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Automation of a Wheelchair using Hybrid BCI System

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ABSTRACT

To translate brain activity signals into control signals for external devices a system called Brain–computer interface (BCI) is used. It is difficult for current BCI systems to provide the multiple independent control signals necessary for the multi-degree continuous control of a wheelchair. The present paper address this challenge by adopting the motor imagery based mu rhythm and the P300 potential to control a brain-actuated real time wheelchair. The main objective of the present work is to provide a greater number of commands for a wheelchair with increased accuracy to the user.

Keywords: EEG, P300, SSVEP, motor imagery, BCI,CSP transformation matrix.

I. INTRODUCTION

Today because of the advantages such as, non-invasive, relatively convenient, and affordable ELECTROENCEPHALOGRAM (EEG)-based brain computer interfaces (BCIs) have attracted a great deal of attention. It is possible to provide a new way of communications for special users who cannot communicate via normal pathways with aid of a BCI system. It can send commands, controlled by brain activity and distinguished by EEG signal processing. The main features which can be extracted from EEG, are classified as six brain rhythms based on the differences in frequency ranges; i.e delta (1- 4 Hz), theta (4-7 Hz), alpha (8-12 Hz), mu (8-13 Hz), beta (12-30 Hz), and gamma (25-100 Hz). The delta and theta rhythms occur in high emotional conditions or in a sleep stage. The alpha rhythm happens in awake and eyes closed relax condition. The oscillation in alpha rhythm has smooth pattern. The beta rhythm pattern is desynchronized and the condition is the normal awake open eyes. The gamma rhythm is acquired from somatosensory cortex and mu rhythm from sensorimotor cortex.

Based on the EEG brain activity patterns, BCI systems is categorized into four different types: event– related desynchronization/synchronization (ERD/ERS), steady state visual evoke potentials (SSVEP), P300 component of event related potentials (ERPs), and slow cortical potentials (SCPs). Compared to other modalities for BCI approaches, such as the P300-based and the SCP BCIs, SSVEP-based BCI system has the advantage of having higher accuracy and higher information transfer rate (ITR) as shown in Figure 1. In addition, short/no training time and fewer EEG channels are required. One important application of EEG-based BCIs is wheelchair control, which can improve the quality of life and increase the independence of a disabled user.

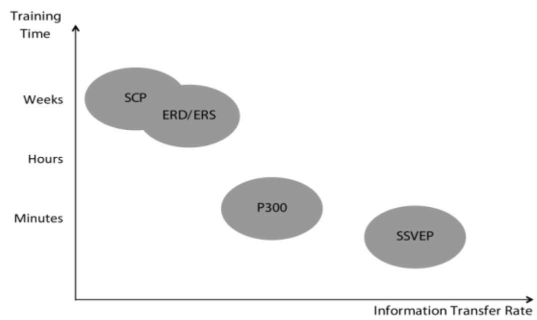

Figure 1. A general comparison of SCP, ERD/ERS, P300, and SSVEP with respect to their training time and information transfer rate.

For EEG based wheelchair control the two types of protocols, synchronous and asynchronous, are used. The EEG signals used for synchronous control depend on the potentials evoked by visual stimuli, including the P300 potential and the SSVEP. This synchronous protocol does not allow the user to change the direction or route of the wheelchair as it moves to its destination. These synchronous protocols provide high accuracy but suffer from a low response speed. For such systems, an effective control commands are achieved after several seconds. The brain signals used for asynchronous control protocols are derived from motor imagery, allowing the user to send an appropriate command to a moving wheelchair. The present paper proposes a hybrid BCI system to provide directional and speed control commands to a wheelchair. The control of the wheelchair speed is useful to the disabled.

The organization of this paper is as follows. Section 2(**Methodology**) will provide detail of BCI system design. Section 3 (**Experimental Results**), present the experimental results of current work. Discussed in Section 4 (**Conclusion**)will conclude with the efficiency of proposed system.

II. METHODOLOGY

The methodologies include the data acquisition system, GUI, control mechanism, models, and algorithms as described in the following section.

A. EEG Data Acquisitions

A NuAmps device is used to measure scalp EEG signals for data acquisition. Each user wears an EEG cap (LT 37) that measures the signals from the electrodes shown in Figure 2. The EEG signals are referenced to the right ear. Two channels, "HEOG" and "VEOG", representing eye movements are excluded (and not shown here). The EEG used for processing is recorded from Ag-AgCl electrodes that are placed at the sites in the frontal, central, parietal and occipital regions. The following 15 channels are included: "FC3," "FCz," "FC4," "C3," "Cz," "C4," "CP3," "CPz," "CP4," "P3," "Pz," "P4," O1," "Oz," and "O2." Fig. 1 shows the locations of each site. All impedances are kept below 5 . The EEG signals are amplified, sampled at 250 Hz, and band-pass filtered between 0.5 and 100 Hz.

B. GUI and Control Mechanism

The GUI used in this process. A rectangular workspace and eight flashing buttons are included. The workspace is 1166 721 pixels. The eight buttons flash in a random order to induce P300 potentials. Each button is intensified for 100 ms, and the time interval between two consecutive button flashes is 120 ms. Thus, one round of button flashes lasts 960ms (1 round here is defined as a complete cycle in which each button flashes once). In this system, the subjects are required to control the direction and speed of the simulated or real wheelchair. Two choices, low and high, are available for speed control. To accomplish these control tasks, the BCI system provides the simulated or real wheelchair with the following four commands: turn left, turn right, accelerate and decelerate.

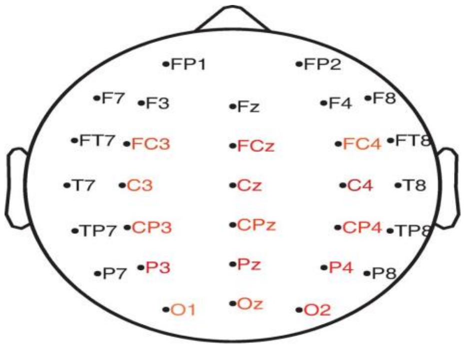

Figure 2. EEG cap electrodes

As shown in Table 1, the user is instructed to implement these commands by performing four tasks to produce these control commands: left-hand motor imagery, right-hand motor imagery, foot motor imagery, and attention to a specific flashing button without motor imagery. If left- or right-hand motor imagery is detected, then the simulated or real wheelchair turns left or right, respectively. Furthermore, the simulated or real wheelchair does not stop before turning. Separately, the system detects foot movement imagery and the P300 potential for speed control.

Table 1. Control Commands

Control command	Mental tasks
Left turn	Left hand Motor imagery
Right turn	Right Hand Motor imagery
Deceleration	Foot Motor imagery
Acceleration	Focusing on a specific flashing button
No control command	Idle state

C. Models and Algorithms

The paper describes a hierarchical decision method to steer the simulated or real wheelchair (Figure 2) by using the directional and speed control commands detected within the user's EEG signals. First, the pattern of motor imagery is extracted to identify the directional control commands. If left- or right-hand motor imagery is detected, then it is interpreted as a directional control command for a left or right turn. Otherwise, the speed control commands are extracted.

The speed control command for acceleration or deceleration is determined by discriminating the following two tasks executed by the user. The first task is that the user imagines foot movement without attending to a specific flashing button, whereas the other task is that the user pays attention to the specific flashing button without performing any motor imagery. The algorithms to detect the direction and speed signals are described in the following paragraphs.

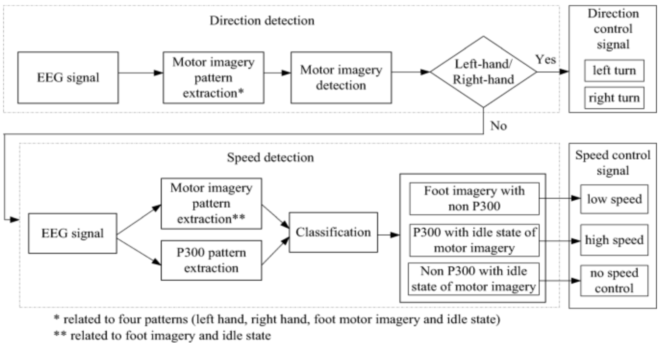

Figure 2. Diagram for algorithm used in detection of direction speed control signals

D. Detection of Directional Control Signals

The left- and right-hand motor imagery events are used to turn the simulated or real wheelchair left and right, respectively. One directional control command triggers a fixed, predefined degree of rotation. Two consecutive left or right turn commands lead to a rotation with twice the defined degree of rotation. Hence, the objective in directional control is to detect the left- and right-hand motor imagery within the online EEG signals. The user may be in one of the following five states: left-hand motor imagery, right-hand motor imagery, foot motor imagery, flashing button attention, or idle. To detect left- or right-hand motor imagery, the EEG signals are first spatially filtered with common average reference (CAR) and then band-pass filtered at 8–32 Hz. Next, compute the spatial patterns using the method of one versus the rest common spatial patterns (OVR-CSP). Based on a training dataset collected before online testing, a CSP transformation matrix (W) is calculated for each class against all of the others using the well-known joint diagonalization method.

There are four classes of motor imagery data: left-hand, right hand, foot and idle state. Thus, we obtain four CSP transformation matrices. The first and last rows of each CSP transformation matrix (W) correspond to a large response in the first and second conditions, respectively. Therefore, the common practice in a classification setting is to use several rows from both ends of the transformation matrix as spatial filters. If the number of the rows used for spatial filtering is too small, the classifier would fail to fully capture the discrimination between two classes; on the other hand, the classifier weights could severely overfit if the number of the rows is too large.

In this study, the first and last three rows from each of the four CSP transformation matrices to construct a new transformation matrix with 24 rows selected for feature extraction following. The logarithmic variances of the projections of the EEG signals from the transformation matrix are used as the features of the signal. Furthermore, the training data set is used to train four linear discriminant analysis (LDA) classifiers with the one versus- rest method for dealing with the multi-class classification problem. For online testing, these four LDA classifiers are applied to the feature vector extracted from the EEG data during the 1000-ms period before the current time point. Hence, four LDA output scores are obtained. Following a loss-based decoding method, the feature vector is given the class label corresponding to the maximal score. This detection is performed every 200 ms. The direction of the simulated or real wheelchair's motion will remain constant if the user imagines foot movement or is idle with regard to motor imagery. In this case, the speed control signals are extracted as described in the next section.

E. Detection of Speed Control Signals

If no directional control signals are detected, then speed control signals are extracted. Unlike directional control, speed control is implemented by combining two types of EEG patterns: the ERD/ERS of the sensorimotor rhythms and the P300 potential. The speed control signal is detected by discriminating two states: foot motor imagery without button attention and focus on a specific button without motor imagery. There are two feature extractions for speed detection (Figure 2): one is for motor imagery detection and the other is for P300 potential detection.

First, the feature extraction for motor imagery detection using the training data is described. Here, the training data set contains two classes of data corresponding to foot motor imagery and the idle state of motor imagery (attention to a specific button). If a trial in the training data corresponds to the idle state of motor imagery, then its label is set to 1. Otherwise, its label is -1, corresponding to the foot imagery. A CSP transformation matrix (W1) is calculated similarly to that described earlier. Thus, a feature vector xj for the jth trial of the training data can be constructed by projecting the jth trial EEG signal on the top and bottom three rows of (W1)and then calculating their logarithm variances as the motor imagery features, where $j= 1,\ldots\ldots,N$.

The P300 feature extraction for the jth trial of the training data ($j= 1,\ldots\ldots,N$) can be performed as follows. First, the EEG signals are filtered between 0.1 and 20 Hz. Then, extract a segment (0–600 ms after a button flash) of EEG signals from each channel for each flash of the button (specifically, the center up button in our experiment)is extracted. The segment is down sampled by a rate of 6 to obtain a data vector from each channel. For each flash of the specific button, a new data vector with 375 dimensions (25 time points x 15 channels) is obtained by concatenating the data vectors from all 15 channels. The feature vector *(pj)* in each trial is obtained by averaging four data vectors corresponding to four repeats of the button flash. If the trial in the training data corresponds to attention to the specific button, then the label is set to 1. Otherwise, the label is -1.

After extracting the motor imagery feature xj and the P300 feature pj based on the training data set, a combination algorithm, PROB, is used to combine the features of these two modalities. Specifically, two LDA classifiers, denoted as(w_X,b_X) and (w_P ,b_P) are trained using the motor imagery feature vectors with labels and the P300 feature vectors with labels, respectively. Two scores for each trial's motor imagery feature vector and P300 feature vector pair are computed using the corresponding classifiers. Next, calculating the sum
of these two scores as

$$D_j = \tfrac{1}{2} \{[w^T_X\ xj + b_X] + [w^T_P\ pj + b_P]\} \quad j=1,\ldots\ldots N.$$

Using D_j, calculating two thresholds D^+_{mean}, and D^-_{mean}, as follows:

$$D^+_{mean} = \frac{1}{|D+|}\sum_{j\in D+} Dj$$

$$D^-_{mean} = \frac{1}{|D-|}\sum_{j\in D-} Dj$$

where D^+ and D^- denote the set of indices of Dj satisfying $D_j > D_{mean}$ and $D_j < D_{mean}$, respectively , D_{mean} is the mean of all , and is the cardinality of a set.

In the test phase, a motor imagery feature vector is extracted every 200 ms using EEG data collected during the 1000-ms period before the current time point, whereas a P300 feature vector is extracted at every flash of the specific button as above. Specifically, the P300 feature extraction is based on the EEG data acquired during four repeats of the button flash (the current flash and the three prior flashes). The speed signal detection is performed every 200 ms based on the motor imagery feature vector updated every 200ms and the P300 feature vector updated every 960 ms (a complete round of button flashes).

A score denoted as is then calculated. A label $\hat{y}$ for this epoch of EEG data is defined as

$$\hat{y} = \begin{cases} +1, & if\ D > D + mean \\ 0, if\ D - mean \leq D \leq D + mean \\ -1, & if\ D < D - mean \end{cases}$$

If $\hat{y}$ =1, then the system decides that the user is paying attention to a specific flashing button and is not performing any motor imagery. This case results in an acceleration command. If $\hat{y}$ = -1, then the system decides that the user is imagining foot movement and ignoring the flashing buttons. This case results in a deceleration command. If $\hat{y}$=0, then the user is considered to be idle with regard to both motor imagery and P300 potential; no speed control command is given to the simulated or real wheelchair.

III. RESULTS AND DISCUSSION

To validate the proposed hybrid BCI system for detecting directional and speed control commands, two experiments were conducted. The first experiment utilized a simulated wheelchair in a virtual environment, and the second experiment used a real wheelchair.The following performance indices are used to assess the hybrid BCI with respect to directional and speed control.

- **Accuracy rate:** the percentage of successful navigation tasks.
- **Path length:** the distance (pixels/meters) traveled to accomplish the task.
- **Path length optimality ratio:** the ratio of the path length to the optimal path length. The optimal path length is the sum of point-to-point distances between each pair of adjacent destinations.
- **Time:** the time (s) to accomplish the task.
- **Time for low speed:** the time (s) during which the simulated wheelchair travels at low speed.
- **Wrong speed control time:** in the second experiment (real wheelchair), the path for the wheelchair is separated into ten segments; five segments are set for low speed and five are set for high speed. This index represents the time that the wheelchair travels at low speed in the segments designated for high speed and vice versa.
- **Collisions:** the number of collisions incurred to the edges of the working space by the simulated wheelchair or to the corridor by the real wheelchair.

IV. CONCLUSION

This paper presents a hybrid BCI that combines the mu/beta rhythm resulting from motor imagery and the P300 potential for the directional and speed control of a simulated or real wheelchair. Four commands are each associated with a mental task. Specifically, the user performs left- or right-hand motor imagery to direct a left or right movement and performs foot imagery or focuses on a flashing button to adjust the speed of the simulated or real wheelchair. Two experiments were conducted. One used a simulated wheelchair in a virtual environment, and the other utilized a real wheelchair. Both experiments demonstrated the effectiveness of this method and system.

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