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Design and Evaluation of a P300-ERP based BCI System for Real-Time Control of a Mobile Robot

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***Abstract*—With the development of Brain-Computer Interface (BCI) systems people with motor disabilities are able to control external devices using their thoughts. To control a device through BCI, brain activities of the user must be accurately translated to meaningful commands and a design of appropiate BCI paradigms play important roles in such tasks. This work presents a design and evaluation of a BCI system that is based on P300 Event-Related Potentials (ERP) in order to control a mobile robot platform into four directions (left, right, front, back). The ultimate goal of this research is to provide convienient way of controlling a mobile robot as an assistive home technology for disabled people. Low cost EPOC Emotiv headset was used in the BCI system to acquire brain signals with a Jaguar 4x4 Wheel robot as a control platform. We discuss a set of signal processing steps employed in detail and the utility of a regularized logistic regression classifier to detect visual stimuli induced P300 ERPs and, to control the Jaguar robot.**

I. Introduction

One of the latest emerging technologies in the field of robotics and artificial intelligence is the system of brain- computer interfaces (BCI), also referred as Brain-Machine Interface (BMI), Mind-Machine Interface (MMI), or direct neural interface [1]. The BCI technology consists of the hardware that is able to recognize brain signals and the software that can effectively process these data [2]. As a result, successfully implemented BCI gives opportunity to control physical objects by decoding electrophysiological signals generated by human brain activities. Essentially, these kinds of signals are extracted from neurons in cortex when the electrodes are placed on a human scalp. These neural signals become useful as an input to measuring electronic devices due to the local field potential, which creates corresponding oscillatory wave [3]. After received brain signals are amplified, they are processed by analog to digital converter such that computer can perform further analysis. There are five commonly referred stages that neural signals are processed through: signal acquisition with preliminary noise reduction, signal preprocessing or enhancement, feature extraction, classification and output control interface [2]. Based on the communication channel between brain and the computer, this method of controlling devices without muscles and peripheral nerves can be implemented to solve problems with mobility impairment. For example, brain-actuated wheelchair is one of the most promising applications of BCIs that can help disabled people to move and interact with surrounded world through the intelligent robotics system [4]. In addition, various other invasive BCI systems have been developed to control external devices, e.g. computer cursors [5] and robotic prostheses/orthoses [6]. Moreover, in recent studies, BCIs have been used to control lower-body [7] and upper-body exoskeletons [8] for stroke and paraplegic recovery and rehabilitation via non-invasive approaches [9].

To control a device via BCIs, different brain activity patterns produced by a user need to be accurately identified by a neural interface system and translated into appropriate commands. To achieve this goal, advanced signal processing and machine learning techniques are of great importance, and have become a research focus in recent years. The design of high performance BCI system is an open research problem in the community. Many techniques have been widely utilized in different EEG-based BCI applications. For instance the following reviews covers machine learning aspects of BCI systems, with emphasis on problems related to signal processing [10], [11], feature extraction [12], classification [13], [14], system design [15], [16] and clinical applications [17]. Despite the above efforts achieving a practical BCI that works outside the lab settings is still a challenging task, however recent research have shown positive progress towards that direction [18]. Our current work aims to contribute to the same efforts of design and evaluation of BCIs to control an external wheel mobile robot. In this study, we are mostly interested in detection of P300 Event-Related Potential (ERP) signals of EEG elicited to visual cue for BCI. ERP is a synchronous time-locked component of EEG signal which is elicited by external stimuli such as visual, tactile or auditory. To drive the mobile device, EEG signals are pre-processed and most significant ERP features are identified, then the output signals are classified to move drive the robot into four desired directions. Visual feedback determined the success or failure of the desired action based on the subject's brain signal command. The entire flowchart of the designed system is summarized in Fig. 1.

II. Materials and Methods

Five healthy right-handed subjects age ranges $19 - 24$ years with no neurological disorders have participated in this study. All of the participants were naive BCI users, who had not participated in any related experiments before. All study participants gave informed consent. The subjects were

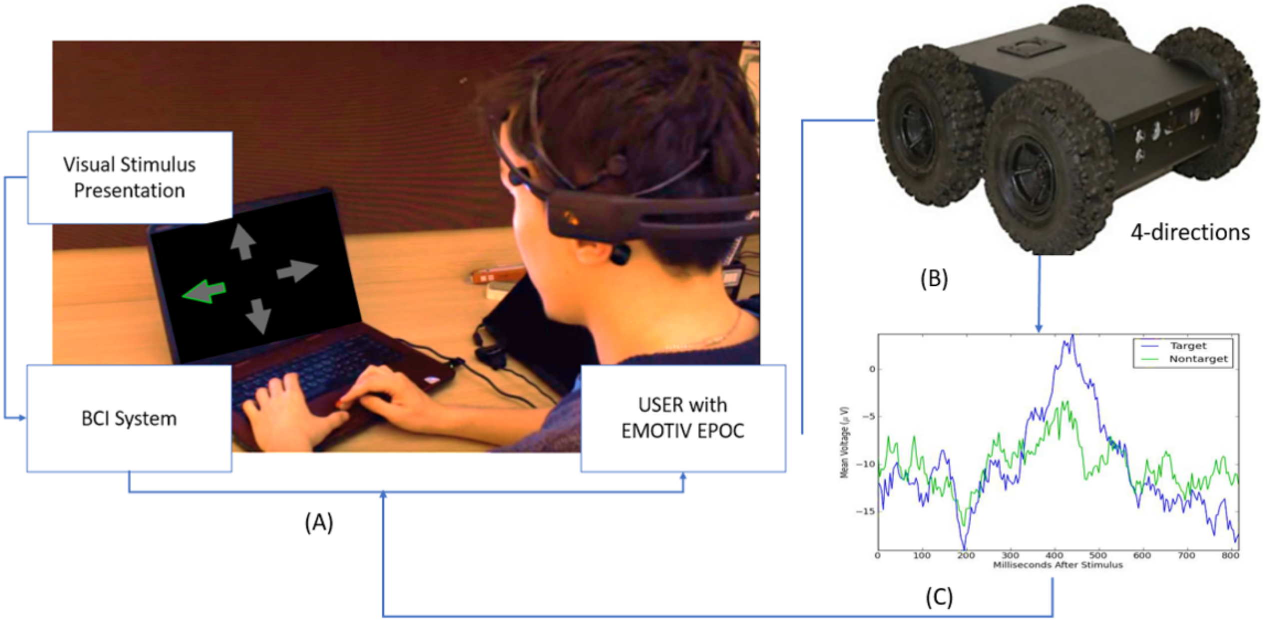

Fig. 1. Different components of presented ERP-BCI system. A) A subject pays attention to a specific character of interest in the provided visual cue in order to drive the mobile robot. Then, the BCI system extracts features of EEG P300 waveform in real-time decodes to identify the intended direction. b) Control platform - Jaguar robot 4x4 wheel. c) Example of an ERP-P300 target and nontarget waveform.

seated in a comfortable chair facing an LCD monitor with the distance about 60 cm in between. For acquiring brain signals, a non-invasive, wireless and cost effective EEG system ”Emotiv EPOC” neuroheadset was used. The signals were measured from 16 electrodes according to the international 10-20 System, 14 of which measure cortical signals (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4) with respect to two reference electrodes. The electrodes cover the area of the frontoparietal regions of the brain cortex. The acquired signals are digitized using a 16 bit A/D converter and with a resulting sampling frequency at a rate of 128 Hz and transferred from the headset to the computer via wireless bluetooth technology. Before the measurement began, subjects were asked to sit relaxed and rest in order to avoid any possible external noise interferences in all channels.

A. *Hardware*

The Jaguar 4x4 Wheel Mobile Platform was utilized to control via BCI system (see Fig.1(B)). Jaguar robot is designed for indoor and outdoor operation capable of running on rough terrains and climbing up vertical slopes. It has integrated GPS and 9 DOF IMU for autonomous navigation. It meets all the requirements: simple control, settable velocity and position, camera, wireless connection. To simplify our task we have decided to give only four directions for the robot: left, right, front, and back.

B. *Software*

FieldTrip toolbox: We used FieldTrip toolbox as the primary tool to work with EEG data [19]. FieldTrip is a MATLAB-toolbox designed for advanced analysis and visualisation of

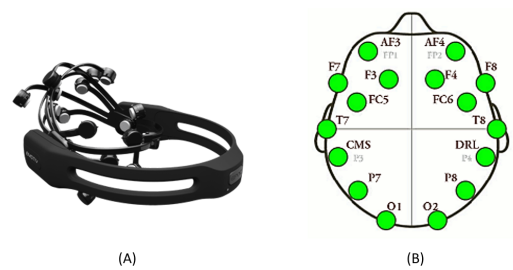

Fig. 2. A) Emotiv EPOC Neuroheadset; B) Emotiv EPOC Sensor Placement

EEG, MEG and other electrophysiological type of data. Being one of the most commonly used softwares for analysis of EEG data, FieldTrip provides enhanced functionality for data preprocessing, event-related response analysis, real-time processing and classification. Additionally, we adopted Buffer BCI framework for our BCI experiments [20] to create working user interface, and to collect synchronous ERP data.

C. *Signal processing*

Noninvasive type of BCIs makes it difficult to process the data. The main reason is the noise, which is also called and ”artifact” in BCI terminology. One of examples is very low signal to noise ratio, that is, the signal looses most of its quality while passing through the scalp and, once the signal is amplified it creates lots of noise. This is only one example of noise generation during the whole BCI process.

Considering all possible types of artifacts, we need to devise signal processing algorithms to remove noise and increase quality of signals. The most influential and frequent types of artifacts are bad channels (when some of sensors reading data from the scalp does not work), slow electrode drifts (once person sets up the BCI device on the head it drifts during the whole process), eye blinks, and muscle movement. Moreover, it is very important to mention that currently the BCI research struggles from the fact that the whole installation set up is very subject and session related, in other words, if the system shows good results for one subject this doesn't necessarily mean that it will work on other subjects also. Therefore, let us describe all steps we used to get better data:

- **Detrending**: As was mentioned above slow drift of electrodes is very common problem for most of BCI systems. This artifact creates trending in signals, which is not desirable for further classification algorithms. Hence we should "detrend" the signal, that is remove any trends and make the signal "flat". The very basic idea how to remove the trending from the signal is to find the best fit line for all chunks of data in real-time and subtract that line from the original signal, so, in this way, it is possible to detrend the signal.
- **Bad channel identification and removal**: Another possible artifact when dealing with BCI systems is unideal headsets [21]. It happens that one of the electrodes (sensors/channels) does not work properly during the data acquisition process and thus creates noise and consequently affects the whole classification period. Once the channel is bad it has very small value of signal to noise ratio, in other words, it has excessively high power. Hence it is more or less easy to remove bad channels just by heuristics that we identified the channel as bad if and only if its power spectrum is higher than 3 times the standard deviation.
- **Spatial Filtering**: Up to now we have considered only the types of artifacts related to only specific channels, while it may happen that the noise is common to all of them. Examples of this kind of artifact is a noisy place, hot/cold weather and other types of obstacles which make the BCI process more difficult. The common idea to remove such a noise is to make an assumption that all of the channels are affected by this noise and find the average signal of all signals and then subtract it from all signals. This algorithm is called CAR (Common Average Reference). But it is also noteworthy that some of channels mutually depend and create interference between each other which makes the classification process more difficult. So, it is also important to use SLAP (Surface Laplacian) filter to remove all interferences and correlations.
- **Spectrally Filtering**: As was described previously the brain signals have different types of frequencies and in this study we are more interested in alpha frequency. To remove other frequency out of range of interest we used ERP Spectrally Filter. This can be seen from the Fig.4.
- **Bad trial identification and removal**: Inner types of noise like eye blinks and muscle movement create excessively high power of the given channel. To eliminate such bad trials we use again a heuristic that if the signal trial with power spectrum of 3 times the standard deviation is noise.

D. User Interface

The user interface, which is used for calibration and testing phases was designed based on Buffer BCI framework, which uses MATLAB GUI for graphic interface and data collection and FieldTrip toolbox as main tool for data processing and classification. On the Fig. 3 below you can see the graphical user interface, which provides visual stimuli to the user. At the very beginning, user is provided set of instructions, where he is explained how the data acquisition and classification process is performed. The black screen consisting of four arrow in different colors is shown. User has to focus on the arrow highlighted by green color. Arrows flash in white and red colors in pseudorandom sequence. User has to mentally react to the flashes of the highlighted arrow. Here, we recommended a user to count instances of arrow flashes, since it is easy and commonly used method for collecting ERP data from such kind of visual stimuli.

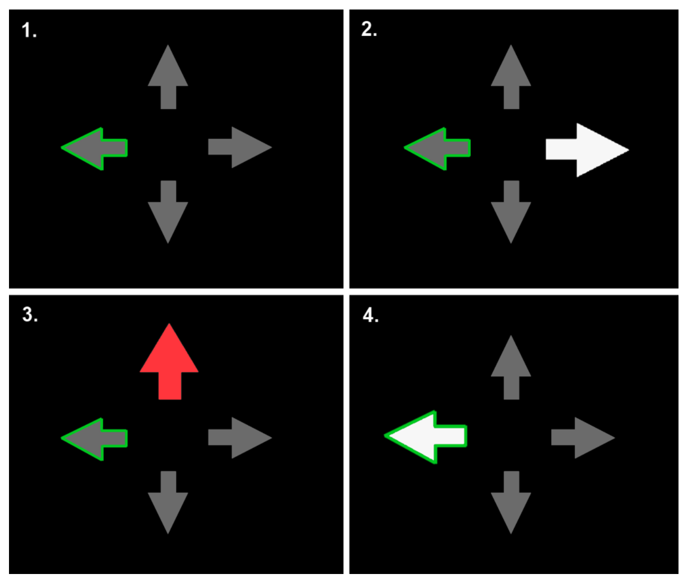

Fig. 3. Visual stimuli (each 4 directions flash)

E. Classification

The classification of data is achieved via tenfold cross validation by regularized logistic regression functions under a supervised learning framework. The idea of logistic regression is to construct a polynomial $h_\theta(x)$ such that it divides two classes with the smallest error.

$$h_\theta(y=+1|x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_1^2 + \theta_3 x_1^2 x_2 + ...) \qquad (1)$$

where $g(z) = \frac{1}{1+e^{-z}}$ is a sigmoid function.

The cost function can be represented as follows:

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m} y^{(i)} log h_\theta(x^{(i)}) + ... \tag{2}$$

$$... + (1 - y^{(i)}) log(1 - h_\theta(x^{(i)})) \tag{3}$$

It is important to use "regularized" version of this algorithm to increase the generalization performance and the classification accuracy. Therefore, we used the followings regularization $\frac{\lambda}{2m}\sum_{j=1}^{n}\theta_j^1$ term to the cost function $J(\theta)$. This penalty term regularizes the $h_\theta(x)$, in other words, it tries to control the level of overfitting versus underfitting. As reported in previous BCI research [22], we also observe no big difference in accuracy between various classification methods, as long as the classifier is regularized and signals are pre-processed. Our choice of regularized logistic regression is because of its time complexity as it works much faster and more applicable in a real-time system.

F. Control

After offline classification process is finished, user can start using the BCI to control Jaguar mobile platform, by running same graphical user interface, where he has to follow similar instructions. The only difference is that now there is no highlighted arrow. User has to choose in which direction he wants Jaguar to move and focus on corresponding arrow on the screen. Arrows will flash in similar manner in white and red colors and user will mentally react to the flashes of chosen arrow. Decision making period for each iteration lasts for 5 seconds. After 5 seconds, classifier tries to predict user's choice and sends corresponding signals to Jaguar robot. Jaguar sends output from the camera, which is opened next to the user interface on the screen, so that user could observe the feedback by peripheral vision and adjust the movement of the robot without any unwanted disturbance.

III. Results

Before giving classification results of the conducted BCI experiments, let us discuss the examples containing step-by-step analysis of waveforms using signal processing steps provided earlier. Subset of EEG signals acquired from each of the 14 electrodes are illustrated in Fig. 4 to reflect electrode positions on the left frontocentral and temporal lobe on the scalp. Specifically, each plot of the electrodes on the Fig. 4 contains waveforms of target and non-target epochs.

In the Fig. 4(A), the waveforms are very much alike, almost constant, due to the scaling of the plots. To increase understanding of the plots and improve accuracy of the classifier later, the raw EEG data was processed with detrending and channel removal algorithms. The Fig. 4(B) shows, in particular, the waveforms obtained for two epochs: target (green) and non-target (blue). As can be noticed from the The Fig. 4 (B) each channel's average and a linear trend within each trial was subtracted which brought the waveforms' mean to zero. The signals obtained after performing CAR as a means of spatial filtering are illustrated in the Fig. 4(C). Comparing figures before and after spatial filtering, one can see that after doing spatial filtering, the seemingly abnormal behavior of T7 is reduced, and all the electrodes now look like more natural EEG traces. For extracting the signals of interest (i.e. ERP), the signals obtained in the previous step further went through spectral filtering. It is very clear from the Fig. 4(D), that high frequency noise components are attenuated and the signals are much more smooth which will aid the classifier training. After obtaining ERP signals, P300 features were specifically chosen, by selecting time points between 300ms and 500ms for classification. To illustrate clearly that differentiation of the target symbols from the non-target ones, one can rely upon the P300 latency range, as provided in the following Fig. 4(E). Blue waves are for the target epoch, while the green ones are for the non-target epoch. Ideally, averaging across target trials should elicit a distinct the P300 waveform in centro-parietal-frontal areas of the brain. Specifically, they are more clearly elicited in Fz, Pz, and Cz electrodes which are absent in the Emotiv electrode placement system [23]. This results in a situation in which ERP signals cannot be seen clearly on all electrodes.

Subject No.	S1	S2	S3	S4	S5
Training (%)	79/75	77/71	83/74	89/75	85/78
Real Time (%)	68	71	65	59	69

TABLE I
OVERALL ACCURACY OF THE DEVELOPED BCI MOBILE ROBOT FROM OFFLINE TRAINING AND REAL-TIME SPELLING EXPERIMENT. THE RESULTS ARE GIVEN IN PERCENTAGE VALUES.

The data obtained from the Emotiv system on five subjects went through those aforementioned pre-processing steps, and were trained with a regularized linear logistic regression (rReg). Off-line performance obtained from the classifier, namely its training and testing accuracy, was very encouraging, however the online testing on the subjects showed varying classifier performance as shown in the table I.

Since both false positives and false negatives detrimentally affect the BCI performance, the subjects' accuracy was obtained using the following formula:

$$Accuracy = \frac{t_p + t_n}{t_p + t_n + f_p + f_n} \tag{4}$$

t_p and t_n are true positive and negative respectively, while f_p and f_n are false positive and negative respectively. As can be seen from the table, the users outperformed during the training phases, but had inferior performance during the real-time phases. Particularly, the training accuracy consists of two accuracy measures. The first one is the classifier's training accuracy, and the second one is its average accuracy obtained by tenfold cross-validation. It is worth to note that during the real-time testing of the system, users reported that the symbol the classifier predicted as a target symbol was actually a neighboring symbol to the target symbol. Literature on P300 BCI spellers calls this notion as an adjacency error [24]. This

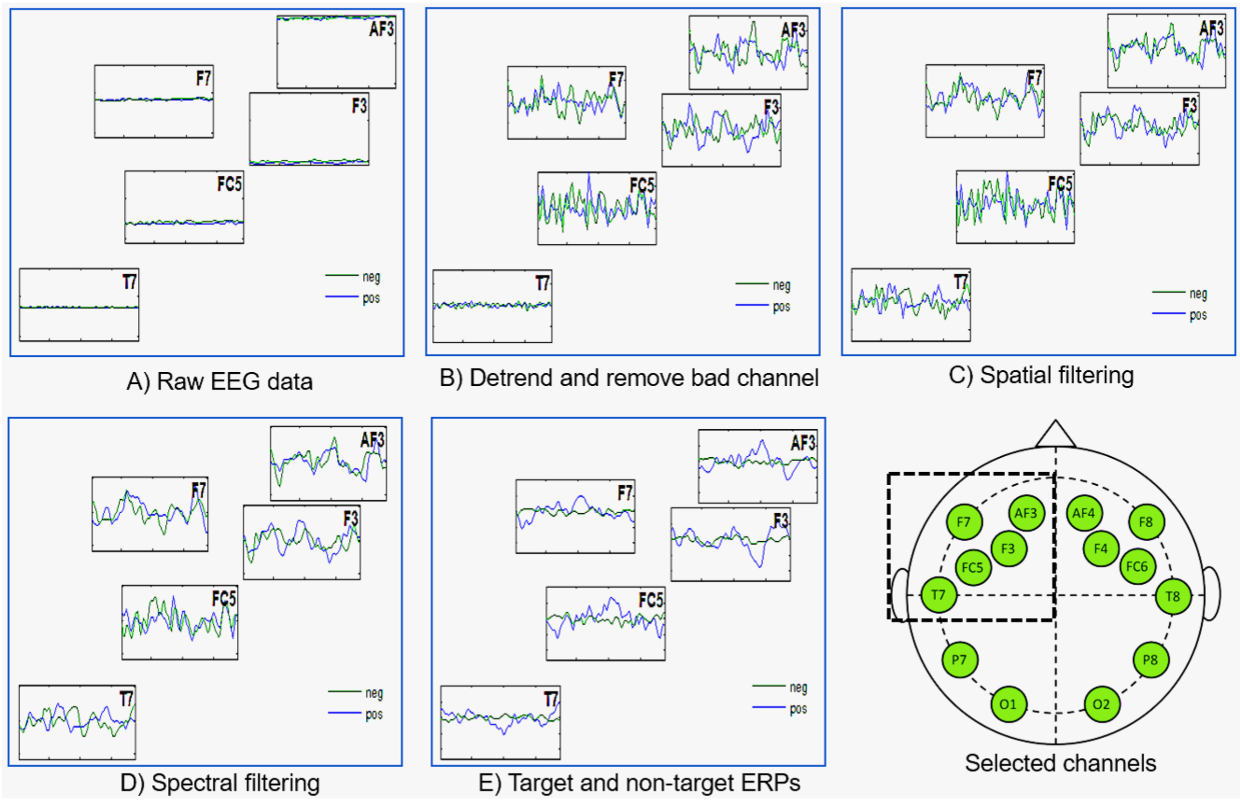

Fig. 4. Example of EEG signal processing results demonstrated for selected channels. Blue waves represent the target epochs, while the green ones are the non-target epochs.

Mean offline training accuracy/st.dev (%)	90.1/6
Mean real-time accuracy/st.dev (%)	64/10.7

TABLE II
DESCRIPTIVE STATISTICAL MEASURES ON THE OVERALL PERFORMANCE OF THE BCI SYSTEM.

type of error occurs when a neighboring row or column is flashed less than 500 ms before the target row or column is flashed, thereby catching the user's attention. Therefore, the classifier could mis-classify a non- target symbol as a target one.

IV. CONCLUSIONS AND DISCUSSIONS

This study presents the design and evaluation steps of a P300 based BCI system in order to control a mobile wheel robot into four directions. The implementation of the system was based on low cost Emotiv EPOC headset, which receives data from the user's brain and sends those signals via buffer to MATLAB wherein the data are filtered and classified in real-time. The classes related to the mental intentions (left, right, front, or back) are sent to a mobile robot while at the same time the robot sends camera stream to the user's interface for a visual feedback. The overall accuracy of the system was around 64%. We contend such low performance to the Emotiv EPOC characteristics. In other words, the system has several drawbacks for BCIs, including its non-flexible structure which prevents you from freely placing electrodes on desired positions. For ERP recording, we are interested in parietal and central lobes of the brain though placing electrodes on those regions were restricted to collect more reliable data [25]. Moreover accuracy and quality of the sensors also is not optimal for such kind of application [26]. During the experiment we experienced lack of conductive gel for a better connection between the electrodes and a scalp. The saline solution that was used tend to dry out fast resulting in very poor signal- to-noise ratio.

This research was an exploratory study by its nature, in the sense that using a low-cost system, we tried to achieve some certain degree of accuracy. This initial design and evaluation study brings us to the next topic of optimizing human-computer interaction via improved graphical user interface and substituting the EEG acquisition system with more flexible high density systems, in that way re-evaluate the overall performance. Eventually, this system is oriented for people with disabilities therefore it should be optimized to be applicable for them, which is also the task of further research.

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