Towards Ambulatory Brain-Computer Interfaces: A Pilot Study with P300 Signals

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ABSTRACT

Brain-Computer Interfaces (BCI) are communication systems that enable users to interact with computers using only brain activity. This activity is generally measured by ElectroEncephaloGraphy (EEG). A major limitation of BCI is the electrical sensitivity of EEG which causes severe deterioration of the signals when the user is moving. This constrains current EEG-based BCI to be used only by sitting and still subjects, hence limiting the use of BCI for applications such as video games. In this paper, we proposed a feasibility study to discover whether a BCI system, here based on the P300 brain signal, could be used with a moving subject. We recorded EEG signals from 5 users in 3 conditions: sitting, standing and walking. Analysis of the recorded signals suggested that despite the noise generated by the user's motion, it was still possible to detect the P300 in the signals in each of the three conditions. This opens new perspective of applications using a wearable P300-based BCI as input device, e.g., for entertainment and video games.

Categories and Subject Descriptors

H5.2 [**Information interfaces and presentation**]: User Interfaces

General Terms

Experimentation, Performance

Keywords

Brain-Computer Interface (BCI), P300, ambulatory interface, electroencephalography (EEG)

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1. INTRODUCTION

Brain-Computer Interfaces (BCI) are communication systems that enable users to interact with computers only by means of brain activity [3]. Even though BCI were initially targeted for disabled people, they have been recently shown to be promising interaction devices for computer entertainment and virtual reality [9, 11, 5]. Most BCI are based on ElectroEncephaloGraphy (EEG), which measures, on the scalp, very weak electrical currents reflecting brain activity [3]. Indeed, EEG is portable, cheap, non-invasive and provides signals with a high time-resolution. However, when using EEG, user movements are likely to provoke motions of the measuring electrodes which can severely damage the signals. Moreover, muscles contractions or eye movements can generate electrical artifacts which polute the signals. Consequently, current BCI require that the user sits and performs as little movements as possible [3]. This seriously reduces the potential use of BCI for applications such as computer entertainment, in which users are unlikely to accept being continuously seated and motionless while playing. Whether BCI systems could be used in an ambulatory context is still an open question.

Recently Lan et al have obtained promising results showing that their BCI system could identify mental states from a user's EEG signals, in an ambulatory application [8]. However, their system was evaluated with a single user and focused on the detection of very rarely used mental states such as "Communicating with a radio". Finally, they did not study the impact of movements on the BCI performances.

In this paper, we focused on the P300 evoked potential, a signal widely used to drive BCI systems [3, 6, 2]. The P300 is a positive increase of the EEG amplitude which appears approximately 300 ms after the user has perceived a relevant and rare stimulus. It should be noted that the P300 cannot be generated voluntarily, without external stimulus. The P300 has been shown to be a very promising BCI signal with numerous potential applications. Indeed, P300-based BCI have been used to control text editors for disabled persons [3], to monitor users' alertness [7] and for Virtual Reality (VR) and Video Games (VG) [9, 2, 5]. In order to move such prototypes from laboratories to practical computer applications, e.g., for entertainment, it is essential to be able to use P300-based BCI in an ambulatory context. For instance, such a BCI could be used for immersive VR and VG applications, by a user walking in a CAVE immersive virtual environment. Here, the P300-based BCI could be used as a new input command, or the virtual environment could be modified according to the monitoring of the user's P300 response. Other examples could include sending mental commands to a partner robot serving people in outdoor or indoor environments.

In this paper we proposed a feasibility study in order to discover whether a P300-based BCI can be used in an ambulatory context, i.e., when a user is standing or even walking. We performed this study using a limited set of electrodes, i.e., only 3 electrodes, as too many electrodes would make a practical system cumbersome and inconvenient to use.

This paper is organized as follows: the first section describes the experiment we have conducted, including the subjects, data and apparatus we have used. The next section presents the method used to assess the BCI performance in the different ambulatory conditions. The third section details the signal processing and classification techniques used to process the EEG signals. The last two sections present the results, discuss them and conclude.

2. EXPERIMENT

2.1 Population and apparatus

Five healthy subjects (all males, aged 27.4±5.46) participated in this experiment. Four of them had already participated in P300-based BCI experiments before, whereas the remaining one was naive in the field.

EEG signals were recorded using a Polymate AP216 system (TEAC CORPORATION, Japan). This system is a portable EEG machine which uses active electrodes. Such active electrodes are designed to provide a lower impedance, and thus a better signal quality than conventional electrodes. The signals were recorded using electrodes Cz, CPz and Pz, according to the international system [1]. These are the locations where the P300 is expected to appear [3, 6]. The reference electrode was placed on the left ear lobe, whereas the ground electrode was placed on the forehead. All these electrodes were attached using an adhesive paste.

P300-based BCI can use different kinds of stimuli such as visual [6] or auditory stimuli [7]. In this work we used an auditory stimuli as in a previous study [7]. Indeed, it would have been difficult for a user to focus on both the visual stimulus and the path he was walking on. Consequently, during the experiments, subjects were wearing headphones from which they could hear the auditory stimuli. They were also wearing a backpack, in which the portable EEG recording device was placed together with a laptop computer which was in charge of generating the stimuli. The experiment took place in the corridors of the university of Tokyo.

2.2 Task

During the experiment, subjects could hear two brief sounds (the auditory stimuli), in the headphones, appearing in a random order. A sound was generated every 1s. One of the two auditory stimuli, the so-called target stimulus, was

Figure 1: Subjects performing the experiment: Left: walking condition, Right: standing condition.

less frequent than the other. For the target stimuli, a "Ding Dong" tone was used whereas for the non-target stimuli the sound of a buzzer was used. The task of the subjects was to count the number of appearances of the target stimulus. As this stimulus was rare and had been made relevant to the subject thanks to the counting instruction, its appearance was expected to trigger a P300 in the subject's EEG signals. In order to identify whether a P300 could be detected in an ambulatory context, subjects' EEG signals were recorded in three different conditions (see Fig. 1):

Sitting: the subject was comfortably seated in an armchair while performing the experiment. He was instructed to move as little as possible. This is the standard condition in which most P300-based BCI experiments are currently conducted.

Standing: the subject was standing while performing the experiment. He was not allowed to walk. In this condition, more muscle artifacts may distort the EEG signals since the subject has to maintain his balance.

Walking: the subject was walking in the corridors while performing the experiment. This was the most extreme condition since a lot of muscle artifacts were likely to occur and motions of electrodes could also deteriorate the EEG signals. However, this was also the closest condition to real-life situations in which we would like to use P300-based BCI systems.

2.3 Procedure

All subjects, except subject S1, performed 4 recording sessions for each of the three conditions. Only 3 sessions per condition were recorded for S1, due to his availability. A session was composed of 150 trials (i.e., 150 auditory stimuli), among which 120 trials corresponded to non-target stimuli and 30 to target stimuli. The sessions were arranged in the following order: sitting condition, standing condition, walking condition, sitting condition, etc. This cycle repeated until all sessions were completed.

For each subject and each condition the 3 first sessions (2 first sessions for S1) were used as the training set. These training EEG signals were used to build and to calibrate the

BCI system. The remaining sessions were used as the testing set, on which the performance of the BCI was evaluated.

3. PERFORMANCE EVALUATION

In order to evaluate the performance of the BCI in the different conditions, we relied on a widely used method: the Receiver Operating Characteristic (ROC) curve [4]. Such ROC curves can summarize the performance of a pattern recognition system in terms of correct detections, and, as such, can measure the performance of a BCI in terms of P300 detection. Indeed, ROC curves can display the True Acceptance Rate (rate of classification of a P300 as a P300) and the False Acceptance Rate (rate of classification of a non-P300 as a P300). A common metric which can be derived from such curves is the Area Under the ROC Curve (AUROCC). The higher the AUROCC the better the BCI. The AUROCC is the metric we used in order to measure the performance of the BCI in the different conditions.

4. EEG SIGNAL PROCESSING AND CLASSIFICATION

In order to evaluate whether a P300 could be detected in the different conditions, the data recorded as described above were analyzed offline. This analysis simulated an online detection of the P300 using a BCI. The BCI had to classify each trial as "P300" or "Non P300", according to the presence or absence of the P300 respectively. This section describes the EEG signal processing and classification techniques employed to design this BCI.

4.1 Preprocessing

The first processing step in a BCI is the preprocessing step, which aims at denoising the data and enhancing the relevant information it contains. Here, we preprocessed EEG signals using 4 successive methods, applied to each channel:

Epoching: we selected a time window of 600 ms starting immediatly after the stimulus. This time window should contain the P300, if any, as this P300 is supposed to appear approximately 300 ms after the stimulus.

Band-pass filtering: the signals were band-pass filtered in 1-12 Hz using a 4^{th} order Butterworth filter. This aimed at reducing the undesired slow variations of the EEG as well as high frequency noise such as power line interference (50 Hz). Moreover, the P300 is a slow wave known to be located within this range of frequencies [6].

Winsorizing: for each channel, in the time-window defined above, the EEG samples with values within the 5% most extreme values were replaced by the most extreme value from the remaining 95% samples from that window and channel. This should reduce the effect of noise and artifacts. Indeed muscle and eye movement artifacts are generally of much larger amplitudes than real EEG signals. Winsorizing has been succesfully used in another P300-based BCI [6].

Downsampling: The signals were finally downsampled to 25 Hz by keeping one sample every 40 samples, the initial sampling rate being 1000 Hz. This aimed at reducing the dimensionality, and thus the complexity of the problem, in order to ease the task of the subsequent classifier. Moreover, as the P300 is a slow wave, it is appropriate to work with a lower sampling rate.

4.2 Feature extraction and selection

The above preprocessing led to a signal with 15 EEG samples per channel (600 ms of data sampled at 25 Hz). These sample values were then concatenated into a feature vector hence containing 45 features. From these 45 features, a subset of them was selected using the Sequential Forward Floating Search (SFFS) feature selection algorithm [12]. SFFS was used to select the subset of features which maximized the AUROCC, with a maximum of 15 features. The AUROCC was estimated using 4-fold cross validation on the training set, with the classifier described in the next section. In other words, we selected the subset of features which should maximize the detection performance of our BCI.

4.3 Classification

In order to classify the features extracted, we relied on a Linear Discriminant Analysis (LDA) classifier. The aim of LDA is to learn a hyperplane that can separate the data representing the two classes. Using this hyperplane, the LDA classifies a new feature vector depending on which side of this hyperplane the feature vector is [10]. This classifier is popular and efficient for BCI [10]. For each condition, the training set was used to select the features and to train the LDA classifier on these features. Then, the trained LDA was used to classify the features extracted from the corresponding testing set.

5. RESULTS

Before analyzing the classification results, an important point to check when doing P300 experiments is whether there was an actual P300 evoked by the target stimuli. In order to do so, we averaged on one hand the target trials altogether and on the other hand the non-target trials altogether. An example of the resulting waveforms for each condition, here for electrode Cz and subject S1, is displayed in Figure 2. On this figure, we can observe a positive increase of amplitude appearing around 300 ms after t = 0 s (i.e., after stimulus presentation), for each condition. This confirms the presence of a P300 during the target trial. However, it should be stressed that these waveforms are signals averaged over multiple trials, which made the noise vanish. For the purpose of our BCI, we aimed at detecting a P300 in **single trial analysis**, i.e., with no averaging, and as such, with much more noise [2].

The performances obtained by our BCI for each subject and each condition, as measured by the AUROCC, are displayed in Table 1. It should be reminded that a random classifier, i.e., a classifier which is unable to detect the P300 in the EEG signals, would have an AUROCC of 0.5. On the other hand, a perfect classifier would have an AUROCC of 1.0.

6. DISCUSSION AND CONCLUSION

A surprising result that has been observed is that not all subjects obtained their best performance during the sitting condition which was expected to be the least noisy. Moreover, the score obtained on average during the standing condition is slightly higher than that obtained during the sitting condition. A subject even obtained his best performance during

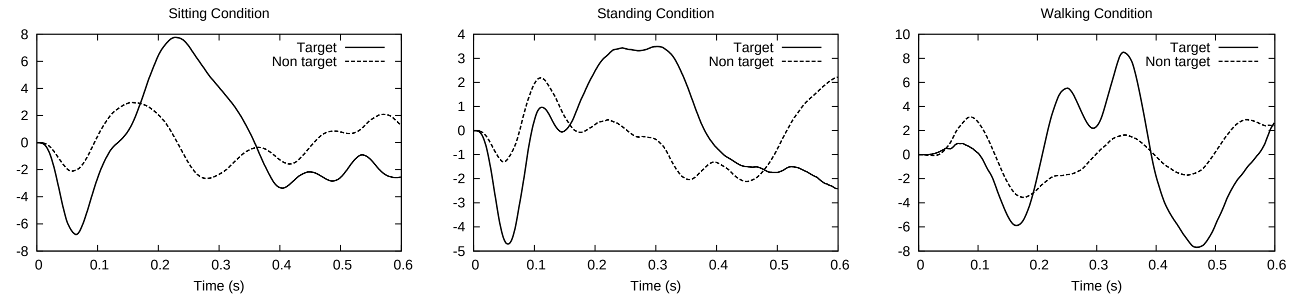

Figure 2: Average waveforms for each condition, subject S1 and electrode Cz, after bandpass filtering and winsorizing. The time t = 0 s corresponds to stimulus presentation. The P300, i.e., the positive wave around t = 0.3 s, is clearly visible in each condition, during the target stimuli.

Table 1: Area under the ROC curve for the different subjects and conditions. The best result for each subject is displayed in bold.

Subjects	S1	S2	S3	S4	S5	Mean
Sitting	**0.7**	**0.74**	**0.67**	0.60	0.64	0.67±0.05
Standing	0.67	0.73	0.64	**0.80**	0.66	**0.7±0.07**
Walking	0.57	0.67	0.59	0.59	**0.75**	0.63±0.08
Mean	0.65	0.71	0.63	0.66	0.68	0.67±0.07

the walking condition which was expected to give the worst results. This may suggest that although being seated may reduce the signal noise, it may also impact negatively the mental states of some subjects. For instance, it might be hypothetized that in the walking condition, subjects were more motivated and engaged in the task than during the sitting condition which was a more passive task. This would have to be studied in further experiments.

Table 1 also shows that the AUROCC obtained by each subject for each condition is higher than random, i.e., higher than 0.5, including for the walking condition. This suggests that P300-based BCI can be used even when the subject is moving, and this, in a single trial analysis with the use of only 3 electrodes. Naturally, the performances obtained for the walking condition are lower than that obtained in the other conditions and remain relatively modest. However these results are encouraging and open the way to promising new applications using ambulatory BCI. It should be stressed that this analysis was performed in a single trial way. In most current P300-based BCI, the trials are averaged a number of times, generally between 5 and 10 times, in order to obtain a more reliable system [6, 7]. Performing such an averaging should improve the BCI performance.

Overall, this study suggested that P300-based BCI could be used by a moving user, while using only 3 electrodes and a single trial analysis. This opens the way to interesting new BCI applications using wearable P300-based BCI. We hope these results will motivate the computer entertainment community to consider BCI as a new input device for the design of creative VG. For instance, new VG could be designed, whose content or difficulty would be changed according to the player's mental workload [2] or concentration level [7], as measured by a P300-based BCI.

Our future work will be dedicated to confirm these results with more subjects and to explore new EEG signal processing techniques in order to increase the performance of our BCI. We could also measure muscle electrical activity to be able to remove the noise more efficiently. Finally we will start exploring new real-time applications that use a wearable P300-based BCI as a new input device.

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