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DEVELOPMENT OF EFFECTIVE SIGNAL PRE-PROCESSING ALGORITHMIC TECHNIQUE FOR HYBRID BCI

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ABSTRACT

A brain computer interface (BCI) is a system enabling humans to interact with surroundings by making use of control signals generated from the electroencephalographic (EEG) activity. Recently a new approach to BCI called as Hybrid Brain Computer Interface is developed where two or more Brain Computer Interface System are combined to process signals in simultaneous or sequential manner. In this paper we discuss novel preprocessing algorithm to develop the hybrid brain-computer interface (hBCI) system using electroencephalogram (EEG) signal by combining the wavelet transform which is used for localizing distinctive spike features, with super-paramagnetic clustering, which is used for automatic classification of the data without the assumptions such as Gaussian distributions or low variance. The main idea is to employ effective methods for reducing the number of channels and optimizing feature vectors. The removal of unnecessary channels and reducing the feature dimension results in elimination of unimportant signals from the needed signal, time saving and improves the BCI implementation. This study introduces a new technique for detecting and sorting action potentials (spikes) of neurons from multiunit recordings. The focus is to develop an integrated artifacts removal technique that can automatically discover and remove the artifacts in order to smooth the progress of EEG assessment. The main goal of the project is to design and develop the optimal Pre-Processing algorithm so that we can gain higher accuracy and which results in overall improvement of the system.

Keywords:* *Artifacts Removal, Brain Computer Interface (BCI), Electroencephalogram (EEG), Spikes.

I. INTRODUCTION

A brain computer interface (BCI) system enables humans to interact with surroundings, without the involvement of the peripheral nerves and muscles, by using control signals generated from electroencephalographic (EEG) activity. In the recent work has validated a new approach to BCI called as Hybrid Brain Computer Interface. The Hybrid BCI is composed of two or more Brain Computer Interface System which detects signals in simultaneous or sequential manner. With the use of brain signals hybrid BCI can achieve much higher goals as compared to that of the conventional BCI. Such systems allow communication for those affected by motor disabilities [3].EEG measures electrical energy fluctuations resulting from ionic current flows within the neurons of the brain through various electrodes placed on the scalp. Multiple channels and set of surface electrodes will be used for this EEG signal extraction. Brain patterns forms unusual wave shapes that are generally precise by 0.5 to 100 µV in amplitude. [2]

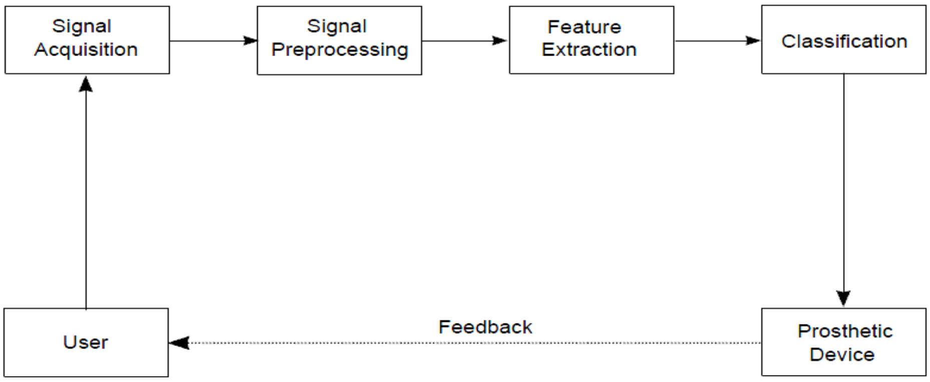

Figure 1: Block Diagram of a BCI System.

The block diagram of a BCI system is shown in Figure 1. The figure depicts a generic BCI system in which a user controls a prosthetic device such as, a powered wheelchair through series of functional components. A BCI is an artificial intelligence system that can recognize a certain set of patterns in brain signals following five consecutive stages: signal acquisition, preprocessing or signal enhancement, feature extraction, classification, and the control interface [1].

In recent years a large amount of research in neurophysiology is based on the analysis of extracellular potentials recorded with microwires that capture the action potentials (spikes) of neurons in their surroundings. For many applications it is crucial to know which spike correspond to which neuron, namely -spike sorting- and since recent acquisition systems allows the simultaneous recording of hundreds of channels, it is also important to do this automatically (or semi automatically) and fast [15]. In our proposed system of spike classification the basic algorithmic steps are as follows: (1) spike detection, (2) Extracting distinctive features from spike shapes, and (3) clustering of spikes using these features. The paper focuses on data processing, artifact removal, signal pre-processing. This paper is organized as follows: section II depicts related works done in Hybrid BCI system. Section III shows the theoretical background of signal preprocessing techniques. Section IV introduces methods for effective signal preprocessing for effective use and to gain higher accuracy. Section V gives the results of the experiment and under section V conclusion are included.

1.1 Related Work

Yuanqing Li et. al. [8] uses Band pass filter for filtering the EEG signals in frequency range between 0.1 and 10 Hz for P300 Potential Detection and the SSVEP EEG signals are filtered within the range of 3–20 Hz. Then they use the minimum energy combination (MEC) to combine the signals from multiple channels, to design hybrid SSVEP and P300 based BCI in simultaneous fashion. They achieve information transfer rate up to 22.11 bits/min.

Erwei Yin et. al. [14] First, the EEG data from the P300 channels were filtered using a 0.1–45-Hz bandpass filter to eliminate signal excursion and high-frequency noise. Then for SSVEP detection the data collected from the SSVEP channels were filtered using a 4–35-Hz bandpass filter. The canonical correlation analysis (CCA) was used to calculate the correlation between the stimulus frequency and the multichannel EEG data. CCA is an effective method for measuring the SSVEP response.

M. Murugappan et. al. [10] proposes a scheme which uses EEG signals collected from 64 channels from the 20 subjects in an age group of 21-39 years for determining discrete emotions (surprise, fear, disgust, happy and neutral) under audio-visual induction (video/film clips) stimuli. The Surface Laplacian filtering is used for preprocessing the EEG signals and decomposing into five different EEG frequency bands (alpha, beta, gamma, delta and theta) using Wavelet Transform (WT). Statistical features derived from these five frequency bands are considered for classification of the emotions using two linear classifiers such as K Nearest Neighbor (KNN) and Linear Discriminant Analysis (LDA). It concludes that KNN outperforms LDA.

Puneet Mishra et. al. [13] proposes a technique for the removal of eye blink artifact from EEG and ECG signal using fixed point or Fast ICA algorithm of Independent Component Analysis (ICA). For validation, Fast ICA algorithm has been applied to synthetic signal prepared by adding random noise to the Electrocardiogram (ECG) signal. Fast ICA algorithm separates the signal into two independent components, i.e. ECG pure and artifact signal. Similarly, the same algorithm has been applied to remove the artifacts (Electrooculogram or eye blink) from the EEG signal.

II. THEORETICAL BACKGROUND

Wavelet Transform: -The wavelet transform (WT) is a time-frequency representation of the signal having two main advantages over the conventional methods: it provides optimal resolution in both the time and frequency domain and it eliminates requirement of the signal stationarity. It is defined as convolution between signal x (t) and wavelet functions $\psi_{a,b}(t)$,

$$W_\psi X(a, b) = (x(t) \mid \psi_{a,b}(t)), \qquad (1)$$

where $\psi_{a,b}(t)$ is dilated (contracted), and shifted version of a unique wavelet function $\psi(t)$,

$$\psi_{a,b}(t) = |a|^{-\frac{1}{2}} \psi\left(\frac{t-b}{a}\right) \qquad (2)$$

where the a and b are scale and translation parameters respectively. Equation 1 can be inverted, thus giving reconstruction of x(t). The Wavelet Transform maps the signal represented by one independent variable t onto functions of two independent variables a, b. This procedure is inefficient and redundant for algorithmic implementations and therefore the WT is usually defined at the discrete scales a and the discrete times b by choosing set of parameters $\{a_j = 2^{-j};\ b_{j\cdot k} = 2^{-j}k\}$, with integers j and k.[12]. Contracted versions of wavelet function matches the high-frequency components, while the dilated versions matches the low-frequency components. Then, by correlating the original signal with the wavelet functions of different sizes, we can get details of the signals at several scales. These correlation with different wavelet functions could be arranged in a hierarchical scheme called multi-resolution decomposition. This multi-resolution decomposition algorithm separates signal into details at different scales and the coarser representation of a signal named "approximation".

Super-paramagnetic Clustering (SPC): -The following is a brief description of the super-paramagnetic clustering (SPC), which is based on the simulated interactions between each data point and its corresponding K-nearest neighbours. The first step is representing the m selected features of each spike i by point $\mathbf{x}_i$ in a m-dimensional phases space. The interaction strengths between the points $\mathbf{x}_i$ is defined as

$$J_{ij} = \begin{cases} \frac{1}{K}\exp\left(-\frac{\|\mathrm{x}_i - \mathrm{x}_j\|^2}{2a^2}\right) & \text{if } \mathrm{x}_i \text{ is a nearest neighbor of } \mathrm{x}_j, \\ 0 & \text{else} \end{cases} \tag{3}$$

where a is the average nearest-neighbours distance and K represents number of nearest neighbours. In second step, an initial random state s from 1 to q is assigned to each point $\mathbf{x}_i$. Then N Monte Carlo iterations is run for different temperatures T. The main idea is that from a given initial configuration of states s, a $\mathbf{x}_i$ point is randomly selected and its state s change to new state s_{new}, randomly chosen between 1 and q. The probability that the nearest neighbours of **xi** will also change their state to s_{new} is given by

$$p_{ij} = 1 - \exp\left(-\frac{J_{ij}}{T}\delta_{s_i,s_j}\right), \tag{4}$$

where T is the temperature. Note only those nearest neighbours of $\mathbf{x}_i$ that were in the same previous state s are the candidates to change their values to s_{new}[17]. Neighbours that changes their values create a "frontier" and cannot change their values again during the same iterations. Then for each point of frontier, we apply equation 4 again for calculating the probability of changing the state to s_{new} for their respective neighbours. The frontier is updated, and the update is repeated until the frontier does not changes any more. At that stage, we starts the procedure again from another point and repeat it several times in order to get representative statistics. Points that are relatively close (i.e., corresponding to a given clusters) will change their state together.[18]

III. PROPOSED ALGORITHM

This section presents the proposed algorithm for detecting and sorting spikes, the three stages of the algorithm: (1) spikes are detected automatically via amplitude thresholding; (2) wavelet transform is calculated for each spikes and an optimal coefficients for separating spike classes is automatically selected; (3) the selected wavelet coefficients then serves as the input to the SPC algorithm, and clustering is performed after automatic selection of the temperature corresponding to the super-paramagnetic phase.

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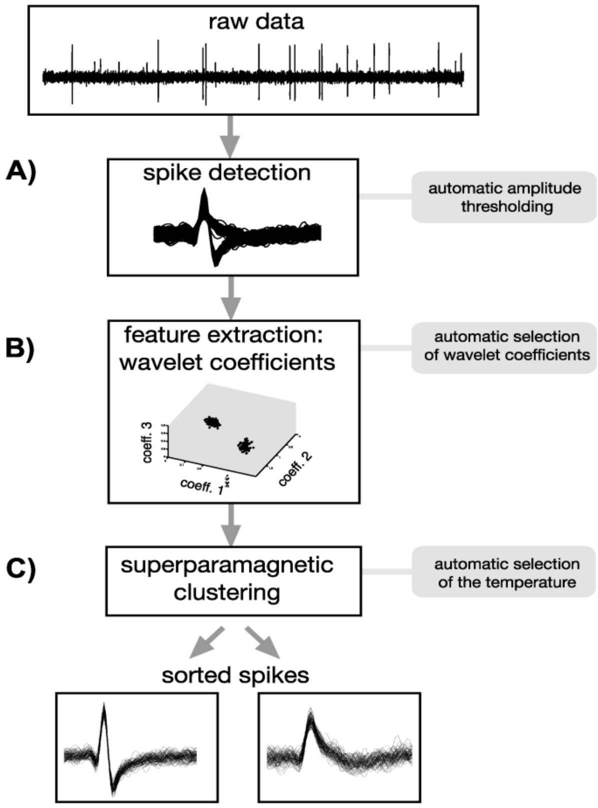

Figure 2. Overview of the Automatic Clustering Procedure

Spike Detection: - This is performed by amplitude thresholding after the bandpass filtering of the signal. The threshold (Thr) was automatically set to

$$Thr = 4\sigma_n; \qquad \sigma_n = median\left\{\frac{|x|}{0.6745}\right\}, \tag{5}$$

where x is bandpass-filtered signal and σ_n is an estimate of standard deviation of the background. Then for each detected spike, 64 samples (i.e., ~2.5 ms) were saved for further analysis. To avoid spike misalignment due to low sampling, spike maxima are determined from the interpolated waveforms of 256 samples using the cubic splines.

Selection of Wavelet Coefficients: - After detecting spikes their wavelet transform is calculated thus providing 64 wavelet coefficients for each spike. The goal is to select a few coefficients that best separates the different spike classes. This selection perform automatically by using the Lilliefors modification of the Kolmogorov-Smirnov (KS) tests for normality. Note that we are interested in deviation from normality as a sign of a multimodal distribution and do not rely on any of the particular distribution of the data. Given a data set x, the test compares cumulative distribution function of data (F(x)) with Gaussian distribution with same mean and variance (G(x)). The deviation from normality is quantified by

$$\max(|F(x) - G(x)|). \tag{6}$$

In our implementation, first 10 coefficients with largest deviation from normality are used. The selected set of the wavelet coefficients provides a compressed representation of spike features that serves as input to the clustering algorithm [22].

SPC and Localization of the Super-paramagnetic Phase: - After the selected set of the wavelet coefficients is chosen, we run SPC algorithm for a wide ranges of temperatures spanning the paramagnetic, super-paramagnetic and ferromagnetic phases. In order to localize super-paramagnetic phases automatically, a criterion which is based on the cluster sizes are used. The main idea is that for both paramagnetic and ferromagnetic phases the temperature increases can only leads to the creation of the clusters with few members each. Indeed in ferromagnetic phase there is almost no changs when the temperature is increased and in paramagnetic phase (i.e. very high temperature) the clusters breaks down into several small ones. In contrast, in super-paramagnetic phase increasing the temperature will creates new clusters with large number of members.

IV. RESULTS

Figure 3 shows the output of a spike sorting algorithm with the real data. The upper subplot shows continuous data and the threshold used for the spike detection. The lower subplots shows the different spike shapes with their corresponding inter-spike interval (ISI) distributions and the values of the first two wavelet coefficient chosen by the algorithm for all spikes. We can clearly see there are 4 different clusters. The plots on the bottom left corner show the size of each cluster as a function of temperature, which is the main parameter which can be varied if automatic solution is not optimal.

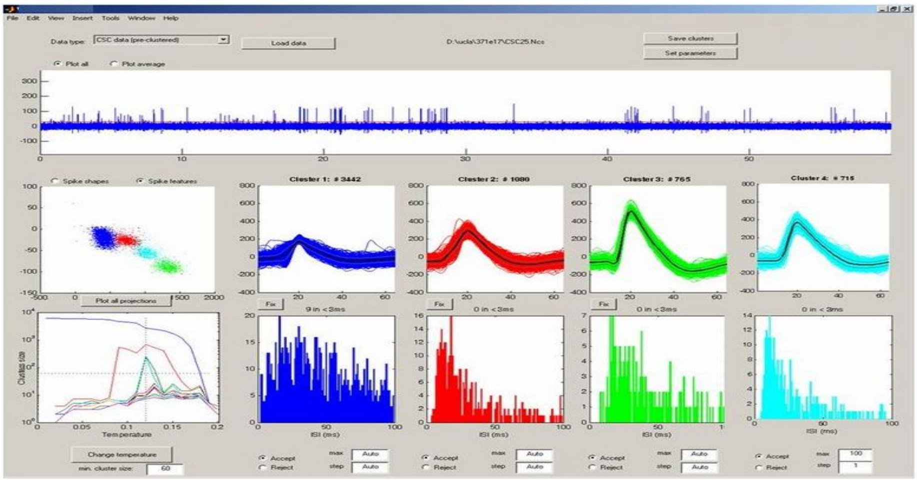

Figure 3. Spike Sorting of a Recording from the Human Medial Temporal Lobe

V. CONCLUSION

A hybrid brain computer interface (hBCI) is a combination of two BCI systems and provides a communications system that enables humans to control various devices by using control signals generated from electroencephalographic (EEG) activity. Unfortunately the acquired EEG signal consists of unnecessary artifacts and noise hence the role of signal pre-processing is crucial in the development of a BCI system. But no one gives any special attention towards this signal pre-processing process. The pre-processing algorithms are one of the most primary factors to decide accuracy as well as to obtain optimal results of BCI system. This paper mostly concentrated on the Pre-processing which is achieved by the use of wavelet transform with super-paramagnetic clustering which allows automatic detection and classification of spikes process. This method improves the quality of separation spikes and artifacts removal. We conclude that the performance of this method is better than other methods and works well in the artifacts cancellation to a wider set of corrupted recordings.

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