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Bayesian Network for EEG Feature Extraction in Multiuser Motor Imagery Brain Computer Interface

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Abstract*—*Brain Computer Interface is a communication pathway between a trained human brain and an external device. For people who are paralysed, BCI acts as an interface to control and regulate external devices and replaces their lost motor functionality. A motor imagery BCI converts a person's imagination about a motor activity into control signals which in turn controls the intended device. For this, the EEG signals that are produced according to the motor imaging need to be processed and analysed using various signal processing algorithms. Learning and modelling the brain activity presents a huge challenge in the accurate classification of this EEG and hence affects the performance of the BCI system. Since the brain regions work in collaboration during an activity, the efficiency of feature extraction stage is of great importance and the correlation between the EEG signals must be considered during this phase. Bayesian Network technique analyses not just the spatial or spectral characteristics, but it takes into account the correlation between different brain regions during an imaginary motion. It is an effective method for feature extraction which works based on the probability of channels during each activity. Wavelet decomposition is employed to extract the mu and beta rhythms which are the sensorimotor rhythms. Since most of the BCI systems are subject specific systems, here a multi-user BCI with increased performance, which can be an adaptive system for multiple users, is being proposed by using Artificial Neural Network for feature classification.

Index Terms*—*Artificial Neural Network, Bayesian Network, Brain Computer Interface, Motor Imagery, Wavelet Decomposition

I. INTRODUCTION

Brain Computer Interface is a technology that has seen rapid growth in the recent years. For people who are fully or partially paralysed [1] or who are suffering from disorders like amyotrophic lateral sclerosis, BCI can act as an interface between the users and an external device. It is a communication pathway between an enhanced human brain and the device. It controls the mechanical or electronic devices based on the brain activity alone. For such people who are paralysed, their brain regions might be working well. So the users can imagine the movement of their body parts and corresponding brain signals will be produced. BCI decodes these signals and interface them to the intended device. It actually restores the movement ability of paralysed users and the lost motor functionality is being replaced. Other than the biomedical applications [2], BCI becomes useful in places where the response time is crucial. It has a wide variety of applications in the fields of neuro-ergonomics, neuro-marketing, educational self regulation, games, entertainment and security.

EEG based motor imagery BCI systems are the most studied form of BCI. Motor Imagery refers to the imagination of movement of body parts. When a movement is being imagined, corresponding brain regions will be activated and the EEG signals will be produced according to the imagined movement. It is the motor areas of the brain that gets activated during the imagination of a motion. The motor imagery modulates the sensorimotor rhythms in the EEG signal. Mu rhythms (8-12 Hz) which is simply the alpha rhythms recorded in the motor areas and the beta rhythms (12-30 Hz) are the sensorimotor rhythms. These variations in the EEG rhythms are analysed and processed in the BCI. The control signals corresponding to these variations are produced and are used to control the intended devices like wheelchair, lamp, robotic arms etc.

The basic structure of BCI, shown in figure.1, includes a source module, a signal processing module and a user application module. The source module carries out the data acquisition and stores the data as such without any processing. In the signal processing module, the pre-processing of the EEG signal is done. The signal is modified to a form in which further processing can be done by removing the artifacts and other noises. The feature extraction and classification is carried out in this module. The accuracy of this module determines the accuracy of the entire system. The user application module interfaces the processed control signal to the intended device. Since it is important to identify the significant features of EEG during a motion and accurately classify these features, the signal processing module is the most important part of a BCI system.

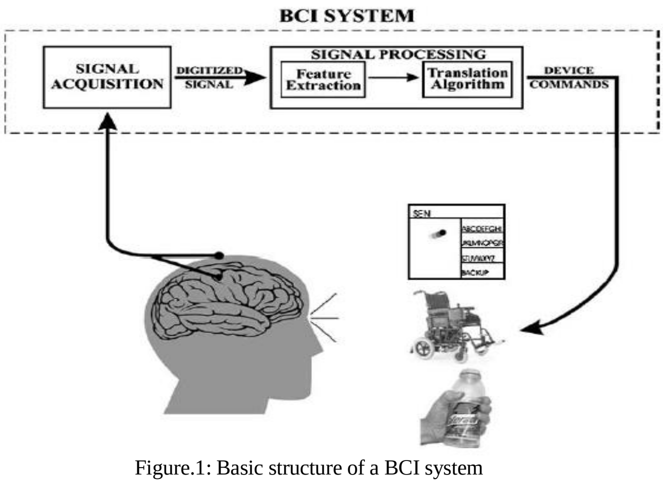

Figure.1: Basic structure of a BCI system

For the feature extraction and classification many methods have been developed by the researchers. Some methods work using the spectral characteristics of the motor imagery EEG signals and some methods work based on the spatial features. The proposed system uses the Bayesian Network approach for feature extraction. Since the brain regions work in collaboration during an activity, certain EEG channels may be dependant for a particular movement. Bayesian network technique not only considers the spatial and spectral characteristics, but also the channel probability for each movement. Most of the BCI systems are subject specific systems. The system will be trained for a specific individual and when another person needs to use this system, it needs to be trained again for the new user. The proposed system is a multiuser system which is an adaptive system for multiple users. The feature classification is done by using the Artificial Neural Network classifier, which ranks the channels for multiple users.

II. LITERATURE SURVEY

A classification method for motor imagery tasks in Brain Computer Interface using Linear Discriminant Analysis [3] is proposed by Roxana Aldea and Monica Fira. In this method the motor imagery feature extraction is done using multiresolution wavelet analysis and the task classification is done by using the LDA method. The two classes being classified are the left or right hand imagery movement and rest. The work is done using the EEG data recorded with 8 g.tec active electrodes by means of g.MOBIlab+ module. The paper tries to make a comparison between the LDA classification method using these acquired EEG signals and the LDA classification method used in the BCI2000 [4] systems.

The performance of BCI systems using a single classifier to recognize the entire feature usually degraded under the situations of individual differences and noisy environments. To solve this problem, Shang-Lin Wu, Yu-Ting Liu, Tsung-Yu Hsieh, Yang-Yin Lin, Chih-Yu Chen, Chun-Hsiang Chuang, and Chin-Teng Lin proposed a BCI system that uses the fuzzy integral with particle swarm optimization [5] to classify EEG feature vectors. The fuzzy integral is a fusion technique that exploits multiple decisions from different sources to get combined information which is infeasible to achieve from each individual source separately. Multiple LDA classifiers are established that employ CSP features to integral multi-classifiers.

Common Spatial Patterns (CSP) [6] is an effective method for the feature extraction in motor imagery BCI systems. An extended form of this is proposed by Amirhossein S. Aghaei, Mohammed Shahin Mahanta and Konstantinos N. Plataniotis, which is the Separable Common Spatio-Spectral Patterns (SCSSP). CSP analyses the data in spatial domain and the spatial features are extracted for further processing. It does not consider the spectral characteristics of the data. Unlike CSP, SCSSP takes into account both spatial and spectral characteristics of the EEG data. This method jointly processes the EEG in both spatial and spectral domains and this is achieved by using a heteroscedastic multi-variate Gaussian model for the EEG rhythms. The work focuses on binary classification problem but it can be extended to multiclass scenario.

Most of the BCI systems developed are subject specific systems. The system will be trained for a specific user and take inputs from that specific user only. When a new user needs to access such a system, it needs to be trained again for the new user. A multiuser EEG classification method for BCI is being proposed by Sylvia Bhattacharya, Rami J. Haddad and Mohammad Ahad. The method uses a network of artificial neural networks [7] for the classification of different imaginary motions. Raw EEG potentials and pre-computed Power Spectral Density are used to train the neural network system using scaled conjugate gradient backpropagation algorithm. A majority vote is used to optimally classify the tasks imagined by multiple subjects. For multiuser classification, the channels are ranked based on their individual classification accuracy and then optimized by elimination method.

III. PROPOSED SYSTEM

The proposed system mainly consists of five stages. In the data acquisition stage, the EEG signals corresponding to the motor imagery movements are acquired based on the 10-20 electrode placement system. In order to extract the mu and beta rhythms in the EEG signal, wavelet decomposition technique is being employed in the pre-processing stage. The feature extraction stage uses the Bayesian Network [8] approach where the probability of each channel is calculated for different movements and the most probable channels for each task is being selected. The classification stage includes the Artificial Neural Network classifier which could categorize the signals for multiple users.

A. DATA ACQUISITION

The dataset used in the evaluation of the proposed system is the EEG motor imagery dataset from the Physionet dataset record. BCI2000 instrumentation system was used in making these records. The dataset contains over 1500 one and two-minute recordings obtained from 109 subjects. Each subject undergoes 14 trials where, the right fist movement, left fist movement, both fist movement, both feet movement and the rest state are the tasks performed by the subjects. The EEG signals were recorded from 64 electrodes as per the international 10-20 system, excluding electrodes Nz, F9, F10, FT9, FT10, A1, A2, TP9, TP10, P9, and P10. Each signal is sampled at a rate of 160 samples per second.

B. WAVELET DECOMPOSITION TECHNIQUE FOR PRE-PROCESSING

Wavelet Transform method is advantageous over the Fourier Transform and the STFT methods. It provides localization in both time and frequency domains and the basis function can be chosen according to the application. It also allows choosing variable window size with the varying signal frequency. The Discrete Wavelet Transform uses two filters, a low pass filter and a high pass filter which decomposes the signal into different scales. The output of LPF is the approximation coefficient and that of the HPF is the detailed coefficient. The approximation signal is again decomposed to many levels of lower resolution components. The forward DWT of signal *f(t)* for *j*-th scale and *k*-th shift is mathematically represented by

$$a_{jk} = \sum_t f(t)\psi^*_{jk}(t)$$

where,

$$\psi_{jk}(t) = 2^{j/2}\psi\left(2^j t - k\right)$$

is the window function.

The acquired EEG signal is composed of beta, alpha, theta, delta and gamma rhythms. Among these the beta and mu (alpha rhythm recorded in the motor area) rhythms are the sensorimotor rhythms. To extract these two rhythms multiresolution wavelet decomposition is employed. A four level decomposition using the daubechies-8 wavelet is done on 0-128 Hz range EEG signal, so that the detailed coefficients of the third and fourth level forms the mu and beta rhythms with frequencies 16-32Hz and 8-16Hz respectively.

C. FEATURE EXTRACTION USING BAYESIAN NETWORK

Bayesian Network (BN) is a probabilistic graphical model structure known as the directed acyclic graph (DAG). It consists of the node set and the directed edge set. The nodes represent the random variables and the edges represent the direct dependence between these random variables. If Xi and Xj are the random variables, then an edge from node Xi to node Xj represents a statistical dependence between the corresponding variables. The node Xi is then referred to as the parent of Xj and node Xj is the child of Xi. For example, let X = (x1, x2,...,xn) be a collection of random variables. A BN over X is specified by a pair (G;P). The set G is given by, G = (V;E) where, V = (v1,v2,...) is the node set and E = (e1,e2,...) is the edge set. An arc from vi to vj, i.e., (vi, vj) = ek ∈ E, is the edge set. P is the conditional probability of dependence between the nodes.

Figure.2 shows a simple Bayesian Network, where the nodes are A, B and C, and the arrows shows the dependence between them.

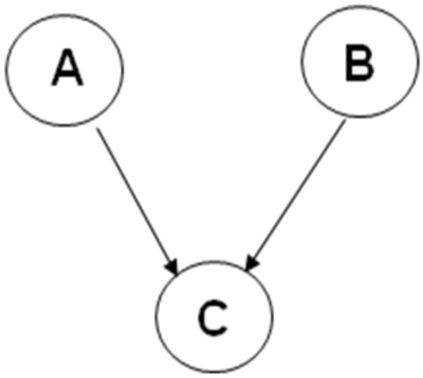

Figure.2: A simple Bayesian Network

The joint probability of the variables A, B and C is given by,

P(A,B,C) = P(C/A,B).P(A).P(B)

The directed edges show the direct dependence between the variables and the absence of an edge shows the conditional independence. Here, A and B are (marginally) independent but become dependent once C is known.

In the proposed work, each EEG channel is considered as the node of a Bayesian Network. During the imagination of a movement there will be correlation between several EEG channels. For a particular movement, certain channels may be dependent and some others will be independent. These dependence and independence are modelled as the nodes and edges of the Bayesian Network. Using this network, the maximum probable channels for each movement is estimated and the beta and mu rhythms from the wavelet decomposition stage are selected for these maximum probable channels. The entropy of the related channels is calculated and this gives the channel probability. Thus the feature vector includes the beta and mu rhythm values along with the probability [9] of related channels. This feature vector is the input to the classifier stage.

D. FEATURE CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK

Neural Network is an assembly of artificial neurons which derives its function similar to that of a biological neuron in the human nervous system. It consists of the input, hidden and output layers and an activation function which functions based on a threshold value. The backpropagation algorithm calculates the error between the initial and final values and the weights of the network are updated so that this error is minimized. The feature vector obtained from the Bayesian Network is fed into the ANN for classification. The channels are ranked based on their accuracy and this enables to classify the tasks for multiple users. The network identifies the movement performed by the subject with increased accuracy.

IV. RESULTS

The system uses the EEG recordings from the Physionet database which includes data from 109 subjects.

Each subject performs 14 trials. The annotation T0 indicates the rest state, T11 indicates the left fist movement, T12 indicates the movement of both fists, T21 indicates the right fist movement and T22 indicates the movement of both feet. Each signal is of duration 10 seconds. The movement occurs in the sample period 656 to 1312. The feature vector includes the beta and mu rhythm values along with the channel probability of each channel for each task. The Bayesian Network calculates the probability of related channels and selects the mu and beta rhythm values for the maximum probable channels. For motor imagery tasks, only certain channels get affected. Hence by selecting these channels for processing, the system becomes more efficient. Figure.3 shows the channel probability of the 64 channels during the movement of the right fist and figure.4 shows the channel probability during the movement of the left fist.

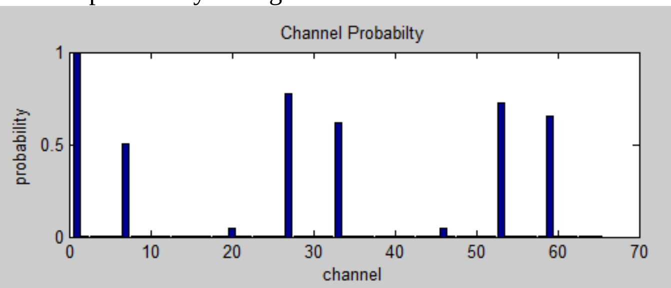

Figure.3: EEG channel probability during the right fist movement

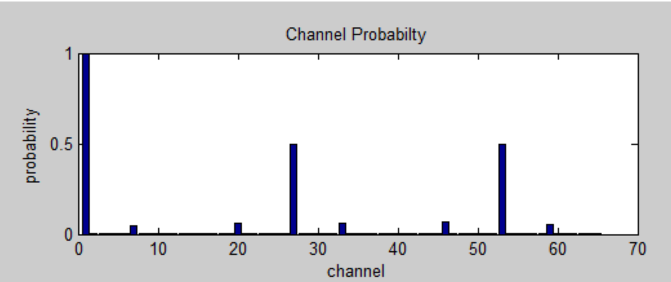

Figure.4: EEG channel probability during the left fist movement

24 channels were found to have maximum probability in motor imagery tasks. Channel probabilities were different for the right fist movement, left fist movement, both fist movement, both feet movement and the rest state. For each task, particular channels have higher probability. These channels were selected for the classification of the features. The Artificial Neural Network classifier ranks these channels and identifies the task performed by the subject, where an accuracy of 81% is obtained.

V. CONCLUSION

There has been a rapid growth in the development of Brain Computer Interface for biomedical and many other applications. Different feature extraction and feature translation algorithms are being developed for increasing the accuracy of BCI systems. The proposed work classifies five tasks performed by multiple subjects. Along with the mu and beta rhythm features obtained by wavelet decomposition technique, it also considers the probability of related channels. This is done by using the Bayesian Network approach. Since the correlation between different brain regions during a motor imagery task is also considered, the system shows high performance. The Artificial Neural Network classifier translates the features for multiple users by considering the maximum probable channels. The future works focus on increasing the accuracy by using more efficient combinations of signal processing algorithms.

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