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Selection of Optimum Features for Neural Network using Genetic Algorithm in Classification of Brain Computer Interface Data

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Abstract: This paper aims to classify three mental task which includes left hand movement imagination, right hand movement imagination and word generation. The classification of three or more tasks is a crucial process. It depends upon how the features are extracted and classified. Various methods are available for extracting features from raw electroencephalographic(EEG) data, but the utilization of irrelevant or superfluous features affects the performance of the classifier. Thus extracting and selecting features is a very crucial step for proper classification. This study demonstrates GA as a feature selection method. Here EEG data from BCI III dataset V is used in which features are extracted by using PSD. Then features are selected by using Genetic Algorithm and finally they are fed to the classifier for classification. For classification Neural Network (NN) is used.

Keywords: EEG, Genetic Algorithm ,Mental task, Neural Network, PSD .

I. INTRODUCTION

A brain-computer interface is an interface system which allows users to control devices without using the normal output pathways of peripherals, instead, by using neural activity generated by the brain [1] . It offers an alternative to natural communication and control. BCI directly measures brain activity associated with the user's intent and translates the recorded brain activity into corresponding control signals for BCI applications. Since the measured activity originates directly from the brain and not from the peripheral systems or muscles, the system is called a Brain–Computer Interface[1].A BCI may also be known as a Mind-Machine Interface [2].BCI technology can be extremely useful in assisting, augmenting or repairing human cognitive or sensory-motor functions.

An electroencephalogram (EEG) is the basic building block for Brain-Computer Interfaces. EEG is used to measure the brain signals pertaining to various activities like imagining hand movements, leg movement etc. The EEG recognition procedure mainly involves feature extraction from EEG and classification of mental task. The useful EEG signals contain huge data of brain signals. Numerous methods have been used to extract feature vectors from the EEG. In this paper features are extracted by PSD using Welch Periodogram Method.

The extracted features contains a feature vector of large dimension. The study is to reduce the dimension of feature vector at the cost of improving the accuracy of the classifier. For this purpose a good feature selection technique is required. Genetic Algorithm is one such technique which helps to select the task relevant features .These selected features are then classified by using Neural Network which uses back propagation algorithm.

II. PROPOSED WORK

This study includes:

1. Obtaining EEG data from BCI data base.
2. Extracting features using PSD technique.
3. Selecting the most important features using genetic Algorithm.
4. Classifying the given mental task by using neural network back propagation algorithm.

The block diagram of the proposed method is shown in Fig.1.

III.METHODOLOGY

In this study, EEG is used as the basic data for classification. This data is obtained from the datset provided by IDIAP Research Institute(Silvia Chiappa,Jose del R.Millan) in the Data Competition III[5].

A. *Dataset*

The dataset contains data from three normal subjects .The subject were told to sit with the relaxed arms on a chair. For each subject four sessions were conducted on the same day. Each session was 4 min long with 5-10 min break in between each session. The subject performed a given task for 15 mins and then switch to another task as instructed by the operator. Three mental tasks were considered [5].

1. Left-hand movement Imagination (left).

2. Right-hand movement Imagination (right).

3. Word generation beginning with the same random letter (word).

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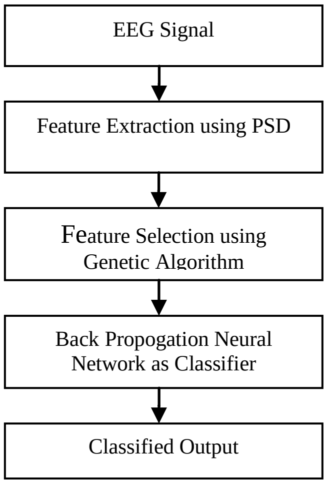

Fig 1: Block Diagram of the Proposed Method

Fig.2 shows the placements of electrodes used in this study.

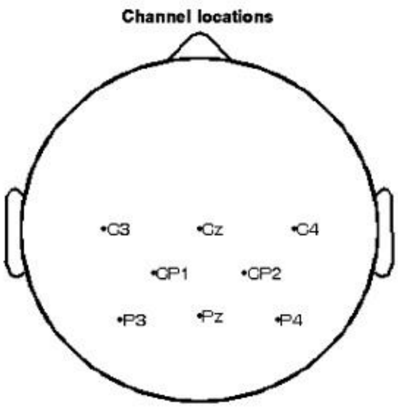

Fig 2: Placement of Electrodes

In this case the EEG signals were recorded with a Biosemi system using a cap having 32 integrated electrodes. These electrodes are located according to the standard positions of the International 10–20 system. The sampling rate was 512 Hz. EEG data was not split into trials. The dataset contained pre-computed features. The raw EEG data was firstly spatially filtered by surface Laplacian. [3]. The PSD was estimated after every 62.5ms (i.e., 16 times per second) in the 8–30 Hz band .Frequency resolution of 2 Hz is used for the eight centro-parietal channels. The channels used are C3, Cz, C4, CP1, CP2, P3, Pz, and P4. The PSD was estimated by Welch periodogram method [4]. Finally an EEG sample data of dimension 96 is obtained[5].

B. Feature Extraction

Various methods are available for extracting features from the raw EEG signal such as time domain, frequency domain, and time-frequency domain. In this work we used PSD for feature extraction.

Welch allows the data segments to overlap and window the data segments prior to computing periodogram. Here the 256 point sequence is subdivided into 8 overlapping segments with 50% overlap; each segment is windowed by hamming window. Then PSD is calculated in the frequency band of 8 Hz to 30 Hz. Thus 12 PSD components were calculated for each channel. Therefore for 8 channels 96 PSD components was obtained.

C. Feature Selection

Feature selection is one of the major tasks in classification problems. The main purpose of feature selection is to choose a subset of features that improves the performance of the classifier specially in case of high dimensional data. Reducing the dimension of the feature space not only reduces the computational complexity, but also increases estimated performance of the classifiers. In the past various algorithms have been used for feature selection. Among them GA is one of the best methods that can be used for feature selection. The GA is a powerful tool for selecting features, particularly when the dimensions of the original feature set are large .

Genetic Algorithms are adaptive heuristic search algorithm premised on the evolutionary ideas of natural selection and genetic .In the past decades it had been widely used in various fields as an optimization technique. In this study it is used an optimization tool to optimize the features. The feature vector contains 96 features. In each generation GA randomly generates 10 features out of these 96 features. These features are generated in binary. Each of them are 8 bit long. They are then converted into decimal number. Each of them are then given to neural network for training and mean square error(mse) is calculated for each of them. The mse is used as a fitness function for next generation. The chromosome with least mse is selected as parent. These chromosomes then undergo crossover and mutation to create next generation. This process is repeated for 20 generations. After 20 generations features with least mse is obtained. That means best features are obtained at the end of 20 iterations.

D. Classification

In this study three mental tasks are considered.GA selects the important and discriminative features. These features are then fed to the classifier. For classification three layer feed forward neural network is used as shown in Fig 3[11].

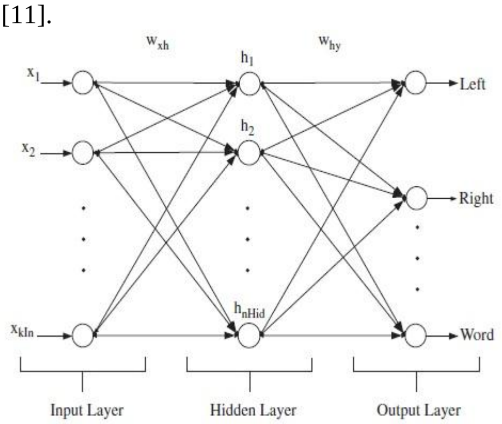

Fig 3:Three-layer feed-forward neural network

In the above figure Kln and nHid represent the number of input nodes and hidden nodes respectively.

In this study .NN consists of two hidden layers and one output layer .The features selected by GA are applied to the input layer. These inputs are then distributed to each unit in the hidden layer. logsig, tansig and purelin activation functions are used in the hidden layers and output layer respectively. The learning rate is set to be 0.1.In one iteration the NN runs 10 times as the number of chromosomes are 10. This process is repeated for 10 iterations. After training the NN is tested on the test data as provided in the dataset.

IV. CONCLUSION

The present study uses EEG from BCI III dataset V and analyses GA for selecting the most relevant features.GA generates different number of features randomly. In each iteration 10 features are generated randomly. These features are then fed to the classifier. For each feature classifier is trained for 1000 epochs. The classifier produces mse which is used a fitness function for GA. This process is repeated for 10 iterations. In each iteration the best chromosome is selected as parent. After training the NN, the network is tested on test data sample as provided in the dataset.

V. FUTURE WORK

The computational time of NN is large. Experiments will be done to reduce the computational time of NN and improve the accuracy of the classifier. Also the experiment is performed on the standard BCI database. In future the experiment can be performed on EEG data recorded using experimental setup.

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