Processing Movement Related Cortical Potentials in EEG Signals for Identification of Slow and Fast Movements

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Abstract— **The extraction of intended kinetic information from an EEG signal can have several applications related to the rehabilitation for subjects with various neurological disorders. However, the task is mainly constrained by the low signal-to-noise ratio for the EEG signals. It is well known that the cortical activity takes place at a very low frequency since it is characterized by the dropping of movement related cortical potential (MRCP) across the sampled EEG signal. The strong variations in the MRCP is indicative of the noise due to various sources. The aim of this work is to remove this noise from the EEG signals using empirical mode decomposition, which decomposes a signal into harmonics (intrinsic mode functions - IMF) of various frequencies. The IMFs pertaining to small frequencies are later used for features extraction where we extract the spatial and spectral features from the selected IMFs. The features are later used for classification using support vector machines (SVM). Our experiments show superior results to the benchmark method for the underlying dataset that has been used in this research.**

I. Introduction

Brain-computer interfaces (BCI), in the last decade have emerged as a promising tool to predict the user's intent accurately [1]. The BCI systems are designed to enable a direct communication between the brain and the computers. Such systems can have a wide range of applications such as development of superior user interfaces, gaming etc [2]. One of the most important application domains for the BCI systems is their usage for the rehabilitation of movement impaired individuals [1], [3]. The inputs to such BCI systems are typically electroencephalogram (EEG) signals. These signals are processed using various signal processing techniques to capture the salient content in the signals and are typically subjected to the classification algorithms in which the supervised training sessions are used to build various decision rules. The prediction of the user's intent for the novel signals is done based on the trained classifier, allowing the BCI interfaces to decode the intent of the individuals. The output of such systems can than be fed to the relevant actuators/transducers which, based on the decision generated from the classification systems can potentially help in generating the intended movements by the impaired individuals. It has been reported in the literature that the somatosensory feedback can help in inducing some plastic changes in neuro sciences, that can be used to facilitate different patient groups e.g., stroke patients.

This idea has been used as a BCI system to detect the movement intention in the patients using the movement related cortical potentials (MRCP). The detection of movement intentions with the help of EEG signals can help in the generation of electrical signals that can signal the robotic devices to trigger the movement that was intended by the individuals. For the replication of this movement, the movement information such as the force, speed, direction etc have to be ascertained before the task onset. Using this methodology the motor control loop can be closed, providing the researchers with a better opportunity to develop the devices that can be used for the rehabilitation of the stroke patients [4].

The extraction of kinetic information from the movement intentions in EEG signals has been done previously [5]–[7] using the marginal distribution of the discrete wavelet transform (DWT) and the temporal features from EEG signals. One of the main challenges that is imminent in the processing of EEG signals is that the EEG signals are very noisy having low signal to noise ratio and large trial to trial variability [8]. Thus, the extraction of useful features from the EEG signals requires pre-processing for noise removal. It is well known that a drop in the cortical potential takes place when the movements are intended [4]. This potential drop takes place at a very low frequency and it is interlaced with noise that produces undesired relatively high frequency variations in the EEG signals. Additionally, it is also known that the factors such changes in the user level of attention, fatigue, difference in impedance of electrodes etc. are responsible for the non-stationarity of EEG signals [8].

Most of the multiresolution filter based methods such as the DWT assumes the stationarity of the signal. The EEG signals are in gross violation of this assumption, making the use of such methods relatively suboptimal for the feature extraction from the EEG signals. Empirical mode decomposition (EMD) is a data dependent signal decomposition method, that does not make any assumptions about the stationarity of EEG signals. It has the ability to extract the underlying harmonics, known as intrinsic mode functions (IMF) from a signal elucidating its resemblance to band pass filters. This paper concerns with the decomposition of EEG signals using EMD followed by the extraction of temporal and spectral features from the selected IMFs.

The outline of this paper is as follows: we present a description of the data that has been acquired for the study

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978-1-4244-7929-0/14/$26.00 ©2014 IEEE

carried out in this paper (Section II), followed by the methods that have been used for the processing of EEG signals (Section III). Later, we present our experimental results (Section IV) and discuss them (Section V).

II. Materials

A. Experimental protocol

Nine healthy subjects (1 female and 8 males 29 +/- 6 years old) participated in this study. Before their participation, a consent was taken from the subjects. The experimental setup was approved by the local ethical committee (N-20100067). All the subjects were made to sit on a chair, with their right foot fixated on a pedal where a force transducer to assess the strain gauge was attached. They were instructed to perform the maximum voluntary contractions (MVCs) followed by four different tasks of real isometric dorsi-flexions of the right ankle. i) 0.5s to reach 20% MVC (f20), ii) 0.5s to reach 60% MVC (f60), ii). 3s to reach 20% MVC (s20), iii). 3s to reach 60% MVC (s60) . A program, *Follow Me* by Knud Larsen, from SMI at Aalborg University, was used to assist the subjects to perform movements with magnitude of force and speed. The experiments were carried out under the supervision of neurological experts. A visual feedback of performance of the subjects was provided to them during the entire length of the experiments. Each of the two tasks was repeated in randomized blocks.

B. Signal acquisition

Ten channels of monopolar EEG were continuously recorded using scalp electrodes. The sampling rate was set to 500Hz. The 20 mm Blue Sensor Ag/AgCl, AMBU A/S, Denmark electrodes were placed on the scalp according to the international 10-20 system at FP1, F3, F4, Fz, C3, C4, Cz, P3, P4 and Pz locations. The reference and ground electrodes were placed on the right earlobe and at nasion, respectively. The EEG was divided into epochs using a trigger that was sent from *Follow Me* at the beginning of each trial (at the beginning of the preparation phase in Fig. 1) to the EEG amplifier. FP1 was used to record EOG activity.

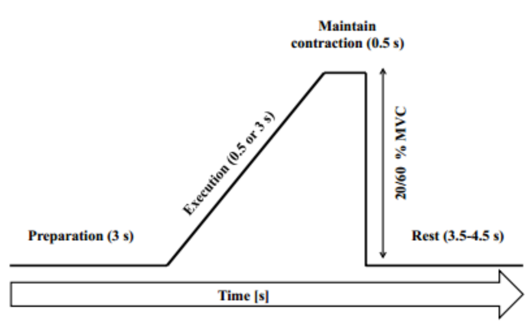

Fig. 1: The subjects has to wait for 3 s before executing the movement. The execution phase lasted for either 0.5 or 3 s. After the desired force level was reached, they maintained the contraction for 0.5 s followed by a resting period (adapted from [8]).

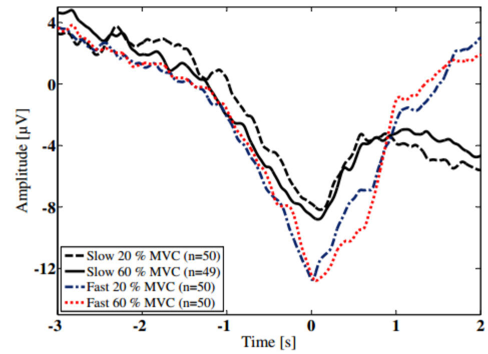

Fig. 2: Average of the four tasks for one subject. 'Fast' and 'Slow' refers to o.5 and 3 s respectively to reach the desired level of MVC. On the time axis, 0s is the time onset and 'n' is the number of trials for which the average is calculated (adapted from [8]).

The recordings for force were made using Mr. Kick (Knud Larsen, SMI, Aalborg University) and used as input to *Follow Me*. The sampling rate for the force was 2000 Hz. A total of 3 MVCs were recorded with an inter-contraction interval of about one minute out of which, the MVC with the highest value was used. Since the basic EEG activity happens at a low frequency, a 2nd order Buttorworth filter was used to bandpass filter the signal from 0.05 to 10 Hz. Buttorworth filtering was followed by spatial filtered using a Large Laplacian spatial filter.

III. Methods

Empirical mode decomposition (EMD) is a data dependent method for performing the decomposition of a signals into its oscillatory components and is usually preferred for handling non-stationary data [9]. Therefore, we have performed feature extraction for the MRCP signals using EMD.

A. Empirical Mode Decomposition

The EMD is a data depending approach and does not make any assumptions about the linearity or stationarity of the data. The components which are obtained after the decomposition are known as intrinsic mode functions (IMF), and they identify various oscillatory components which are present in the data. Each of these components satisfy two conditions: 1). the number of extrema and the number of zero crossings must be the same or differ by at most one, and 2). at any point, the mean value of the envelope defined by the local maxima and the envelope defined by local minima is zero. Given a signal $x(t)$, the decomposition takes the following steps [10]:

- Determine the extrema (maxima and minima) of the dataset.
- Generate the upper and lower envelopes $e_m(t)$ and $e_l(t)$, respectively, by connecting maxima and minima with cubic spline interpolation.
- Calculate the local mean $m(t) = \frac{e_m(t)+e_l(t)}{2}$.
- Extract the detail $d_1(t) = x(t) - m(t)$.

- Decide whether $d_1(t)$ is an IMF or not (criteria described above).
- Repeat steps 1 to 4, until $d_1(t)$ is an IMF.

Once the first IMF is obtained, we define $c_1(t) = d_1(t)$, which is the smallest temporal scale in $x(t)$. A residue $r_1(t) = x(t) - c_1(t)$ is obtained which is than used as the new $x(t)$ for extracting more IMFs. The process is repeated until the final residue is a constant and no more IMFs can be extracted. The decomposition of the signal can be represented as:

$$x(t) = \sum_{m=1}^{M} c_m(t) + r_M(t) \quad (1)$$

where M is the total number of IMFs in the signal, $r_M(t)$ is the final residue and $c_m(t)$ represents the m^{th} IMF.

B. Choosing relevant IMFs

After obtaining the IMFs using EMD, we need to select the relevant IMFs which contain the information about MRCP. We are aware of the fact that the signal content of MRCP is composed of very low frequency components, the high frequency components mostly contain noise. The EMD find IMFs in the order of decreasing empirical frequencies which are available in the signal. Conceptually, the last IMFs (having low frequencies) contain the information about the MRCP and the first few IMFs will exhibit the noise components, which are contaminating the original potential drop due to MRCP [11]. Due to this relation, we choose the last two IMFs for feature extraction to classify the MRCP.

C. Feature extraction

Two different types of features are obtained from the EEG signals: 1). statistics of the IMFs and 2). mel-frequency cepstral coefficients.

1) Statistical features: After performing EMD on the EEG signal, we divide the signal into a number of time windows, each composed of 250 samples. For each window, the following statistics are calculated: mean energy of the IMFs, and variance of the IMF.

2) Spectral features: The scale relevant to the motor activity is selected using the IMFs with very small frequencies since the EMD behaves as a bank of filters in which the IMFs with low frequencies contain information about the MRCPs. It is well known that the fast and slow movements exhibit the fundamental frequencies which are different from one another. The mel-frequency cepstral coefficient (MFCC) features give a representation of a short term power spectrum of the signal based on a discrete cosine transform (DCT) of a log power spectrum on a non-linear *mel* scale of the frequency [12]. The DCT sorts the transformed coefficients in the order of decreasing variance and extraction of the first few coefficients of the DCT can give us significant information about the spectral envelope of the underlying signal [13]. Additionally, the cepstrum is able to identify the fundamental frequency of a signal which are typically different for fast and slow movements [3], [14]. Therefore, for the extraction of spectral MRCP features, we have used MFCC features. The MFCC coefficients are calculated as follows [15]:

$$C_i(e^{jw}) = \sum_{n=-N/2}^{n=N/2} c_i(t) e^{-jwn} \quad (2)$$

$$\log C_i(e^{jw}) = \log |(C(e^{jw})| + j\theta(w) \quad (3)$$

$$s_i(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \log C_i(e^{jw}) e^{jw} dw \quad (4)$$

where $c_i(t)$ is the i^{th} IMF (the last two IMFs in our implementation), $C_i(e^{jw})$ is the Discrete-Time Fourier Transform of $c_i(t)$ and $\theta(w)$ is the unwrapped phase spectrum. In our experiments, we have used the first 10 MFCC features of each window (250 samples) of the selected IMFs for feature extraction.

D. Dimensionality reduction

The feature extraction is followed by dimensionality reduction. In our experiments, we have used principal component analysis (PCA) for dimensionality reduction [16]. The PCA detects the variance structure of the data and the dimensions along which the data subspace exhibits high variance. The signal is projected onto a lower dimensional space that covers the maximum variance of the data. In our implementation, we select as many dimensions as are required to accommodate 95% variance of the data.

E. Classification

For classification, we have used support vector machines (SVM). The SVM, originally proposed by Vapnik et al. [17] mainly consists of constructing an optimum hyperplane that maximizes the margin of separation between two different classes. This approach typically constructs the classification models which have excellent generalization ability thus making it a powerful tool in various applications. For our implementation, we have used SVM with linear kernel for classification.

IV. Experimental results

In the data collection phase, it was realized that for the tasks mentioned above, the classes which are statistically separable are the 'f60' and 's20'. Therefore, we have analysed a 2-class problem in our experiments i.e, classification between the 'f60' and 's20' classes. We have used 10-fold cross validation in our experiments. The data collected from all the trials for all subjects was included in our analysis. The results of our experiments are presented in Table I. We have compared the performance that we have obtained using the proposed feature set with a set of temporal features used by M. Jochumsen [18] in their experiments. The experimental setup was kept consistent for both the feature sets.

Our experiments show that the proposed methodology gives a classification accuracy of about 77%, which is about 5% better as compared to the results obtained in [18] on

TABLE I: Classification results when different feature extraction methods are used for MRCP signals.

Methods	TP Rate	FP Rate
Novel	**0.77**	**0.23**
M. Jochumsen [18]	0.72	0.28

the same data. This is because, we have complemented the temporal features with the spectral features resulting in more discriminative features giving better results in the classification of slow and fast movements. A confusion matrix was obtained to asses the performance of the classifier on the individual classes (Table II). This detailed analysis shows that we get better true positive rates for the classification of ‘s20’ data.

TABLE II: Confusion matrix

		Predicted Class	
		fast60	**slow20**
Actual Class	**fast60**	387	136
	slow20	109	410

V. Discussion

In this paper, we have proposed to use a feature set for the classification of cortical activity in EEG signals. The preprocessing phase includes an empirical mode decomposition (EMD) of EEG signals. The main motivation for using EMD was that it is a data dependent method of decomposing a signal into a number of harmonics. There is no assumption on the stationarity of data for EMD unlike other methods such as wavelets. The drop in cortical potential corresponds to the smallest frequency of the MRCP signals thus EMD can be used for removing the noise from MRCP signals. For feature extraction, we have used temporal and spectral features. The temporal features are mean and variance of the selected intrinsic mode functions (IMFs) whereas the spectral features are constituted by the MFCC features. The MFCC features are used because they have the ability to extract compact information about the spectral envelope in the signals. The features are used in an SVM classifier for the classification of movements. The data collected from experimental protocol shows that better separability for the ‘f60’ and ‘s20’ EEG signals and thus a 2-class classifier constituting these two experiments was used in this paper. The data collected for other cases such as ‘s60’ and ‘s20’ etc. is not statistically separable and thus cannot be effectively formulated as a classification problem.

For the future work, two lines of research can be clearly constituted. i). A need to investigate more adequate features, and ii). Early detection of movements based on MRCPs.

Acknowledgements

We would like to thank National University of Sciences and Technology, Islamabad, Pakistan and Aalborg University for providing us with the financial support that was necessary for carrying out this research.

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