Using EEG/MEG Data of Cognitive Processes in Brain-Computer Interfaces

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Abstract. Brain-computer interfaces (BCIs) aim at providing a non-muscular channel for sending commands to the external world using electroencephalographic (EEG) and, more recently, magnetoencephalographic (MEG) measurements of the brain function. Most of the current implementations of BCIs rely on EEG/MEG data of motor activities as such neural processes are well characterized, while the use of data related to cognitive activities has been neglected due to its intrinsic complexity. However, cognitive data usually has larger amplitude, lasts longer and, in some cases, cognitive brain signals are easier to control at will than motor signals. This paper briefly reviews the use of EEG/MEG data of cognitive processes in the implementation of BCIs. Specifically, this paper reviews some of the neuromechanisms, signal features, and processing methods involved. This paper also refers to some of the author's work in the area of detection and classification of cognitive signals for BCIs using variability enhancement, parametric modeling, and spatial filtering, as well as recent developments in BCI performance evaluation.

Keywords: Brain-computer interface, electroencephalography, magnetoencephalography, cognitive brain activity.
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INTRODUCTION

A brain-computer interface (BCI) is a communication system that allows a subject to act on his/her environment solely by means of his/her thoughts, i.e. without using the brain's normal output pathways of muscles or peripheral nerves [1]. Non-invasive BCIs rely on electroencephalographic (EEG) or magnetoencephalographic (MEG) measurements of the brain's activity to read out the intentions of the subject and translate them into commands for a computerized system.

In recent years, the use of EEG signals in BCI implementations has improved due to a widespread research effort. However, the use of MEG data in BCI is still limited because of the expensive technology associated to MEG, its immobility, and its signals being vulnerable to urban magnetic noise which can be six orders of magnitude larger than the measured magnetic fields [2]. Still, the use of MEG data in BCI is considered due to intrinsic advantages compared to EEG: the electric potentials measured by EEG are distorted by the inhomogeneities of extracerebral tissues, whereas the magnetic fields are not affected as long as the electric inhomogeneities are concentric. Therefore, MEG signals are more local than the corresponding EEG signals. Also, MEG is easier to interpret than EEG because no reference is needed in MEG measurements. Then, the use of MEG in BCI will probably spread in the future as those advantages are exploited, and as technology progresses to the point of having portable MEG devices (see e.g., [3]).

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Current BCIs rely on different neuromechanisms as control signals [4], but the most commonly used are those originated from sensorimotor brain activity such as changes in brain rhythms (mu, beta, and gamma), movement-related potentials, and other event-related potentials extracted from EEG/MEG signals filtered to frequencies below 30 Hz [5]. Recently, BCI systems based on non-movement mental tasks have been developed, specially those based in motor imagery, as their characteristic EEG/MEG signals are closely related to movement planning, which is a relatively straight-forward task to detect [6]. BCI systems based on cognitive signals may also assume that different mental tasks (e.g., solving a multiplication problem, imaging a 3D object, and mental counting) lead to distinct, task-specific distributions of EEG/MEG patterns [7]. In any case, cognitive tasks have shown some advantages compared to sensorimotor ones, such like easier discrimination due to their larger amplitude and longer duration, less skill and training time required to control them at will, and more flexibility to relate them to a person's specific ability [8].

The aim of this paper is twofold. First, this paper briefly reviews the use of EEG/MEG data of cognitive processes in the implementation of BCIs. In specific, this paper looks at the neuromechanisms, signal features, and processing methods used to develop a cognitive EEG/MEG data-based BCI system. The second aim of this paper is to bring to the reader's attention some of the author's work in the area of detection and classification of cognitive signals for BCIs using variability enhancement, parametric modeling, and spatial filtering, as well as recent developments in BCI performance evaluation. Such work is part of the author's efforts to help developing a BCI system in realistic working conditions.

BCI SYSTEMS BASED ON COGNITIVE SIGNALS

The most recent achievements on using cognitive signals in BCI systems have involved the development of powerful signal processing techniques to enable reliable and accurate control over mental tasks. However, most of the work done in this area has been based on EEG data of motor imagery tasks. Some of the feature extraction methods often used include spectral parameters, parametric modeling, signal complexity, eigenvalues of correlation matrix, among others (see [4] for a comprehensive survey of methods). Still, little attention has been paid to the ways of generating and controlling EEG activity [9].

While technological advances are essential, reliability of BCI systems will also be influenced by user's performance, as some tasks may be inappropriate for certain groups of subjects. For instance, motor imagery may be difficult for a person who has been paralyzed for many years, as visual tasks and feedback may be inappropriate for some visually impaired people. In [10], four different cognitive tasks were investigated in order to find EEG patterns that could be differentiated most reliably: spatial navigation around a familiar environment, auditory imagery of a familiar tune, and right and left imaginary movements of the hand. One important conclusion of this study is that the selection of the cognitive task has to be done accordingly to the subject's best capacities, i.e. the reliability of tasks needs to be evaluated.

One of the few examples of BCI systems based on cognitive signals different to motor imagery is the work in [7], where more complex cognitive processes were considered: a baseline task, mental multiplication, geometric figure rotation, mental letter composing, and visual counting. Even though this work reported excellent results in classifying such processes, the focus of the investigation was on the signal modeling rather than taking advantage of specific characteristics of the signals to achieve better classifications rates.

Another interesting example of using a higher cognitive task for BCI applications is proposed in [11]. There, the activation of the working memory system in a mental calculation task is measured with functional magnetic resonance imaging (fMRI). Moreover, activity measured in the dorsolateral prefrontal cortex (DLPFC) indicated that the region is active for the duration of the mental process. This supports the notion that DLPFC can be activated, and remains active, at will. Further confirmation was obtained with electrocorticographic (ECoG) measurements from a patient. Those measurements showed that gamma power within DLPFC increased during mental calculation and remained elevated for the duration thereof. The results in [11] indicated that cortical regions involved in higher cognitive functions may serve as a readily self-controllable input for BCI applications.

BCI SYSTEMS BASED ON MEG DATA

Many technological facts are against using MEG data in BCI applications: the expensive technology associated to it, its immobility, and its vulnerability to magnetic noise are some of them. However, using MEG has the advantage of being easier to interpret than EEG, MEG signals suffer far less spatial blurring due to the different isolating layers of the head effect compared to EEG, and bimodal EEG/MEG systems are becoming more available every day. Therefore, some research groups are exploring the use of MEG data in BCI applications hoping that the improved MEG signal properties translate into increased BCI communication speed.

The first demonstration of a functioning MEG-based BCI was reported in [12]. In this work, MEG signals corresponding to the imaginary task of moving the tongue or the left little finger were used to operate a BCI with a combination of feature selection techniques, recursive channel elimination, and linear Support Vector Machines (SVM). The classification performance ranged, across five subjects, from chance level up to 92%, while it was possible to reduce the number of used MEG channels to less than 5% of the original 150 channels without significant loss of classification performance. The work in [12] also gave evidence that an imaginary left hand versus right hand movement task might be better suited for future MEG-based BCI systems.

Another MEG-based BCI was reported in [13]. In this case, the cognitive task was a continuous visuomotor coordination experiment which required subjects to continuously manipulate a track-ball to compensate the random rotations of a cube projected on a display screen. Even though the interface required direct motor intervention of the subject, the problem was considered of cognitive nature due to the visual feedback, and the problem then focused on extracting oscillatory brain activities involved in this continuous task. The study showed that Second Order Blind Identification (SOBI) could be applied to ongoing MEG signals to create a highly interpretable representation of the signal which improved the BCI performance. In [14], SOBI was compared to other blind separation methods in the problem of classifying MEG recordings. However, in this case the study used MEG time-locked recordings corresponding to the presentation of distinct words in the auditory and visual modalities. The results of this work suggested that mean classifications rates can be improved by spatially decomposing the MEG data before being classified rather than using SOBI. Still, the performance rates are highly dependent to the cognitive task used. The study in [14] also confirmed that linear classification methods can achieve higher mean classification rates than non-linear methods.

Other studies have focused in comparing MEG-based BCIs to EEG-based ones (see [15] and [16]), and also to invasive systems based on ECoG data from epileptic patients [17]. While the cognitive tasks were different in these studies, as well as the selected classification algorithms, all three concluded that classification accuracy is quite similar in MEG-based BCIs to those obtained in comparable EEG and ECoG studies. Still, MEG signals were easier to interpret and required less spatial filtering, i.e. there was no appreciable difference in performance between classification of the raw MEG signals and classification of a linear combination of signals from different channels. Therefore, such good spatial resolution of MEG could be advantageous in multicategory classification when multiple tasks involve activity in distinct brain areas. Finally, these results suggest that an MEG-based BCI is feasible and efficient in terms of the user, given that the training period to control the BCI is faster using MEG than EEG, and comparable to those reported for ECoG, but without being invasive.

TOWARDS A COGNITIVE EEG/MEG DATA-BASED BCI

In order to implement a cognitive EEG/MEG data-based BCI, some issues need to be addressed:

- The selection of the cognitive task has to be based on the best subject's abilities.
- Such selection has to use a standardized evaluation system in order to accurately determine the performance of the BCI in realistic conditions.
- The use of bimodal EEG/MEG systems should be considered, at least in the training phase of BCI developing, so the complementary information of those two modalities provide is exploited.

The solution to those problems cannot be achieved by a single method, but by an organized and well justified number of processing steps. An example of such approach was presented in [18], where the same cognitive EEG data from [7] was used, but in this case it was treated in a different way. The method proposed in [18] included a pre-processing step based on the length and energy transforms in order to enhance the signal's variability, then autoregressive (AR) models were used to reduce the dimensionality of the problem, and finally the classification was performed using the Mahalanobis distance-based classifier. As result, a more accurate classification was achieved when the data was transformed through the length or energy transform even for low-order AR models, having the length transformation a slightly better performance.

In terms of the evaluation of the BCI's performance, most studies have looked at the speed and/or accuracy of the classification. However, such performance is usually computed under *ad hoc* conditions, and an evaluation of the BCI for those circumstances may not be sufficient to predict its performance on real-life conditions. In [19], the performance of a BCI is assessed in terms of the estimated probability density function (PDF) of the percentage of correct classifications when using single-trial EEG/MEG data. The PDF is then considered to vary as a function of the number of measuring channels, the amount of data (number of independent trials) used for training the classifier, and the signal-to-noise ratio (SNR). Preliminary results show that, even though decreasing any of these three variables reduces the performance of the classifier, both the number of channels and the amount of training data can be adjusted in real-life BCI applications, while the SNR is more difficult to control. For this reason, a spatial filter designed for a two-class discrimination problem is proposed in [20] to increase SNR of the signals and, therefore, improve the performance of the classifier.

In order to take full advantage of using cognitive data in BCI applications, it is necessary to establish a rigorous task selection procedure, as to warranty that the task corresponds to the best subject's abilities. Then, the use of neuropsycological test batteries (NTBs) need to be considered as tools for selecting the cognitive processes in addition to signal processing tools. NTBs would then be focused in doing a user-based selection of the cognitive process, while signal processing techniques would be in charge of highlighting specific characteristics of the chosen signal (task specificity). Such procedure could provide further support for designing a BCI system based on a broader range of reliable tasks, so that a choice is made available for different subjects.

CONCLUDING REMARKS

This paper has briefly reviewed some of the current developments and issues related to building a BCI system based on EEG/MEG measurements of cognitive tasks. Even though there are a number of very successful procedures to reliably and quickly identify brain waves, there is still much work to do in order to develop a robust BCI system which is functional in real-life conditions. The application of MEG technology in BCI applications needs to be explored in more detail. Since the brain signals exploited by EEG and MEG are fundamentally the same, users could benefit from working on a MEG-based BCI in a training stage, and then move to a more portable EEG-based system in a real-life scenario. Furthermore, a more intensive exploration of cognitive tasks, as well as operant conditioning methods, is required. Unless such variety of tasks is made available and their reliability evaluated, current BCI technology may have limited value for disabled people.

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