Feature Extraction and classification of EEG based Motor Imagery Signals

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Abstract: Brain Computer Interface (BCI) interfaces the brain with an outside application. Electroencephalograph (EEG)-based brain–computer interfaces (BCI’s) require current detection of state of mind from spontaneous EEG signals of the particular area of brain. Many people are affected by neural diseases such as multiple Sclerosis, cerebral palsy, spinal cord injury etc. impairing the neural pathways which control muscles. Also these diseases can cause severe paralysis and the persons may suffer from what is called “Locked in syndrome”. This main motive of the project is to provide an alternate pathway in case of impairing of neural pathway that controls muscles. Motor imagery EEG signals reflect the different movements of body parts. Here the classification of the motor imagery signals obtained by non-invasive electroencephalography (EEG) technique. These EEG signals having small magnitude in the range of microvolts come out with different artifacts. So getting a pure signal without any noises and its robust feature extraction for classification are our objectives in this project. The obtained signals are preprocessed using a band pass filter for the range of interest for motor imagery signals which is 8Hz-30Hz. Features are extracted using DWT and STFT which are classified using SVM with an accuracy of 90% and 88% respectively for left hand and right hand motor imagery signals.

1. Introduction

Electroencephalography (EEG) is a process of recording the electrical activity of the brain utilizing electrodes placed on the scalp. The history of EEG dates back to 1875 when the first EEG recording from an animal was made by Richard Caton. The first recording from human was conducted by Hans Berger in 1924.

Data set provided by Fraunhofer-FIRST, Intelligent Data Analysis Group (Klaus-Robert Müller), and Freie Universität Berlin, Department of Neurology, Neurophysics Group (Gabriel Curio)

EEG signals are commonly recorded using silver-silver chloride electrodes and the value of the signal which are obtained are in the range of 0.5–100 μV. Depending on the frequency, amplitude, EEG waveforms are classified.

BCI systems into different categories according to the signal acquiring methods or the signal itself
(1) Invasive or Noninvasive BCI,
(2) Dependent or Independent BCI,
(3) Synchronous or Asynchronous BCI, and
(4) Spontaneous or Evoked.[1]

Apart from EEG, other techniques like electrocorticography (ECoG) in which the electrical signals are recorded using electrodes placed inside of the skull over the cortical surface and local field potentials (LFP) in which the electrodes are inserted inside of the brain. The main difference between them is the placement of the electrodes.

BCI can be regarded as a new channel of motor control except that it does not involve muscles. Normal neuromuscular motor control involves two fundamental components firstly to control the body, and secondly to predict the consequences of the control command, which is called motor prediction and is essential for skilled motor behaviors because of the inherent delay in the sensorimotor system. Brain Computer Interface (BCI) directly interfaces the brain and external world without any muscle movements of hands, feet etc. The group of neurons around the electrode generates the electrical activity that is seen by an electrode. BCIs using the imagination of muscle movements are an interface where a motor imagery movement of body parts such as hands, feet, and tongue is taken as an input which is referred as motor-imagery based BCI (MI-BCI). As an example of the MI-BCIs, a task of the motor imagery of right hand and a task of the imagination of the motor imagery of left hand are the tasks to be classified from brain signals. Motor prediction can predict the dynamic state of both our body and the environment we interact with.

BCI provides with control signal from the obtained electrical signals of brain. The brain waves are differentiated into five major types depending on the range of frequency as -
Delta (0.5–4 Hz) — the slowest brain rhythm, during sleep this rhythm is the strongest one; theta (4–8 Hz) — does not occur frequently in adult humans; Alpha (8–13 Hz) — predominant wave during wakefulness, present over the area of visual cortex, strongest when the eyes are closed or when a person is in state of relaxation, mu (8–13 Hz) — have the same frequency range as alpha, but are present over the motor cortex; beta (13–30 Hz) — are connected to states of alertness and attention; gamma (30 > Hz) — are related to information processing.

In this paper, a new EEG motor imagery movement recognition algorithm combining discrete wavelet transform (DWT) and short time fourier transform (STFT) with SVM classifier was developed. Comparing both of these methods in terms of feature extraction and classification to obtain higher classification rate.

2. Methodology

Brain Computer Interface (BCI) interfaces the brains and external worlds without any muscle movements of hand, feet, etc. A proper algorithm is set from the signal acquisition to its classification. The blocks describe the designed system represented in fig. 1.

![Block Diagram of Proposed System](image)

The different blocks of the system describe a procedure of BCI system is explained in the following steps.

2.1. Signal Acquisition

For acquiring the EEG signal a non-invasive technique of EEG signal acquisition is used. Our database of the EEG signal has been recorded through NeuroScan amplifier and a silver/silver chloride electrode cap from ECI. The device consist 28 silver/silver chloride electrodes channel. The sampling frequency of that device is 1000 Hz and the recorded signals were band-pass filtered between 0.05 Hz and 200Hz. The sampling rate for each electrode channel was selected at 1000, so we got 1000 digital value for each second. The obtained digital signals were imported in MATLAB for further processing.

2.2. Signal Pre-Processing

Once the signals are obtained, these must be cleaned from various artifacts using proper filtering of the signal. Signal pre-processing mainly deals with the data filtering. This can be done using different types of filters including the spatial filters like surface Laplacian (SL) and temporal filters like finite Impulse Response filter (FIR) filter. As FIR filters have more stable response compared to IIR filters, FIR filter of desired frequency range is used. A bandpass equiripple FIR filter for the frequency range of 7Hz and 30 Hz i.e. the mu frequency band which consist of alpha and the beta frequencies levels is used.

2.3. Feature Extraction

The energy changes of particular frequency bands are termed as features of the MI tasks. Moreover, the changes of spatial patterns depend on the kind of the motor imagery movement. For example, it has been observed that the motor imagery movement of a left hand evokes energy changes on the right side of a motor cortex region of the brain and vice versa. So accordingly these features are extracted by appropriate feature extraction method. The loss of hidden information present in the signal decreases if proper features are extracted. Moreover proper features extracted minimize the complexity of implementation, reduces the cost of information processing describes the large set of data is accurately and there is no need to compress the information.

2.3.1 Discrete Wavelet Transform (DWT):

DWT is suitable for analysis of non-stationery signal act as a mathematical tool for EEG signal processing and analysis as it, moreover it delimits the artifact components in the signal. Different families of these filters can be used for decomposition of EEG signals. These includes filters such as Daubechies, Coiflets, Symlets, Haar etc. Among this Daubechies-8 (db8) decomposition filter has been considered in this paper. A single individual wavelet known as the mother wavelet \( \Psi(t) \) is decomposed into different wavelets by dilations and shifting:

\[
\Psi(x,y)(t) = \frac{1}{\sqrt{2}} \Psi\left(\frac{t-x}{y}\right) \\
\]

where \( x \) is the dyadic scaling parameter and \( y \) is the dyadic shifting parameter.
Daubechies 8(db8) decomposes the average power of imagery hand movements in time window into 8 levels by and thus \( f(t) = A8 + D8 + D7 + \ldots + D1 \). The corresponding bands were followed by 0Hz - 1Hz, 1Hz - 2Hz, 2Hz - 4Hz, 4Hz - 8Hz, 8Hz - 16Hz, 16Hz - 32Hz, 32Hz - 64Hz, 64Hz - 128Hz, 128Hz - 256Hz.

2.3.2. Short Time Fourier Transform (STFT):-

The STFT may be considered as a method that splits the non-stationary signal into many small segments. Now these small segments of the signal can be assumed to be locally stationary, and conventional FFT is applied to these segments. The STFT of a signal \( s(\tau) \) is obtained by multiplying the signal by a window function, \( h(\tau) \), centered at \( \tau \), to get a modified signal. Since the modified signal lay emphasis on the signal around time \( \tau \), Fourier Transforms will reproduce the distribution of frequency around that time. The energy density spectrum at time \( \tau \) is formulated as follows:

\[
S_\tau(\omega) = \int_{-\infty}^{\infty} s(\tau) h(\tau - \tau) d\tau 
\]

The energy density spectrum at time \( \tau \) is formulated as follows:

\[
P(\tau, \omega) = |S_\tau(\omega)|^2 = \int_{-\infty}^{\infty} s(\tau) h(\tau - \tau) d\tau |^2
\]

For each different time, we get a different spectrum and the group total of these spectra gives the time-frequency distribution \( P(\tau, \omega) \), which is termed as Spectrogram. The main drawback of the STFT is the resolution tradeoff between time and frequency. The width of the window \( h(\tau) \) determines the time resolutions and frequency resolutions.

2.3.3. Classification:- Classification step is mainly performed to automatically assign a class to the feature vector extracted from the former step. This class describes the mental task. This classification step is generally used by the BCI user and denotes the type of mental task executed by the user. Classification is attained using algorithms known as “classifiers”. Classifiers are smart enough to identify the class of a feature vector using training sets. The classifiers are divided into five major categories. They are namely, linear classifiers, nonlinear Bayesian classifiers, neural networks, nearest neighbor classifiers and combinations of classifiers.

Support Vector Machines are proving very useful in classification tasks. Support Vector Machine (SVM) separates all data points of two different class by deciding the best hyperplane that separates all data points of two different class for classification. SVM uses a kernel function to achieve this nonlinear mapping into a higher dimensional feature space and then a construction of a linear ideal separating hyperplane is between the two classes in the feature space is done. A two level classification approach has been undertaken in this study for the motor execution dataset. For the motor imagination dataset, the classifier was trained only for left/right classification. SVMTRAIN and SVMCLASSIFY are used for training SVM.

3. Results

Starting with the signal acquisition which is initiated by taking the EEG signals from C3 and C4 electrodes for the left hand and right hand imagery movements from the database which contains these signals at 14th and 18th row. Since Motor related signals are mainly in mu (8-13) Hz and beta (13-30) bands, we used a frequency range of 8-30 Hz for Band pass filter. Also the Power line interference at 50Hz is removed.

**Feature Extraction Stage**

Feature Extraction is done by Short Time Fourier Transform And Discrete Wavelet Transform.

**Short Time Fourier Transform (STFT) Plots.**

The STFT plots for Left hand imagined and right hand imagined movements of three electrodes C3, C4 and CZ where the motor imagery signals are supposed to be generated is plotted as shown in fig 3.
Discrete wavelet transform (DWT) provides decomposition of the signal into detail and approximate part of the signal for left hand imagined and right hand imagined movement. The number of decomposition levels is according to the sampling frequency of the EEG Signal. The corresponding bands were followed by 0Hz -2Hz, 2Hz -4Hz, 4Hz -8Hz, 8Hz -16Hz, 16Hz -32Hz, 32Hz -64Hz, 64Hz -128Hz, 128Hz -256Hz, 256Hz -512Hz, for A8, D8, D7, D6, D5, D4, D3, D2, D1 as shown in Fig 4.

Classification of these signals using SVM classifier and the accuracy is calculated for the different hand movement using different methods of feature extraction is shown in Table I. and Table II. for DWT features and STFT features respectively and is represented in fig. 5.

\[
\text{Accuracy} = \frac{\sum \text{True Positive} + \sum \text{True Negative}}{\sum \text{Total Population}} \quad (6.1)
\]
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Table I. Accuracy using DWT Features.

<table>
<thead>
<tr>
<th>Term</th>
<th>Number of Detected Signals</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_p$</td>
<td>23</td>
<td>Right hand detected as Right hand correctly.</td>
</tr>
<tr>
<td>$F_n$</td>
<td>2</td>
<td>Right hand movement detected as Left hand movement.</td>
</tr>
<tr>
<td>$T_n$</td>
<td>22</td>
<td>Left hand detected as Left hand correctly.</td>
</tr>
<tr>
<td>$F_p$</td>
<td>3</td>
<td>Left hand movement detected as Right hand movement</td>
</tr>
</tbody>
</table>

Accuracy = \frac{tp + tn}{tp + fn + tn + fp} \times 100

Accuracy = \frac{(23 + 22)}{(23 + 2 + 22 + 3)} \times 100

= 90%

Table II. Accuracy using STFT Features.

<table>
<thead>
<tr>
<th>Term</th>
<th>Number of Detected Signals</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
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<td>22</td>
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</tr>
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<td>3</td>
<td>Left hand movement detected as Right hand movement</td>
</tr>
</tbody>
</table>

Accuracy = \frac{tp + tn}{tp + fn + tn + fp} \times 100

Accuracy = \frac{(22 + 22)}{(22 + 3 + 22 + 3)} \times 100

= 88%

Table 4.3. Classification Accuracy Using SVM

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>STFT</td>
<td>88%</td>
</tr>
<tr>
<td>DWT</td>
<td>90%</td>
</tr>
</tbody>
</table>

4. Conclusion

Brian computer interface is advancing every single day so there is the need for classification of different movements. Although numerous feature extraction methods have been proposed for BCI, it is very difficult to identify the most efficient ones due to a lack of comparisons. It seems also important to extract a small number of features which represents subject-specific information, in order to reach good performances. As such, it seems interesting to use features that can be tuned as well as dimensionality reduction or feature selection techniques in order to facilitate the subsequent work of the classifier.C3 and C4 electrodes depicts the signals for Left hand and Right hand motor imagery movements. Here results clearly show that both methods of feature extraction are providing robust features for classification. As DWT offers better temporal resolution compared to STFT the time domain features are better for DWT than that of STFT. The classification accuracy of SVM classifier shown in results proves that there is proper detection of left hand imagined movement and right hand imagined movement using SVM classifier. But as the number of movements increases the classification with DWT features is better compared to STFT features.

5. References


[3] Li Ming-Ai WANG Rui HAO Dong-Mei YANG Jin-Fu “Feature Extraction and Classification of Mental EEG for Motor Imagery” Fifth International Conference on Natural Computation.2009


[11] Data set provided by Fraunhofer-FIRST, Intelligent Data Analysis Group (Klaus-Robert Müller), and Freie Universität Berlin, Department of Neurology, Neurophysics Group (Gabriel Curio).