A Tactile P300 Brain-Computer Interface: Principle and Paradigm

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Abstract. The P300 based non-invasive brain-computer interfaces (BCIs) are the focus of several research communities in order to move a BCI from a laboratory demonstration to real-life applications. The development and implementation of a BCI system might be the only option left for severely disabled patients to be able to communicate with environment. Therefore, most of the BCI researches have been based on the visual stimulation using the electroencephalogram (EEG) for measuring the brain waves such as event-related potential (ERP). However, recent studies revealed that the tactile modality offers a gaze-independent alternative to the user for reducing eye strain and fatigue. In this context, we investigated a tactile brain-computer interface (tBCI) based on ERP responses using vibro-tactile stimuli around the face and fingers. With regard to novelty oddball paradigm and target-processing, the users have exhibited a different event-related potential in case of a target stimulus. The results of our experiments showed very clear shape of P300 component caused by tactile stimuli which is going to be used in real-time control applications. The efficiency of our ERP-based BCI is strongly related to mean amplitude of the P300 components which was used as a feature over 14 EEG channels in the phase of support vector machine (SVM) classification.

Keywords: EEG, P300, Tactile brain-computer interface (tBCI), Oddball paradigm, Somatosensory.

Introduction

Brain-computer interface (BCI) defines a communication protocol in which information is transmitted directly from the user's brain to the external world via computer without utilizing muscles or peripheral nervous system [1]. Nowadays, BCI applications, especially P300-based BCIs, are consistent and do vary from the enhanced spellers such as "active" or "reactive" BCI spellers to the control of robots. Furthermore, this technology is willing to cross the line from the laboratory prototypes to final market products such as EEG-based BCI system with a Virtual Reality system in order to control a smart home. However, this field still holds several challenges, wait-

ing to be unfolded by the research communities. One of the most challenging problems is the design and use of a tactile non-invasive BCI. In this paper, we propose a spatial four degree of freedom tBCI for severely disabled patients like people suffering from diseases such as locked-in syndrome, Lou Gehrig's disease, and muscular dystrophy. A tBCI could be especially suitable not only for disabled patients but also for patients whose vision or eye movements are impaired.

Following the above idea, we propose a real-time experimental paradigm with a preliminary analysis to get a real data instead of using a public EEG database. Figure 1 displays the general flowchart of our proposed tBCI system that can operate on the following outline: Firstly, a random stimuli sequence is produced by the stimuli generator program with regards to the oddball paradigm; secondly, our homemade developed hardware converts the previous sequence to tactile stimuli and delivers it to the user. In the same time, the brainwave monitoring program will monitor the subject's EEG signals and extracts the event-related potential (ERP) responses to the attended and ignored spatial tactile stimuli. We developed this program within the OPENVIBE[1] framework. Finally, the BCI classifies the brain responses to generate the command matching the user request.

From now on the paper is organized as follows. The first section will describe the overall architecture of the proposed BCI system. Further, we discuss the favored methods, as well as our experimental protocol. In the third section, we show our results for three conducted experiments. Finally, we review the results obtained from an offline analysis of EEG data recorded during online BCI sessions. We will summarize this paper with the conclusions and the future research remarks.
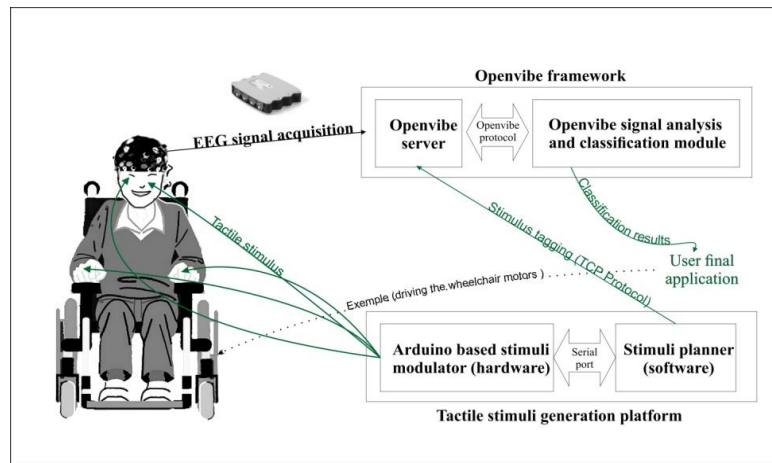

Fig. 1. Schematic diagram of the proposed tBCI application. EEG signals are processed and classified by OpenVibe [2] software processing stages in synchrony with presented tactile stimuli to generate interactive commands.

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[1] Open source Framework for brain-computer interfaces software development and real-time neurosciences. Link: http://openvibe.inria.fr.

METHODS

In the proposed BCI model in this study, we employ a tactile paradigm utilizing a fact that given a tactile stimulus, the subject's brain will produce the ERP pattern [3]. Additionally, depending on user's intention the tactile evoked potential is modulated generating a P300 response. The user's brain evokes this specific response in an odd-ball paradigm, where rare targets stimuli are presented together randomly with distractors (non-targets).

The efficiency of a BCI can be measured using Wolpaw ITR [4]. This metric provide us with an easy way to benchmark our prototypes. Nevertheless, it is a given that the accuracy rate of the classifier and the speed of the classification are the main criteria when talking about BCI efficiency. The primary accuracy rate is higher when a machine learning algorithm accurately classifies the P300 brain response. The classification accuracy can be proportional to the amplitude of the ERPs which is inversely proportional to the subject's confusion rate. In our study we propose a model using four tactile exciters that will deliver the stimuli to the user's face and fingers; these locations are one of the most sensitive parts of the human body. According to the Homunculus model, both the face and the fingers hold a big portion of brain-cells in the somatosensory cortex [5]. Utilizing this technical setup we do hope to get higher amplitude P300 responses to facilitate the ERPs features classification later.

In this study, we focus on using the ERPs metric to investigate the EEG signals and determine the appearance of a P300 brain response. We explain our proposed system architecture, experimental settings, and the chosen electroencephalography (EEG) data processing methods. After that, we show the resulting ERPs measurements.

1.1   Proposed tactile BCI Architecture

We realized an experimental environment formed of two modules:

- The front module handles the tactile stimulus generation and communication with the user. This part contains a software program component that manages the stimulus delivery to the user and a hardware component that uses ARDUINO-UNO to modulate the tactile stimulus.
- The second module runs in the background and carries out EEG signals' acquisition and processing; P300 features extraction; classification and controls generation. We used an open-source development environment (OpenVibe) to implement this module.

The two experimental modules interact together, the tactile stimuli platform (TSP) sends time triggers to the OpenVibe acquisition server to indicate the type of the stimulus using the TCP/IP communication protocol. Then, the server encodes the stimulus tag with the EEG signals on a separate channel. The second module operates the EEG signal classification and sends results to the user using a Python script and UDP sockets.

Fig. 2. The P300-based tactile brain computer interface experimental setup.

The figure 2 shows the actual system where the EEG signal is captured in real-time (figure 2.A). The subject was setting on a comfortable position during the time of the experiment. The tactile exciters were added to drive the user's brain to generate tactile event-related potentials responses (figure 2.B-C). Then, we recorded brain activity using g.tec gusbAmp with dry electrodes [6] to ensure a correct EEG signals quality (figure 2.D).
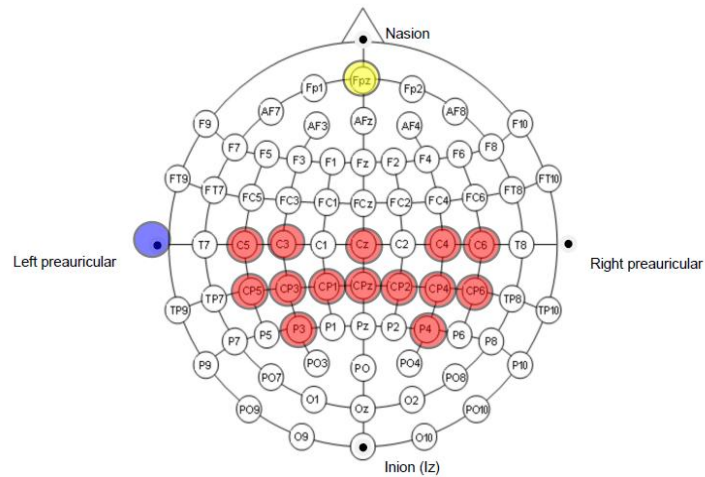

Fig. 3. The EEG electrodes placement. The EEG g.tec Sahara electrodes were placed mostly on the scalp area above the sematosensory cortex (in red). The ground electrode was attached to FPz (in yellow) and the reference to the left-earlobe (in blue).

1.2 EEG recording and experimental paradigm

We used the g.USBamp EEG amplifier system (g.tec medical engineering, Austria) with fourteen active g.Sahara electrodes. The electrodes were attached to the following head locations C5, C3, Cz, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6, P3 and P4 according to the 10/10 extended international system [7] as shown in Figure 3. Ground and reference electrodes were attached at FCz position and a left earlobe, respectively. A sampling frequency was set at 256 Hz and then to 512Hz.

For generating the tactile stimuli, the four vibro-tactile sensors were placed on the face (right and left cheeks) and on two fingers (right and left middle fingers).

A healthy tBCI novice subject took part in the experiments. During the trials, the subject was instructed to concentrate and count the particular target stimulus appearances. We conducted all the trials using an laboratory-based EEG apparatus at University of Sciences and Technology of Oran, Algeria.

1.3 Offline ERPs Analysis

We employed a bandpass filter in a range of [0.01 ~ 30.00] Hz to isolate the strong electromyographic (EMG) interferences and the amplifier drift from the useful EEG data carrying the tactile events related potentials. We also applied a notch filter to discard the power line interference in a rejection band of [48 ~ 52] Hz. Moreover, we utilized amplitude-based thresholding identification and rejection technique with an absolute value set to 80 µV to suppress eye-blink related muscular interferences.

Taking advantage of the time triggers marking the tactile stimuli onsets we segmented the EEG signals to 1000 ms long "epochs." Then, 10-fold cross-validated (partitioned) support vector machine (SVM) classifier was used to distinguish between two classes (P300 Vs. Non-P300) using a mean ERPs amplitude between 200 ms and 600 ms. In the end, we compared the results of SVM classifier with a linear discriminant analysis (LDA) classifier.

The following flowchart shows all steps of ERPs analysis using 14 EEG channels for decoding brain activity using machine learning.
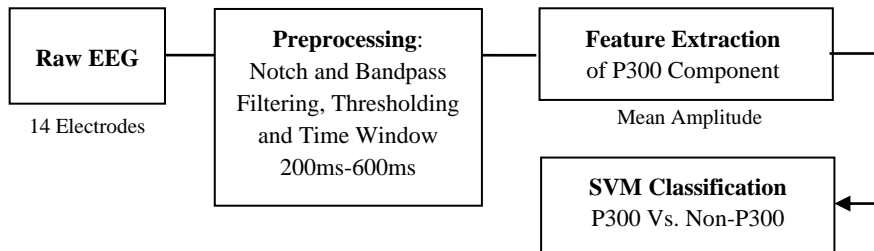

Fig. 4. Flowchart of the offline ERPs Analysis.

The following figures 5 and 6 show the wave shapes of ERP for all the channels in two situations (the presence or absence of P300 component).
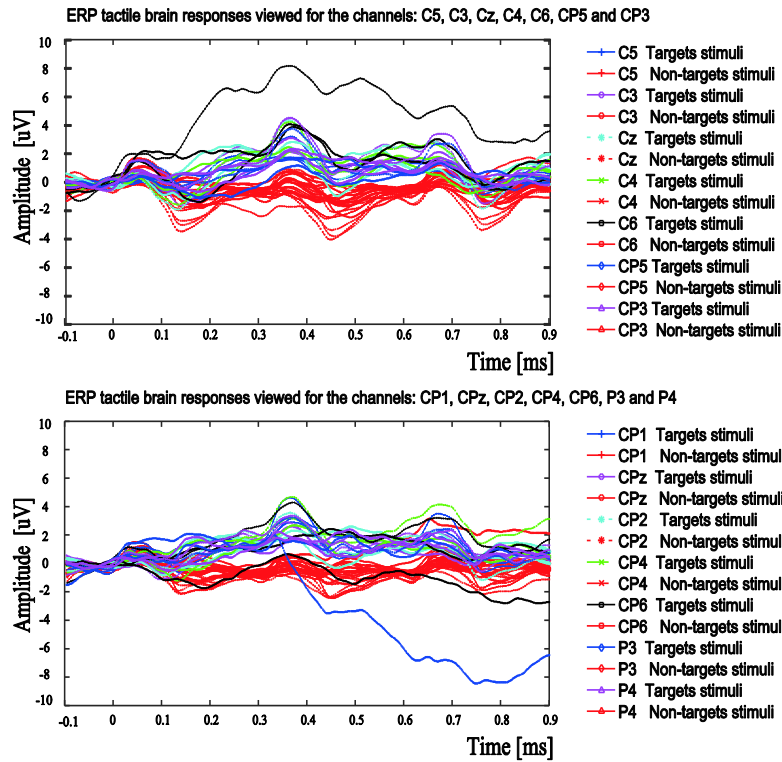
ERP tactile brain responses viewed for the channels: C5, C3, Cz, C4, C6, CP5 and CP3

C5 Targets stimuli	
C5 Non-targets stimuli	
C3 Targets stimuli	
C3 Non-targets stimuli	
Cz Targets stimuli	
Cz Non-targets stimuli	
C4 Targets stimuli	
C4 Non-targets stimuli	
C6 Targets stimuli	
C6 Non-targets stimuli	
CP5 Targets stimuli	
CP5 Non-targets stimuli	
CP3 Targets stimuli	
CP3 Non-targets stimuli	

ERP tactile brain responses viewed for the channels: CP1, CPz, CP2, CP4, CP6, P3 and P4

CP1 Targets stimuli	
CP1 Non-targets stimuli	
CPz Targets stimuli	
CPz Non-targets stimuli	
CP2 Targets stimuli	
CP2 Non-targets stimuli	
CP4 Targets stimuli	
CP4 Non-targets stimuli	
CP6 Targets stimuli	
CP6 Non-targets stimuli	
P3 Targets stimuli	
P3 Non-targets stimuli	
P4 Targets stimuli	
P4 Non-targets stimuli	

Fig. 5. The grand mean average tactile ERP brain responses per channel for three different trials with a total of 1032 distractors and 340 targets stimuli.
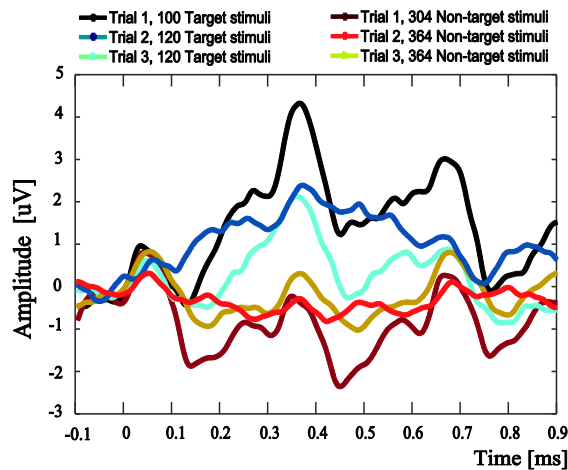

Trial 1, 100 Target stimuli	Trial 1, 304 Non-target stimuli
Trial 2, 120 Target stimuli	Trial 2, 364 Non-target stimuli
Trial 3, 120 Target stimuli	Trial 3, 364 Non-target stimuli

Fig. 6. The grand mean average tactile ERP brain responses per trial. For trial 1, we used 256 Hz. The trial 2 and 3 were executed with a sampling frequency of 512 Hz.

Results and discussion

In the above figures of EEG data, the positive deflections (the so-called P300 or "aha-responses") within latencies of 200 ~ 600 ms could be found. We obsereved that the positioned electrodes in the scalp region of the motor cortex area display a clear P300 component due to the brain's incredible conductivity. All the electrodes channels have the same behavior and the number of electrodes required in the system can be reduced. As a result, our system exhibits a correct P300 response that we can rely on further on the online experiment. This analysis had confirmed the location choice of the tactile stimulators and the workability of this setup.

Most BCI studies usually rely on LDA technique [8]. However, using a machine learning algorithms such as SVM classifier results in high classification accuracy [9]. In this paper, using ERP trials with 10 repetitions, we achieved an average accuracy of 76.30% (standard deviation (SD): 3.89%) among two classes (chance level is 50%) using SVM classification. Furthermore, we achieved a classification accuracy of 62.23% (SD: 14.63%) using LDA method. The statistical difference between classification accuracies obtained using LDA and SVM classifiers was quite remarkable.

Through this work, we can combine a EEG and EOG to increase the classification accuracy of EEG-based tactile BCIs. Recently, Belkacem et al. [10, 11, 12] proposed an algorithm to extract eye blinking and EOG information from EEG data for real-time classification of eye movements in five different directions and this algorithm was used for controlling a video game even with closed eyes. The combined use of EEG and EOG has also gained interest in the research community, and some research has attempted to use EOG artefacts as an extra source of information to improve the performance of EEG-based BCIs. We sought to contribute to the development of hybrid tactile BCIs combining brain activity and eye movements.

CONCLUSIONS

We carried a series of EEG experiments to evaluate our proposed tactile EEG-based BCI system. The offline chosen methods can be implemented for a next online experiment which is a target of our near future project. The preliminary classification result among two classes demonstrates the promise of portable tBCI systems and the proposed sensor positions. We will continue this line of research in order to further improve and validate the proposed tBCI paradigm for severely disabled patients in Algeria.

REFERENCES

[1] J. Wolpaw and E. W. Wolpaw, Eds., Brain-Computer Interfaces: Principles and Practice. Oxford University Press, 2012.

[2] Y. Renard, F. Lotte, G. Gibert, M. Congedo, E. Maby, V. Delannoy, O. Bertrand, and A. Lecuyer, "Openvibe: an open-source software platform to design, test, and use

brain-computer interfaces in real and virtual environments," Presence: teleoperators and virtual environments, vol. 19, no. 1, pp. 35–53, 2010.

[3] Hamada, K., Mori, H., Shinoda, H., & Rutkowski, T. M. (2015). Airborne Ultrasonic Tactile Display BCI. In Brain-Computer Interface Research (pp. 57-65). Springer International Publishing.

[4] Obermaier, B., Neuper, C., Guger, C., & Pfurtscheller, G. (2001). Information transfer rate in a five-classes brain-computer interface. IEEE Transactions on neural systems and rehabilitation engineering, 9(3), 283-288.

[5] Penfield, W., & Rasmussen, T. (1950). The cerebral cortex of man; a clinical study of localization of function.

[6] g.tec g.SAHARA dry electrodes product : http://www.gtec.at/Products/Electrodes-and-Sensors/g.SAHARA-Specs-Features

[7] V. Jurcak, D. Tsuzuki, and I. Dan, "10/20, 10/10, and 10/5 systems revisited: Their validity as relative head-surface-based positioning systems," NeuroImage, vol. 34, no. 4, pp. 1600 – 1611, 2007.

[8] CB. Blankertz, S. Lemm, M. Treder, S. Haufe, and K.-R. Muller, "Single-trial analysis and classification of ERP components — A tutorial," NeuroImage, vol. 56, no. 2, pp. 814–825, 2011.

[9] A. Belhaouari, N. Berrached, TM. Rutkowski (2015). "Classification improvement and analysis of P300 responses with various inter-stimulus intervals in application to spatial visual brain-computer interface." In 2015 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA) (pp. 1054-1058).

[10] A.N. Belkacem, S. Saetia, K. Zintus-art, D. Shin, H. Kambara, N. Yoshimura, N. Berrached, Y. Koike. "Real-time Control of a Video Game using Eye Movements and Two Temporal EEG Sensors"., Computational Intelligence and Neuroscience, vol.2015, pp. 1-10, 2015.

[11] A.N. Belkacem, D. Shin, H. Kambara, N. Yoshimura, Y. Koike. "Online Classification Algorithm for Eye-movement-based Communication Systems Using Two Temporal EEG Sensors"., Biomedical Signal Processing and Control, (2015), 16: 40-47.

[12] A.N. Belkacem, H. Hirose, N. Yoshimura, D. Shin, Y. Koike. "Classification of Four Eye directions from EEG Signals for Eye-movement-based Communication Systems"., Journal of Medical and Biological Engineering, (2014), 34(6): 581-588.