, leads to the best estimates of SSSEP amplitudes, much better than CCA and PLS. The following analysis on real EEG data lead to similar results, with LiA with CSD giving the best results overall, way better than CCA and PLS. I have to mention though, that the comparison with CCA and PLS was not fully fair, or at least was not using CCA and PLS as best as possible. Indeed, LiA was used with a strong prior on the relevant channel of interest, since it was used only on C3 and C4 where it is known that the SSSEP are expected. In contrast, both CCA and PLS were used on all 64 channels, i.e., including many channels that are known not to be relevant for estimating SSSEP. That made the learning tasks much more complicated for CCA and PLS. Why not using neurophysiological prior for CCA/PLS as well, e.g., by using them only on motor and sensorimotor channels rather than on all channels? That is typically what is used for SSVEP, with CCA being used only on occipital channels, and not on all channels. Additionally, it was shown for SSVEP that, when using CCA, training the reference target signals on users’ EEG (rather than using pure sinusoidal terms), lead to even better SSVEP detection accuracy (Zhang 2014). I am wondering whether that could help making CCA better for SSSEP as well. Finally, the focus was here on the amplitude estimation. However, as far as BCI is concerned, the correct estimation of amplitude is not what really matters. What matters is whether those estimated amplitude could be used to distinguish different mental commands – which may be a different problem and may lead to different results. Nonetheless, this chapter provided a very nice approach to compare various algorithms, based both on relevant model-based simulations and real EEG data analyses, and including neurophysiological analyses as well, which should be commended.

Chapter 4 presents an EEG and BCI experiment, in which the actual gating hypothesis is tested, with subjects being stimulated with vibro-tactile stimulus, and performing either rest or various MI tasks. The experiment is nicely conducted and rigorous, and enables various analyses. This chapter notably reports on neurophysiological analyses of the recorded EEG, showing that there is indeed a gating effect with MI, but that this gating effect is not specific to the MI tasks, contrary to initial expectations. While this is a negative result, that is still a relevant, valid and useful result, definitely contributing to the knowledge base about SSSEP and BCI.

Chapter 5 presents follow-up analyses to that of the previous chapter, in particular classification analyses, both online and offline ones. For the offline ones, it would have been nice to mention which classifier was used to classify the two-dimensional vector into 4 classes. The various offline classification analyses performed revealed that unfortunately, better than chance classification performances could not be obtained. It should be noted here that the chance level threshold used was very conservative and probably more strict than the real chance level – indeed the chance level for 10 trials per class was used, whereas multiple random train and test splits were used, meaning than in the end many more than 10 trials have been used for testing. Thus the obtained performances are probably not as far from being better than chance as it may seem.

Chapter 6 presents two gaming applications that could be controlled by the proposed 4-class SSSEP+MI BCI, and that are studied from a Human-Computer Interaction (HCI) and Human Factors point of view. It notably studies the User eXperience (UX) of various BCI users with these two applications, using sham feedback, which provides various useful and relevant insights and the pros and cons of both applications – from a UX perspective - when used with a given BCI.

Finally, chapter 7 presents a global discussion, summarizing the thesis contributions, its limitations and providing various relevant and promising perspectives for future works following up on this thesis.

Overall, this thesis contributes various new knowledge and methods for the design, analysis and use of SSSEP-based BCI. It is quite remarkable that these contributions span a number of different disciplines and skill sets, notably a very strong state-of-the-art, theoretical and applied signal processing, EEG/BCI experiments, neurophysiological analysis, offline machine learning as well as Human-Computer Interactions and Human Factors studies. This is all very good, and a lot of very good work that not many people would be able to do. Moreover, the thesis is globally very well written, being clear, very easy and pleasant to read, and very well illustrated. For all these reasons, I am thus very happy to recommend this thesis to be defended.

References:

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15/11/2022

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