Wavelet Based Feature Extraction For Classification Of Motor Imagery Signals

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***Abstract*—The analysis of EEG signals play a significant role in brain related studies. Accurate investigation and analysis of the EEG signals from a subject can interpret the inherent information about the intention of the person to some extent. The accuracy of such interpretation or detection can be of utmost importance for various brain computer interface (BCI) based applications. For instance, within the last decade, BCI has been widely investigated and employed to assist in the restoration of sensory and motor functions in paralyzed individuals. EEG typically contains numerous information about the cognitive thinking and intention of a person, particularly in terms of motor movements. Due to this, comprehensive methods of EEG signal arrangement and pattern recognition through signal classification techniques are required to precisely predict the intended set of movements. In this study, an EEG classification technique based on a combination of wavelet transform analysis and Neural Networks (NN) is presented. Daubechies wavelet decomposition (db8) has been employed to decompose the recorded EEG signals into four levels. These decomposed level details are then used to calculate the feature set which is input to NN classifier for further classification. A total of 6 features were used to perform feature wise classification, where Integrated EEG (IEEG) feature set has been found to possess the highest classification accuracy of 89.39 % with a NN classifier of 9 hidden layers. Whereas, a classification accuracy of 94.86 % was achieved when the features were arranged and cascaded horizontally in form of a dataset as input to a NN classifier of 5 hidden layers.**

Keywords—EEG;Motor Imagery signals;Wavelet decomposition; Feature extraction;Classsifciation

I. INTRODUCTION

Electroencephalograms (EEGs) are one of the most common medically recorded and analyzed biological signals. These signals are basically the measurements of the potential difference along any two or more areas of the human scalp [1]. Human brain generates minute electrical pulses to communicate with the other parts of the body. This electrical variation in the pulses can be collected from the surface of the scalp which can indicate about the internal neural activity. Such method is called non-invasive EEG recording as it does not include penetrating the surface of the scalp. The presence of these electrical signals offer a variety of communication techniques where the brain of a person can be used to command, control and execute the relative intentions of movement without actual physical limb movements [2].

Brain-computer interface (BCI) employs the thought modulated activity of a subject at one end to command the connected device at the other end. The possibility of controlling a corresponding device, by only using the brain signals, offers a variety of potential applications. There are some applications that involve the human body, for example, rehabilitative equipment, which involves MI signals, as a consequence requiring BCI system to be very accurate to avoid any related injuries. Therefore, it is crucial to precisely analyze, classify and translate the MI signals in the desired set of movements [1]. Accurate estimation of these MI features can play a vital role to assist motor disabled patients in communication as well as in performing the activities of daily life.

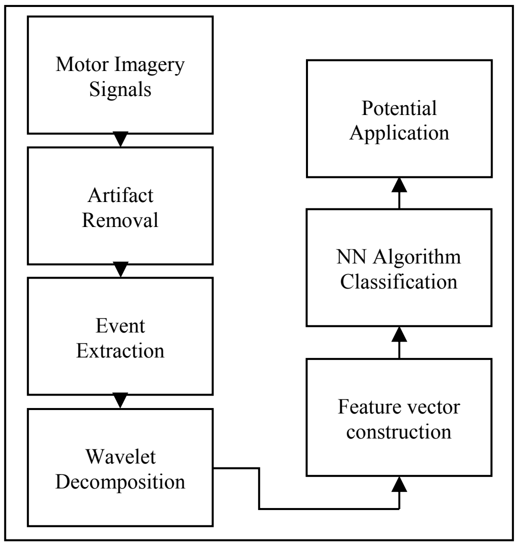

Figure 1. Basic block diagram of EEG classification system

Figure 1 shows the fundamental block diagram of a typical EEG classification system. Raw brain signals are collected from the scalp of the subject and then pre-processed to remove any unwanted artifacts. Representative features are then calculated to signify the thought modulated activity.

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These signals are then identified based on various classification techniques to understand the desired intent of the subject. Raw EEG or Motor Imagery (MI) signals are transformed in to set of commands, at the output, which can be used to derive various applications [3]. Subsequent sections include; Motor imagery dataset section which discusses about the EEG dataset that has been used to conduct this study; the signal de-noising techniques which are employed to enhance the dataset; the illustration of the measures that are used to calculate the discriminatory EEG features; and finally, the achieved classification results.

II. Motor Imagery (MI) Dataset

This study has been conducted on the open access MI dataset which is available online at http://www.physionet.org. It was created by the developers of the BCI2000 [4], (www.bci2000.org), instrumentation system and contributed to Physionet [5]. The dataset comprises of the EEG data for 109 healthy subjects, while performing different tasks as they appear on a computer screen. A 64 channel EEG setup has been employed to record the relative EEG activity along the scalp. The obtained EEG signals were recorded according to the international 10-20 system as seen in Figure 2.

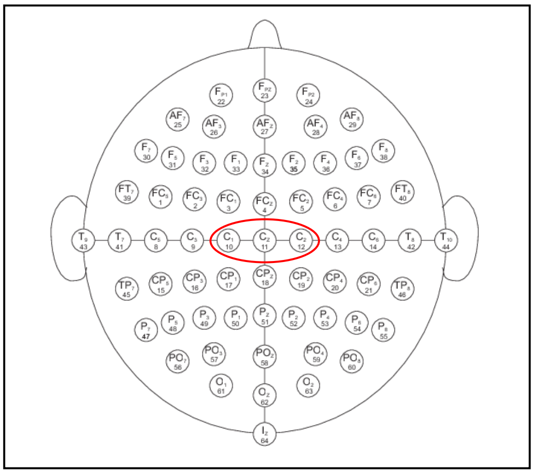

Figure 2. Annotation of 64 channel EEG electrode setup (Adapted from www.physionet.org, [5])

The data has been divided into 14, two minute runs of recording for each subject. It includes two initial baseline runs of eyes open and eyes closed. The other 12 runs include three repetitions of four tasks including; opening and closing of left or right fist, imagine opening and closing of left or right fist, opening and closing of both fists or both feet, imagine opening and closing of both fists or both feet. These tasks are repeated 15 times during each two-minute run. A total of three runs of Task 4, that is, the imagination of opening and closing of both fists or both feet for 20 subjects has been employed in this study. As the task is repeated 15 times in each run, a sample of 900 vectors is used to perform the classification of imagination of either both fists or both feet.

It has been discussed in the previous MI related studies that the most active EEG channels during MI tasks imagination are C3, Cz and C4 [6] which are located at the central scalp region as shown inside the red circle within figure 2. Hence, in this study, only the aforementioned three channels are analyzed. It allows the classification system to be more accurate and also reduces the overall computational time. These channels are numbered as electrodes number 9, 11 and 13 respectively in the arrangement of total 64 electrodes.

III. Pre-processing

A. Artifact removal

The data provided by Physionet are raw EEG recordings of MI signals. Therefore, it is necessary to filter out the unwanted components from these signals. The EEG signals used here are recorded at a sampling frequency of 160 Hz. To remove various unwanted frequency components, a band pass filter of frequency range 0.4 - 40Hz is implemented. After normalizing the EEG signals, baseline filtering and the muscle artifacts, including Electrooculograhy (EOG) and Electromyography (EMG), removal is performed using Blind Source Separation (BSS) algorithm implemented in Automated Artifact Removal (AAR) plug-in within MATLAB toolbox, EEGLAB [7, 12, 13]. Normalization of the signals is very important to perform the classification of signals using any machine learning technique [8]. It is performed by using Source Information Flow Toolbox (SIFT) plug-in within EEGLAB [14].

B. Event information extraction

The data for the aforementioned 15 tasks as performed by the subjects in each of the three runs is extracted using the code which is provided publically by [6] available at www.researchgate.net. This program extracts and splits the original data for each run into 656 samples for each executed task. The relative task annotation is also acquired using the same code. This annotation represents the executed task in either T1 or T2. Where T1 represents the imagination opening or closing both fists and T2 represents the imagination of opening or closing both feet. This annotation data is used later in the classification phase to train the NN classifiers.

IV. Feature Selection

Wavelet transform is one of the widely used techniques for the analysis of non-stationary signals, particularly for EEG analysis. With this technique, mother waveform is divided into smaller wavelets, which makes it easier to investigate the specific set of frequency components in a signal [10]. There are different types of wavelets which are available to be applied, such as, Daubechies, Symlets, Coeiflets, Gaussian and Shannon [11].

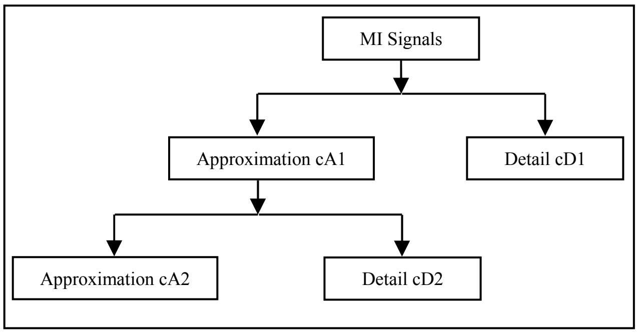

Figure 3. Block diagram of wavelet decomposition

Figure 3 shows the functional block diagram of the wavelet decomposition. It can be seen that the mother wavelet is divided in to two parts; Approximation and detail. This continues until the desired decomposition level is achieved. This study employs 'db8' version of daubechies wavelet, up to four levels. Upon application, it decomposes the signal into multi-level details according to their respective frequencies. According to previous studies [6], mu (8-12 Hz) rhythm and beta rhythm (13-30 Hz) are the most commonly active frequency components that are recorded when there is an intention of movement. Hence, as shown in Table 1, the decomposed level detail cD2, cD3 and cD4 can fully represent the MI signal for imagination of opening and closing of either both fists or both feet.

Table 1. Decomposed level according to their frequencies

Detail level	Frequency component
cD1	40 – 80Hz
cD2	20 – 40Hz
cD3	10 – 20Hz
cD4	5 – 10Hz
cA4	0 – 5 Hz

These detail levels include various decomposed frequency components lying within the original MI signal. From these decomposed signals, three details, that is, cD2, cD3 and cD4 are used to calculate the corresponding features that can represent the MI modulated brain activity. In the literature, a number of different statistical as well as mathematical measures have been reported to be used for obtaining the useful discriminatory features in classifying the MI signals. Some of the most commonly employed and reliable measures which provide high classification accuracy are discussed in [6, 9]. These include Root Mean Square (RMS), Mean Absolute Value (MAV), Integrated Encephalograms (IEEG), Simple Square Integral (SSI), Variance of EEGs (VAR) and Average Amplitude Change (AAC). These measures can be obtained as follows:

Root Mean Square (RMS)

$$RMS_i = \sqrt{\frac{1}{N}\sum_{n=1}^{N} D_i^2(n)} \qquad \text{Eq. (1)}$$

Mean Absolute Value (MAV)

$$MAV_i = \frac{1}{N}\sum_{n=1}^{N} |D_i\,(n)| \qquad \text{Eq. (2)}$$

Integrated Electroencephalogram (IEEG)

$$IEEG_i = \sum_{n=1}^{N} |D_i\,(n)| \qquad \text{Eq. (3)}$$

Simple Square Integral (SSI)

$$SSI_i = \sum_{n=1}^{N} |D_i\,(n)|^2 \qquad \text{Eq. (4)}$$

Variance (VAR)

$$VAR_i = \frac{1}{N-1}\sum_{n=1}^{N} D_i^2(n) \qquad \text{Eq. (5)}$$

Average Amplitude Change (AAC)

$$AAC_i = \frac{1}{\mathrm{N}}\sum_{n=1}^{N} |D_i\,(n+1) - \mathrm{D_i(n)}| \qquad \text{Eq. (6)}$$

Where D_i represents the decomposed level of wavelet detail and N represents the total number of samples decomposed for each event. The feature vectors are calculated for each of the details, that is, for cD2, cD3 and cD4. This process is repeated for all three channels. Hence a total of 54 features obtained from 3 channels each containing 6 features, each feature described by 3 details (3 channels x 6 features x 3 details = 54 features) were calculated. This was done for a total of 20 subjects obtained from 3 runs containing 15 events each (= 900 vectors), by using equations 1 to 6. As, each of the feature is calculated by using three details for each channel, therefore, each of the features for three channels contain 900x9 data matrix.

V. RESULTS

MI signal classification for imagination of opening and closing both fists or both feet has been performed by using cascade-forward back propagation Neural Network (NN) classifier algorithm. A total of 720 samples for each feature, that is, 80% of data is randomly selected and used for training, while 180 samples, that is, 20% of data is used for testing and validation. Firstly, feature wise dataset (900x9) of corresponding features were used for training the NN classifier.

It is performed by creating six neural networks, with 9 input nodes and 1 output node for each of the features. The average accuracy is calculated based upon the output regression value where a regression of 1 is equal to 100% accuracy level. An average accuracy of multiple training sessions for 5 different hidden layers is then calculated.

The feature wise classification accuracy of the aforementioned features is listed in Table 2.

Table 2. Accuracy of classification according to regression graph

Hidden Layers	RMS	MAV	IEEG	VAR	AAC
20	82.80 %	78.20 %	86.94 %	76. 22 %	83.81 %
19	85.60 %	81.25 %	**89.39 %**	82.02 %	74.59 %
17	79.49 %	73.76 %	80.55 %	77.45 %	83.39 %
11	86.33 %	84.62 %	83.05 %	69.91 %	79.29 %
9	84.34 %	80.88 %	79.98 %	71.12 %	76.99 %

It can be observed that the best average classification accuracy of 89.39 % is achieved by training an NN classifier with 19 hidden layers using IEEG feature set.
Secondly, the dataset for all aforementioned features is cascaded horizontally to form a 900x54 data matrix, and used to train an NN classifier with 54 input nodes and 1 output node. After multiple training runs of NN classifier with 5 hidden layers, an average accuracy of 94.86 % is achieved.

VI. Discussion

Through the comparison of the accuracy level between the two performance evaluation methods, it can be observed, that, when the features are cascaded horizontally, the number of discriminatory features increase from 9 features to 54 features. This provides the neural network with an added amount (6 times) of training data compared to the feature wise classification. It is observed that, consequently, the optimal classification accuracy is also increased from 89.39 % in the feature wise classification method, to 94.86 % in the subsequent technique.

VII. ConclusionS

This study presents an MI based EEG signal classification technique based on a combination of wavelet transform analysis and Neural Networks. A total of 6 features, each containing 900x9 samples matrix, were used to perform feature wise classification, where Integrated EEG (IEEG) feature set has been found to possess the highest classification accuracy of 89.39 % with an NN classifier of 9 hidden layers. Whereas, a classification accuracy of 94.86 % was achieved when the features were arranged and cascaded horizontally to form a dataset of 900x54 samples matrix as input to a NN classifier of 5 hidden layers. Daubechies wavelet decomposition (‘db8’) has been employed to decompose the recorded EEG signals into four levels. These decomposed level details are then used to calculate the feature set which is then input to a NN classifier for further classification.

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