A Statistical Approach for Feature Extraction in Brain Computer Interface

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Abstract: Brain computer interface also known as the Brain Machine interface (BMI) is direct communication between brain and computer devices without the any muscle reaction.BCI researchaimsto provide communication ability to the people who are totally paralyzed or suffer neurological neuromuscular disorders like amyotrophic lateral sclerosis, brain stem stroke or spinal cord injury. The efficient classification of motor imagery movements for disabled people can lead toexact design of Brain Computer Interface (BCI). In this paper data are taken from the UCI data repository BCI competition III dataset 1. Statistical featuredescriptors such as mean, maximum, minimum and standard deviation from each channel in every trial are extracted to reduce the dimensionality. Finally multilayer perceptron and J48 classification algorithms are applied to compare the efficiency of the proposed model.

Keywords: Brain Computer Interface, Multi Layer Perceptron, J48, Statistical Features.

I. Introduction

Brain-computer interface (**BCI**) is relationship between a brain and a computer device which enables signals from the brain to direct some peripheral activity. The interface which means a direct communications pathway between the brain and the object to be controlled. Researches aim to provide a communication capable to the lock-in neurological neuromuscular disorders. Different disorders can disturb the neuromuscular channels. Disorders are Amyotrophic lateral sclerosis (ALS), brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis, and numerous other diseases harm the neural pathways that control muscles or spoil the muscles themselves. They affect nearly two million people in the United States alone, and far more around the world. Most of the people lose all voluntary muscle control, including the eye movements and completely locked in their full body unable to communicate with others in any way [1]. In BCI System, there are five important factors. Signal acquisition records the signals from the scalp non-invasive and invasive. Non-invasive make a use of Electroencephalography (EEG), Magneto Encephalography (MEG) and function Magnetic Resonance Imaging (fMRI).Second feature extraction, used to extract the feature vector. Third feature translator classified the component to logical controls. Fourth control interface converts logical controls to semantic controls. Device controller used to changes semantic controls to physical device commands, different from one device to another based on application. Finally, commands are executed by device [2].



Figure: 1 Brain Computer Interface System

To measure the electrical activity of the brain is using Electroencephalography (EEG) signal. .EEG signals are recorded using the electrodes. It provides very poor quality of signals as the signals cross the scalp skull and other layer of the brain which means EEG signals are week and poor.EEG recording system is consists of amplifiers, electrodes, A/D convertor and devices. Amplifiers process the analog signals, the electrodes get

International Conference on Computing Intelligence and Data Science (ICCIDS 2018) 90 |Page Department of Computer Studies Sankara College of Science and Commerce Saravanampatty, Coimbatore

signals from the Scalp and A/D converter can digitalize the signals in a most accurate form. EEG signals are classified according to their frequency with rhythms [3].

Table 1: EEG Rhythms with frequency				
Rhythms	Frequency (Hz)			
Delta	0.1 -4			
Theta	4 - 7.5			
Alpha	8 - 12			
Beta	12 - 30			
Gamma	30 - 100			
Mu	Around 10			

This paper is organized as follows: Section 2 gives out the related works Section 3 explains the methodology, Section 4 elucidates the results and discussions and Section 5 concludes this paper with scope for further research.

II. Related Works

Aswinseshadri K. et.al [4] proposed Genetic Algorithm Based Feature Selection for the Classification of Electrocardiogram Features in Brain Computer Interface. In this work ECoG indications are pre-managed and attributes are mined over practice of Wavelet Packet Trees as well as Common Spatial Patterns. Selecting the feature is carried out by Genome Process and signals are classified by using the Naïve baye classification.

SaadatNasehi et.al [5] proposed a novel effective feature selection based on Statistical-Principal Component Analysis (S-PCA) and Wavelet Transform (WT) features in medical and BCI application. In this method signals are decomposed to six sub bands by four mother wavelets (sym6, db5, bior 1.5 and robi02.8). Then five features (such as the number of zero coefficients, the smallest and largest coefficients, the mean and standard deviation of coefficients) are extracted from each sub-band as feature vector. In this algorithm, S-PCA is used to select ten effective features among WT features. Finally, KNN classifier and seven different signals of brain activities are used to evaluate the proposed method. The results show that improvement of the classification performance provided good result compared to current method.

Pharino Chum et.al [6] proposed the basic power of density of EEG signal used to extract the optimal features. The EEG signals from the electrodes are filtered using spatial and temporal filters to enhance the signal to noise ratio. Short-time Fourier transform extracted the time frequency feature and average power in sub-Window band. Optimal feature extraction was used for BCI Competition III data set and extracted feature are applied for support vector machine. The genetic algorithm was used for optimal features and classification accuracy is 80%.

Aparna Chaparala et.al [7] proposed the BCI system which extract features using Discrete Cosine transforms and two stage of filtering are used, first stage is butter worth filter and moving average 15 point Spencer filter in second stage. Removed random noise by using the filters and at the similar maintaining a sharp step response. The signals are classified by using the proposed Semi Partial Recurrent Neural Network. The proposed method has very good classification accuracy result compared to conventional neural network classifiers.

Robert Jenke et.al [8] proposed a statistically-motivated electrode/feature selection method, based on Cohen's effect size f^2 and compared inter and intra individual selection on a Self-recorded database. Features are extracted using mean, min, max and var from the frequency domain. Feature selection is done using Cohen's effect size f^2 which is a generalization to more than two classes. Classification is done through the navie baye classification.

Akilandeswari et.al [9][10] used Walsh Hardmard Transform for feature extraction and Bagging techniques for classification. In year 2014, they have implemented Particle swarm optimization for feature selection. The classification accuracy of 95.83% is attained by them. In 2015, a new Binary Particle Swarm Optimization (BPSO) is used for feature selection algorithm. Multi-layer Perceptron Neural Network (MLPNN) is used as a classifier with back propagation training algorithm and Levenberg-Marquardt training algorithm classify selected features. In 2017, weight optimization is done using Hybrid Particle Swarm Optimization (PSO) for Multilayer Perceptron Neural Network classifier which selected features by using Principal Component Analysis and Hybrid PSO.

Dragi Kimovski et.al [11] implemented two different parallel evolutionary models, the parallel computation of the cost functions for the individuals and the parallel execution of evolutionary multi-objective procedures on subpopulations. The experiments accomplished on different benchmarks, including some related with feature selection in classification of EEG (Electroencephalogram) signals for BCI (Brain Computer Interface) applications, prove that decreases the running and improved solution in parallel processing.

International Conference on Computing Intelligence and Data Science (ICCIDS 2018)91 |PageDepartment of Computer Studies Sankara College of Science and Commerce Saravanampatty, Coimbatore

Farid Ali Mousa [12] used high pass filter to remove artifacts, discrete wavelet transform algorithms for feature extraction and statistical features. Principal component analysis is used to reduce the size of feature vector. He developed an integrated model to classify the brain signal.

Juan Tian et.al [13] worked on the feature extraction and pattern recognition of left and right motor imagery EEG signals. In BCI competition III data set, first pre processing the EEG signals and extract the feature from the channels by using the wavelet then pattern recognition is carried out in the radial basis function neural network and resulted in good accuracy.

Shubhangi Gupta et.al [14] carried out preprocessing, feature extraction and classification of EEG signals of Brain Computer Interface. Different mental activities are recorded and filtered out for noise reduction in the first step. Second the useful features are calculated from the EEG signals Feature vectors. Finally classified the feature vector by using the SVM classification.

III. Methodology

In signal processing there is a need for dimensionality reduction of feature representation from the continuous form. Features are extracted using simple statistical approaches namely mean, maximum, minimum and standard deviation. Four features are extracted from the original BCI data. Then the classification carried out using WEKA tool. The subsequent sections detail each procedure in detail.



BCI Dataset

For an experimental analysis BCI Competition III, Data Set - I is taken. In which subjects performs imagined movement of left small finger and tongue. Train and test data were recorded for subject with same task. All recording are with the sample rate of 1000Hz. Every trail consists of imaginary tongue or finger movements recorded in 30 seconds in the interval of 0.5 seconds. For training 278 trails with 64 channel information each with 3000 samples. Each trail in the training data has an associated label. Test data has 100 trails without label.

Feature Extraction

In real-world, many features are used as an attempt to ensure accurate classification. Used all those feature to the classification. Then they operate in high dimensions, and the learning method becomes difficult, which leads to high classification failure rate. So, there is a need to reduce the dimensionality of the feature before classification. The main objective of dimensionality reduction is to convert the high dimensional data samples into the low dimensional feature. If the dimensionality gets reduced, it will be more helpful to improve the accuracy of the classifier and it reduces the computational complexity. Dimensionality reduction derived into feature selection and feature extraction [15].

Feature extraction is used to minimize the noise and reduced high dimensionality into lower one. High complex of the data attributes into smaller numbers of attribute. Feature extraction techniques are principal component analysis, independent component analysis and linear discriminant analysis. Instead of using these feature extraction simple statistical approach such that mean, maximum, minimum, standard deviations were used for the purpose of reducing the dimension. In BCI competition III dataset 1 the data format is 278 trails and 3000 samples for every trail from 64 channels, so the data is high dimension in nature. To reduce the dimension the mean values for samples in every trail is taken. Hence we calculated the mean value for 3000 samples in 64 channels. It reduces the dimension to 278×64 . Similarly minimum, maximum and standard deviation are calculated.

Classification

Classification is a supervised learning method which learns from the data input given to it and then uses this learning to build new classify data. The data may be bi-class or multi class. Supervised learning is where you have input variables (A) and an output variable (B) and use an algorithm to learn the map function from the input to the output $\mathbf{B} = \mathbf{f}(\mathbf{A})$. The goal is to approximate the map function so well that when you have new input data (A) that you can predict the output data (B) for that original data.

Multilayer Preceptron

Multilayer Preceptron is one x input layer one or more k hidden layer d output layer. Every layer in neuron are inter connected network and simply called neurons. Each neuron in a layer is connected to the neuron in the consequent layer and so on. The weights are interconnected between the layers. It mimics the human biological neuron. Multilayer perceptron is used for the supervised learning and back propagation algorithm. Back propagation is systematic method for training multilayer. It extends the gradient descent based delta learning rule and minimizes the total squared error. Multilayer perceptron uses for logistic sigmoid function.

J48 decision tree

J48 is a decision tree algorithm used for handling missing values, decision pruning tree, continuous attributes value ranges, derivation of rules, etc. It builds the decision tree based on the information gain measures. Spilt the table until all the instances are in the same class. J48 is optimized version of the c4.5 algorithm. This algorithm generates the rules from which particular identity of that data is generated. The objective is increasing generalization of a decision tree until it gains equilibrium of flexibility and accuracy.

IV. Result and discussion

The experiment is conducted using Dataset1 from BCI competition III. For feature extraction is implemented in MATLAB and WEKA tool is used for Classification. Features are extracted using the statistical methods such as mean, minimum, maximum and standard deviation. Then extracted features are classified using the Multilayer Perceptron and J48. Among the four features Mean and Standard deviation produces the better result. Further analysis is done by combining means and standard deviation to give out 128 features for all the trials. Classification is done using 10 folds cross validation. Mean and standard deviation gives high accuracy rate as 96% for Multilayer Preceptron and J48 94% respectively. Figure 3 show the result obtained using J48.Table 2 and Table 3 reports the classification accuracy for different features using different classifiers. Diagrammatic representation of same the result is in the Figure 4 and 5.

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Figure	3:	Classifier	output
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Features	MLP	J48			
Mean	88	82			
Maximum	80	78			
Minimum	87	81.65			
Standard deviation	87	81			

Table 2: Comparison of Classification Accuracy.



Table 3: Comparison of Classification Accuracy with Combined





Figure 5: Classification Accuracy for Combined Features.

V. Conclusion

As computerized system are becoming one of the main tool in the Brain computer Interface. A BCI system should categorize between various brain signal patterns accurately to enable a user to perform various mental tasks. BCI competition data set 1 is with two imaginary movements is tongue and small middle finger. Experiments were carried out through 10 fold cross validation and with classifiers MLP and J48 and the highest accuracy (96%) is achieved when considering mean and standard deviation of data from all 64 channels. More statistical features can also be experimented with good feature selection and better classifiers.

International Conference on Computing Intelligence and Data Science (ICCIDS 2018) 94 |Page Department of Computer Studies Sankara College of Science and Commerce Saravanampatty, Coimbatore

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