BCI Based Analysis Of Hand Movement Trajectories For Rehabilitate Patients

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Abstract— **For many years people have speculated that electroencephalographic activity or other electrophysiological measures of brain function might provide a new non-muscular channel for sending messages and commands to the external world – a brain–computer interface (BCI). This paper investigates the application of a non-invasive Electroencephalography (EEG)-based BCI to identify brain signal features in regard to actual hand movement trajectories. An experiment was performed to collect EEG data from subjects while they performed right hand movement at two different speeds, namely fast and slow, in four different directions. The informative features from the data were obtained using the Wavelet-Common Spatial Pattern (W-CSP) algorithm that provided high temporal-spatial-spectral resolution. The immediate goal is to provide these users, who may be completely paralyzed, or 'locked in', with basic communication capabilities so that they can express their wishes to caregivers or even operate word processing programs. The classified result is provided by the SVM classifier. The spatial patterns of the W-CSP features obtained showed activations in parietal and motor areas of the brain. The results achieved promises to provide a more refined control in BCI by including control of movement speed.**

Index Terms— Brain-Computer Interfaces, Electroencephalography, Movement related Parameters, Discrete Wavelet Transform, Common Spatial Patterns.

I. Introduction

An electroencephalogram (EEG) is the representation of electrical activity of brain. By using different types of EEG electrodes, EEG is taken and picked up signal is conditioned to make it suitable for recording and analysis. The EEG is of prime importance in medical cases [4]. The signal conditioning is required because the picked up EEG signal will be having minute amplitude levels.

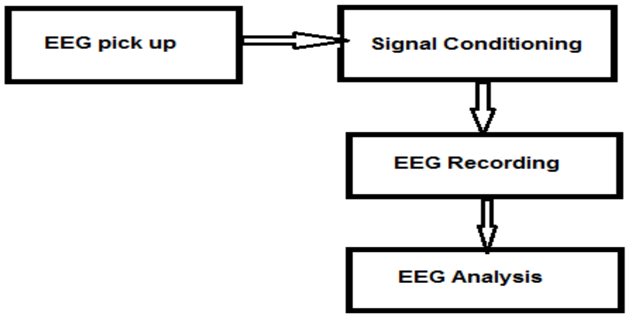

Fig.1. Stages of EEG recording

The most popular scheme used in the placement of electrode for the EEG pick up is the 10-20 electrode placement system. As the cranial area is divided into four main regions, the electrodes are placed accordingly in the different regions. Main regions of cranium are frontal, parietal, temporal, occipital regions. The 10-20 electrode placement system is internationally used. In this set up the head is mapped by four standard points. They are nasion, inion, and left and right ears. The ability of an individual to control his EEG through imaginary mental task enables him to control devices through a Brain Machine Interface (BMI) or Brain Computer Interface (BCI).

The BCI is a direct communication pathway between the brain and an external device. BMI are often aimed at assisting, augmenting or repairing human congestive or sensory motor functions [1,3]. BCI are used to rehabilitate people suffering from neuro-muscular disorders as a means of communication or control. The methodologies of BCI can be separated into two approaches namely invasive and non-invasive. Invasive BCI are accurate. However there are risk of the infection and the damages. Furthermore, it requires the operation to set the electrodes in the head. On the other hand, non invasive BCI are inferior to invasive BCI in accuracy, but cost and risks are very low. EEG approach is the most studied potential non invasive interface mainly due to its fine temporal resolution, ease of use.

The core components of a BCI system [3, 4] are brain signal acquisition, pre-processing, feature extraction, classification, translation and feedback control of external devices. Electroencephalography (EEG) [4] is a widely used non-invasive BCI due to its low expense and high temporal resolution. The EEG data acquisition is followed by a pre-processing stage which attenuates the artifacts and noises present in the brain signal, to enhance the relevant information. The subsequent feature extraction stage is responsible for forming discriminative set of features in the form of frequency patterns [16], temporal patterns [17], time-frequency patterns [18], autoregressive models [19], or spatial patterns [20] for each task performed. The features extracted are used to train a classifier to decode the users' intent and subsequently translate the features into a set of output commands for operating an external device. The challenges in developing an efficient feature extraction and machine learning technique in an EEG-based BCI are the high temporal-spectral and spatial resolution, high robustness and online adaptation capability to compensate for non-stationarity.

In BCI (Brain-Computer Interface) research community, most BCI research is focused on bioelectrical brain signals recorded by EEG (electroencephalography) as it's noninvasive and thus readily available. While the EEG signal processing methods in EEG based BCI are appealing, they face substantial practical problems. Due to the limitation of EEG signal recording technology, physiological artifacts, especially those generated by eye (EOG, electrooculography), interfere with EEG, may change the characteristics of the neurological phenomena in EEG, and make those signal processing performs incompetently. Linear combination and regression is the most common used technique for removing ocular artifacts from EEG signals where a fraction of the EOG signal is subtracted from the EEG [10]. One problem is that subtracting the EOG signal may also remove part of the EEG signal, for the EOG signal to be subtracted is also contaminated with the EEG signal. In this paper, a new EOG correction model is introduced for EOG artifacts, where the EEG contained in the EOG is considered, and thus avoid removing part of the EEG signal by subtracting the EOG signal. In order to apply this new model in online BCI signal processing, this paper adopts the AR (autoregressive) filtering model of the EEG activity to detect the EOG artifacts, only if it exists, the EEG correction method are performed.

In my current work, the pre-processing step of the recorded EEG data included low pass filtering at 100 Hz and a notch filter at 50 Hz. Electrooculographic (EOG) artifacts were removed using Independent Component analysis approach which nullified the signal components that are highly correlated with the recorded EOG. The time segments for analysis were chosen, as the last one second of movement preparation and the first one second of movement execution. The data pre-processing was followed by the feature extraction where the proposed Wavelet-CSP algorithm was used to extract the features. Also the data could possibly be affected by Electromyography (EMG) due to muscular activation. EMG signals reflect activation of multiple muscles and hence activate multiple motor units of brain thereby producing a diffused activity in scalp. Hence, we used a Laplacian spatial filter that accentuates localized activity whereby the diffused activity of EMG is suppressed.

Here an experiment was performed to investigate the presence of movement-related parameters from EEG signals in the LF band. The focus of this work is to classify and reconstruct the speed and direction of movement using LF components of EEG and to study how these are affected if the movement is performed in four different directions. The aim of this research is to develop a BCI with a more refined control or increased number of control commands for movement by including information regarding movement speed.

The challenges in developing an efficient feature extraction algorithm in EEG-based BCI research are to address the issues of low signal-to-noise ratio (SNR), non stationarity and spatial localization of the discriminative features [1]. To tackle these problems, a Wavelet-CSP algorithm was used. The Wavelet-CSP algorithm is used to extract the speed related features from EEG and the algorithm has been enhanced to extract the optimal levels of wavelets. The proposed approach in this work decomposes the pre-processed EEG using wavelets and subsequently reconstructs it at different levels to yield sub band signals that are further spatially filtered using Common Spatial Pattern algorithm.

II. DATA RECORDING AND ANALYSIS

A. *Data Recording*

EEG data were recorded using Ag/AgCl electrodes from 128 scalp positions distributed over the entire scalp using a Bio Semi Active Two EEG system [4] (Bio semi, Inc.). Eye movements were monitored by additional bipolar horizontal and vertical EOG electrodes. All signals were amplified and digitized at a sample rate of 256 Hz. Electrode locations were measured with a 3-D digitizer system.

B. *Data Processing and Analysis*

Here, we only focused on estimations of planned direction of movement. Therefore we first separated the trials for each subject into three classes (left, right, and center) for offline analysis. In each class, the three tasks with different effectors (hand, eye, both) were mixed together. Data were analyzed using tools in the EEGLAB toolbox. Epochs from the response delay period, 0 to 700ms following direction cue onset, were extracted from the continuous data, and labelled by movement direction. The period [0, 100ms] was used as baseline for each trial. Electrodes with poor skin contact were identified by their abnormal activity patterns and then removed from the data. For each subject, electrode locations were co-registered with a spherical four-shell head model used for dipole source localization.

C. *Spatial Filtering*

Independent component analysis (ICA) has been widely used in EEG analysis. It can decompose the overlapping source activities constituting the scalp EEG into functionally specific component processes. Here, we used ICA as an unsupervised spatial filtering technique [5,11] to extract parietal EEG independent component (IC) activities that excluded noise from eye and muscle components as well as brain activities from other functional processes (e.g., in motor, visual, and frontal areas). For each subject, all trials were band-pass filtered (1-30 Hz), concatenated, and then decomposed using the extended infomax ICA algorithm. Two lateralized temporo-parietal components were easily identified in each subject’s decomposition by their spatial projections and significant contributions to the average event-related potential (ERP) waveforms time locked to onsets of the movement direction cue.

D. ERP Modulation

To extract the direction-specific portion of the ERPs, we compared the spatiotemporal patterns of the parietal EEG components for the different movement directions. For all four subjects, we found a consistent hemispheric asymmetry over the parietal cortex during the delay period (0-700ms, 0-100ms used as baseline) in which motor planning can be presumed to have continued until cued movement onset (after 700ms). The projected PPC ICs produced a significant contra lateral negativity and ipsilateral positivity with respect to intended movement direction. Scalp maps of left, right, and center classes for one subject were shown in Fig.2. For the “left” and “right” classes, their maps showed significant ipsilateral positivity. For instance, the left hemisphere has much higher amplitude than the right hemisphere when planning left movements. For the “center” condition, the map has a symmetric distribution on both sides and the amplitudes are much lower compared to “left” and “right” conditions. To further investigate the time course of this hemispheric asymmetry, difference wave was calculated by subtracting the contra lateral activity from the ipsilateral activity with respect to movement direction. Two electrodes with highest weights in the two parietal IC maps were selected to represent the left and right hemispheres. In the difference wave averaged across the “left” and “right” trials, the hemispheric asymmetry was characterized by two contra lateral negativities peaking 200ms and 320ms after the direction cue respectively, with mean amplitudes of 1.9Mv and 3.8μV across subjects (see Fig.3).

II. PROPOSED FEATURE EXTRACTION ALGORITHM

The very aim of BCI is to translate brain activity into a command for a computer. To achieve this goal, either regression or classification algorithms can be used. Using classification algorithms is the most popular approach. These algorithms are used to identify \patterns" of brain activity. In this paper, we consider a BCI system as a pattern recognition system and focus on the classification algorithms used to design them. The performance of pattern recognition depends on both the features and the classification algorithm employed. These two components are highlighted in this section. In order to select the most appropriate classifier for a given BCI system, it is essential to clearly understand what features are used, what their properties are and how they are used. This section aims at describing the common BCI features and more particularly their properties as well as the way to use them in order to consider time variations of EEG. The very aim of BCI is to translate brain activity into a command for a computer. To achieve this goal, either regression or classification algorithms can be used. Using classification algorithms is the most popular approach. These algorithms are used to identify \patterns" of brain activity. In this paper, we consider a BCI system as a pattern recognition system and focus on the classification algorithms used to design them. The performance of pattern recognition depends on both the features and the classification algorithm employed. These two components are highlighted in this section. In order to select the most appropriate classifier for a given BCI system, it is essential to clearly understand what features are used, what their properties are and how they are

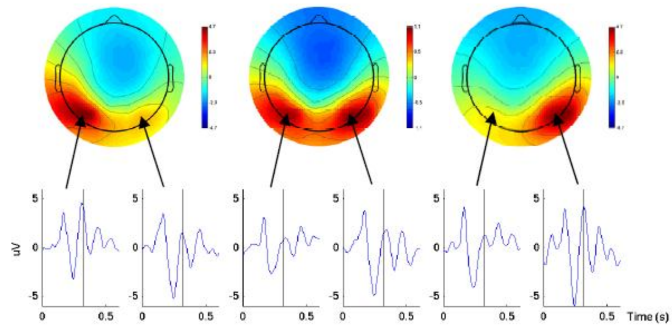

Fig.2**.** Scalp maps and ERP waveforms of the summed, back projected parietal ICs for one subject in the three different direction conditions

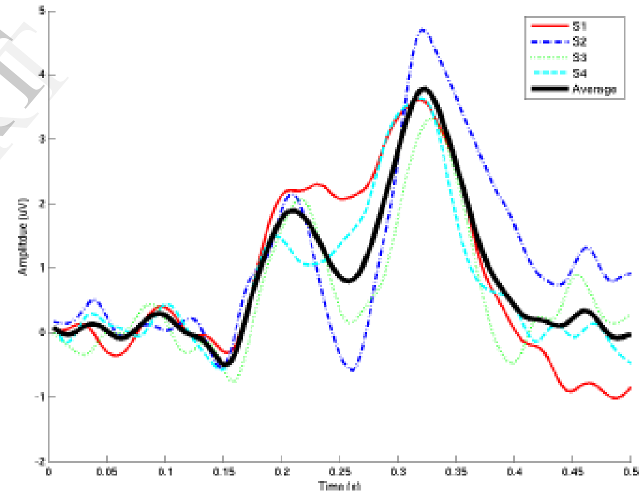

Fig.3**.** Ipsilateral minus contra lateral difference waves averaged over the “left” and “right” trials.

In order to extract the features corresponding to speed and direction from LF region of EEG, a feature extraction algorithm that can provide high resolution decomposition of very low frequency signals is required. This property is assumed to provide higher performance for classification or reconstruction of movement parameter-speed and direction. An orthogonal filter bank-based Wavelet transform [2] suits this requirement with the added advantage of high temporal localization. Wavelet analysis is widely used in BCI systems to extract the discriminative features from time-frequency plots. The proposed Wavelet-CSP algorithm incorporates spatial filtering using the Common Spatial Pattern (CSP) algorithm, which is an efficient method to extract the discriminative EEG features. The CSP algorithm has been enhanced with various frequency band optimization techniques such as Filter Bank CSP (FBCSP).

A. *Wavelet Transform (DWT) and Filter Banks*

The discrete wavelet transform effectively addresses the trade-off between time and discrete frequency resolution in non-stationary signal analysis. Wavelets [2, 13] are single prototype functions, similar to a band pass filter, whose contracted version (high frequency) performs fine temporal-analysis and dilated version (low frequency) performs fine frequency analysis [30]. The Wavelet Transform (WT) of a continuous time signal *x(t)* can be defined as,

$$X_W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} h^*\left(\frac{t-b}{a}\right) x(t)dt \qquad (1)$$

where $a \in R_+$, $b \in R$ and $h^*(.)$ represents the conjugate of basis function obtained by the translation and dilation of single prototype wavelet [29]. To remove the redundancy caused by the continuous parameters (*a*, *b*), discretization is carried out as

$$a = a_0^m \text{ and } b = n a_0^m b_0,\ a_0 > 1,\ b_0 \neq 0,\ m,n \in Z$$

Thus on the discrete grid, WT is obtained as DWT given by,

$$X_W(m,n) = a_0^{-m/2} \int_{-\infty}^{\infty} h\,(a_0^{-m}t - nb_0)\ x(t)\ dt \qquad (2)$$

B. *Common Spatial Pattern (CSP)*

The CSP algorithm is often used to optimally discriminate between two classes of EEG data based on simultaneous diagonalization of two covariance matrices. A brief description of CSP is given in this sub-section. Given that, the pre-processed EEG data in a single trial is represented as matrix *X* of size *N* x *T*, where *N* is the number of channels used and *T* is the number of samples recorded in each trial from each channel. The CSP projection matrix *W* is used to obtain the spatially filtered [11] EEG signal as in (3)

$$Z = WX \qquad (3)$$

The rows of *W* are the stationary spatial filters and columns of W^{-1} represent the common spatial patterns.

The normalized spatial covariance matrix of the EEG data is computed as $C = \frac{XX'}{tr(XX')}$, where X' denotes the transpose of matrix *X*, and *tr* (·) represents its sum of diagonal elements of two classes *1* and *2*. CSP analysis [5, 11] aims to simultaneously diagonalize these matrices by designing *W* such that it satisfies,

$$W^T C_1 W = \lambda_1, \quad W^T C_2 W = \lambda_2, \qquad (4)$$

Where λ_1 and λ_2 are diagonal matrices and satisfies,

$$\lambda_1 + \lambda_2 = I \qquad (5)$$

C. *The Wavelet-CSP (W-CSP) Algorithm*:

In this sub-section, describe the proposed Wavelet-CSP algorithm. The first step is to construct an orthogonal filter bank using wavelets. From a signal processing approach, we can define DWT as applying filters and samplers on square summable discrete time sequences, to perform a coarse half resolution approximation of the original time sequence. The wavelet decomposition [3, 11] involves filtering with a half band low-pass filter and half band high-pass filter followed by sub-sampling by 2. The signals can be reconstructed from these subspaces using the reverse process, i.e., up sampling by 2 and filtering using time reversed filter sequences. Fig. 4(a) demonstrates the process where the impulse response of decomposition and reconstruction filters are represented by $h_{0/1}(n)$ and $h\hat{}_{0/1}(n)$, where h_0 provides the lower half band and h_1 gives higher half band filters and h^ denotes the time reversed *h*.

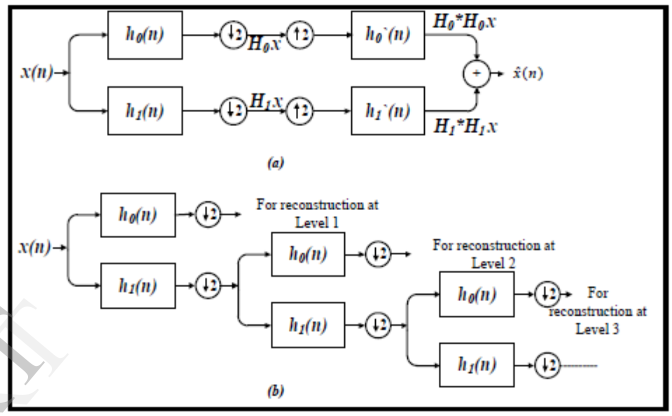

Fig.4. Signal decomposition & reconstruction.

The proposed wavelet-csp algorithm is

Step 1: The EEG data is acquired and preprocessed with low pass and notch filtering.

Step 2: The pre-processed signal is projected into sub bands by wavelet decomposition.

Step 3: The signals at different sub bands are reconstructed using wavelet reconstruction.

Step 4: The sub band signals are spatially filtered using CSP.

Step 5: The discriminative features are extracted from W-CSP filtered signal. A SVM classifier is trained using these features and performance of algorithm in terms of classification accuracy is determined.

Step 6: The W-CSP filtered signal is used to reconstruct the speed profile and the decoding accuracy in terms of correlation coefficient is calculated.

D. *Support Vector Machine (SVM) Classifier*

In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated that analyze data and recognize patterns, used for classification and regression analysis. SVM constructs a hyper planes or infinite dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyper plane that has the largest distance to the nearest training data point of any class, since in general the larger the margin the lower the generalization error of the classifier.

Classifying data is a common task in machine learning. Suppose some given data points each belong to one of two classes, and the goal is to decide which class a new data point will be in. In the case of support machines, a data point is viewed as a p-dimensional vector, and we want to know whether we can separate such points with a (p-1) dimensional hyper plane. This is called a linear classifier. There are many hyper planes that might classify the data. One reasonable choice as the best hyper plane is the one that the distance from it to the nearest data point on each side is maximized. If such a hyper plane exists, it is known as the maximum –margin hyper plane and the linear classifier it defines is known as maximum margin classifier; or equivalently, the perceptron of optimal stability.

III. EXPERIMENT

An experiment was performed to collect EEG data while the subjects performed right hand movement at two different speeds in four different directions. Visual cues were provided to instruct the subjects to perform the task. The types of hand movements studied were, fast and slow movements in four directions: North, South, East and West. The movements were performed in the horizontal plane. North refers to hand movement outwards and away from the body, South refers to movement inwards and towards the body. East and West refer to movement towards the right and left side respectively. The slow movement refers to movement that takes more than 1200ms and fast refers to movement that takes less than 400ms to perform a movement covering 15 cm in this plane in the specified direction. These details of the experiment protocol are shown in Fig. 3.

The experiment timeline along with the visual display provided is shown in Fig. 5 (iii). The subject was seated on a chair with arm resting on a table and facing a computer monitor that provided visual feedback. The subjects were requested to refrain from the eye movements to prevent EOG artifacts. The home screen showed an encircled cross as given in Fig. 5 (iii-a) and this was shown during the entire rest period. At the end of 4 seconds of rest, cue was given as shown in Fig. 5 (iii-b) which corresponds to North direction. The target location, presented as an empty circle, could be anywhere in the four directions mentioned. This was followed by a preparation time for 2 seconds, at the end of which the circle around the cross disappeared as in Fig. 5 (iii-c). This denoted the onset of movement in which subject was given up to 3 seconds to complete a movement, at the end of which the cross appeared at the target position Fig. 5 (iii-d). If subject fails to reach the correct target within the given time, the trial was flagged and later rejected.

The subject was notified this during the following 2 seconds. A successful trial was indicated by the reappearance of circle as in Fig. 5 (iii-e). The display is returned to home screen and this cycle was repeated. The experiment was conducted in two sessions of 50 cycles each. In each cycle, eight trials were performed by the subject.

Each cycle was divided into slow and fast movement sets of four trials each. The task-slow was cued by 11.25mm diameter target circle and the task-fast was cued by a target circle with a diameter 1.5 times that of target circle for task-slow. Each of these sets comprised of trials in four directions in a randomized order. Each trial took around 13 seconds to perform and the total recording time for a single subject was approximately 2 hours and 45 minutes.

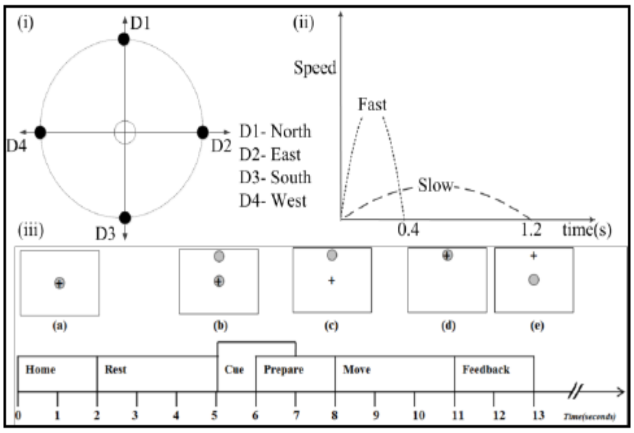

Fig.5.(i-ii) Directions and speed studied (iii)Experimental Timeline.

A. Data Analysis

The pre-processing step of the recorded EEG data included low pass filtering at 100 Hz and a notch filter at 50 Hz. Electrooculographic (EOG) artifacts [10] were removed using Independent Component analysis approach which nullified the signal components that are highly correlated with the recorded EOG. The time segments for analysis were chosen, as the last one second of movement preparation and the first one second of movement execution. The data pre-processing was followed by the feature extraction where the proposed Wavelet-CSP algorithm was used to extract the features. The cross validation analysis splits the dataset into non-overlapping training and test data. The W-CSP filter was constructed using the training dataset which is later used to filter the test data. The features obtained from the training dataset were used to train a SVM classifier and the classification performance on the test dataset was measured in terms of mean classification accuracy and standard deviation.

IV. CONCLUSION

The objective of this work was to design an algorithm that can extract the information regarding movement related parameter: Speed and direction. It is implemented in MATLAB. The low frequency bands of movement related potentials recorded by EEG were exploited using a highly time-frequency-space localized algorithm in order to extract features relevant to speed. A Wavelet-CSP algorithm has been proposed, which effectively localizes signal in time, frequency and space and provides discriminative features for classifying speed. The filtered signals are also applied to reconstruct the speed profile. The algorithm was validated using EEG data collected during an experiment where the subject executed right hand movement in two different speeds in four different directions. It was confirmed that the performance of the algorithm was not influenced by EMG by using Laplacian filtering.

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