BCI Research at Inria Bordeaux: making BCI designs usable outside the lab

Fabien Lotte, Florian Larrue, Martin Hachet

BCI Research at Inria Bordeaux: making BCI designs usable outside the lab

F. Lotte[1], F. Larrue[1], M. Hachet[1]
[1]*Inria Bordeaux Sud-Ouest/LaBRI, Talence, France*

Correspondence: F. Lotte, Inria Bordeaux Sud-Ouest, 200 rue de la vieille tour, 33405 Talence, France.
E-mail: fabien.lotte@inria.fr

Abstract. This paper presents an overview of the recent BCI research conducted by scientists from Inria Bordeaux. It aims at designing practical BCI systems and applications that could be used outside laboratories. More precisely we describe 1) our work on signal processing and machine learning to make BCI more efficient, robust to noise and with minimal calibration times, as well as 2) practical applications in the research fields of spatial cognition and gaming.

Keywords: motor imagery, signal processing, machine learning, calibration, feedback, features, virtual reality, gaming

1 Introduction

Although Brain-Computer Interfaces (BCI) have demonstrated their tremendous potential in numerous applications [van Erp et al., 2012], they are still mostly prototypes, not used outside laboratories. This is mainly due to the following limitations: *1) Performances:* the poor classification accuracies of BCI make them inconvenient to use or simply useless compared to available alternatives; *2) Stability and robustness:* the sensibility of ElectroEncephaloGraphic (EEG) signals to noise and their inherent non-stationarity make the already poor initial performances difficult to maintain over time; *3) Calibration time:* the need to tune current BCI to each user's EEG signals makes their calibration times too long. At Inria Bordeaux, in team Potioc (team.inria.fr/potioc), we notably aim at addressing these limitations, to design practical BCI systems, usable and useful outside laboratories. This is part of our general research objective to make human-computer interfaces, in particular 3D ones, usable and useful for everyone. We describe here our recent work on signal processing to reach this objective and present two practical BCI applications we designed.

2 Signal processing contributions

Performances: To improve BCI performances, we explored and designed new features to represent EEG signals. We notaly explored multifractal cumulants and predictive complexity features [Brodu et al., 2012], as well as waveform length features together with an optimal spatial filter that we designed for such features [Lotte, 2012a]. All such features proved useful to classify EEG signals, and, more importantly, increased BCI classification performances (by 2 to 4% on average) when combined with the gold standard features, namely, band power features.

Stability and robustness: To make BCI more robust to noise and non-stationarities (which incidentally also improves their performances), we proposed to integrate a-priori knowledge into machine learning algorithms. Such knowledge represents any information we have about what should be a good filter or classifier for instance. This can be neurophysiological a-priori, data (EEG signals) or meta-data (e.g., good channels) from other subjects, etc. This knowledge is used to guide machine learning algorithms towards good solutions even with noise and non-stationarities. We successfully demonstrated this approach to learn robust and stable spatial filters [Lotte and Guan, 2011].

Calibration time: To reduce BCI calibration times, we have to design BCI from very few training EEG signals. We have explored three approaches to do so. First, we used statistical estimators dedicated to small sample size problems, such as automatic covariance matrix shrinking [Lotte and Guan, 2010]. Secondly, we used EEG signals from other subjects (who performed the same mental tasks) to regularize machine learning algorithms, which proved even more efficient [Lotte and Guan, 2010]. Finally, we proposed to generate artificial EEG signals from the few EEG trials initially available, in order to augment the training set size in a relevant way [Lotte, 2011]. All these approaches enabled us to calibrate BCI systems with 2 to 3 times less data than standard designs, while maintaining similar classification performances, hence effectively reducing the calibration time by 2 or 3.

3 BCI applications

So far, most of our application-related work has been around Virtual Reality (VR) [Lotte et al., 2013]. Here we focus on two practical applications: using BCI as a tool 1) to study spatial cognition and 2) for multiplayer gaming.

3.1 BCI as a tool to study spatial cognition

We proposed a new application of BCI: using it as a tool to study spatial cognition and transfer from VR Environments (VE) to Real Environments (RE). In particular, since BCI can be used to navigate a VE without any motor activity (see Figure 1, left), BCI can be used to assess how much motor activity and vestibular information is really needed to transfer spatial knowledge from a VE to a RE. To do so, we compared a motor imagery-based BCI and a treadmill to make users learn a path in a VE and retrieve it in the real world. Contrary to previous beliefs, our results suggested that motor activity and vestibular information are not necessary to learn a path in VR. Performing an action - even only a cognitive one (e.g., imagining hand movements) - seems enough to enable spatial transfer [Larrue et al., 2012].

3.2 Multiplayer BCI Gaming

We developed and studied a multiplayer BCI-based video game (see Figure 1, right) [Bonnet et al., 2013]. In this game, players had to collaborate or to compete (depending on the game mode) to bring a ball towards a given goal, using motor imagery of the corresponding hand. Such an application proved interesting at two levels. First, players enjoyed the game, and enjoyed it even more than its single player version. Second, the BCI performances of several players was improved during multiplayer games as compared to single player ones.

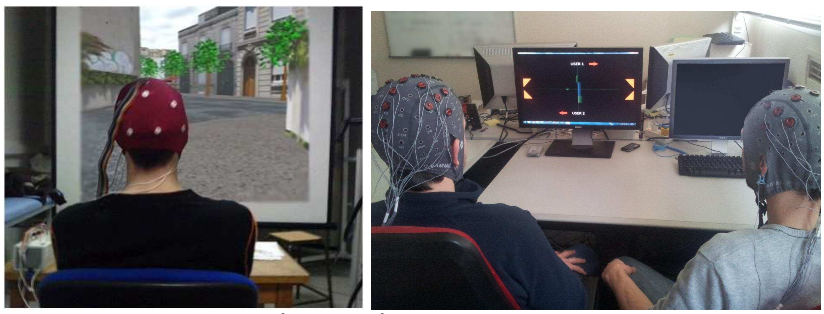

Figure 1: *Left: A user navigating a virtual model of the city of Bordeaux with a BCI, in order to learn a specific path [Larrue et al., 2012]. Right: Two users playing a competitve BCI-based video game [Bonnet et al., 2013]*

4 Discussion and Perspectives

In summary, our research work on signal processing has led to improved BCI performances, robustness and calibration times. From an application point of view, we have showed that BCI could be a tool to study spatial cognition, and stressed once more the advantages of combining BCI and gaming, both for BCI and gaming.

However, much work still needs to be done, with BCI performances still far too low and calibration still necessary. Moreover, besides signal processing, studying educational research made us realize that current BCI feedback training approaches are probably suboptimal and a major cause for BCI limited performances [Lotte, 2012b]. We are therefore working on the design of more efficient user feedback training paradigms. Finally, we are starting a couple of projects on passive and affective BCI, a very promising application area that deserves more attention [van Erp et al., 2012].

References

Bonnet, L., Lotte, F., and Lécuyer, A. (2013). Two brains, one game: Design and evaluation of a multi-user BCI video game based on motor imagery. *IEEE Transactions on Computational Intelligence and AI in Games*.

Brodu, N., Lotte, F., and Lécuyer, A. (2012). Exploring two novel features for EEG-based brain-computer interfaces: Multifractal cumulants and predictive complexity. *Neurocomputing*, 79(1):87–94.

Larrue, F., Sauzeon, H., Aguilova, L., Lotte, F., Hachet, M., and Nkaoua, B. (2012). Brain Computer Interface Vs Walking Interface in VR: The Impact of Motor Activity on Spatial Transfer. In *Virtual Reality Software and Technologies (VRST 2012)*.

Lotte, F. (2011). Generating artificial EEG signals to reduce BCI calibration time. *5th International BCI Conference*, pages 176–179.

Lotte, F. (2012a). A new feature and associated optimal spatial filter for EEG signal classification: Waveform length. In *ICPR*.

Lotte, F. (2012b). On the need for alternative feedback training approaches for BCI. In *BBCI workshop*.

Lotte, F., Faller, J., Guger, C., Renard, Y., Pfurtscheller, G., Lécuyer, A., and Leeb, R. (2013). Combining BCI with Virtual Reality: Towards new applications and improved BCI. In *Towards Practical Brain-Computer Interfaces*, pages 197–220. Springer Berlin Heidelberg.

Lotte, F. and Guan, C. (2010). Learning from other subjects helps reducing brain-computer interface calibration time. In *ICASSP*, pages 614–617.

Lotte, F. and Guan, C. (2011). Regularizing common spatial patterns to improve BCI designs: Unified theory and new algorithms. *IEEE Transactions on Biomedical Engineering*, 58(2):355–362.

van Erp, J., Lotte, F., and Tangermann, M. (2012). Brain-computer interfaces: Beyond medical applications. *IEEE Computer*, 45(4):26–34.