Performance Analysis of SVM, k-NN and BPNN Classifiers for Motor Imagery

Indu Dokare[#1], Naveeta Kant[*2]

[#1]Assistant Professor, [*2]Associate Professor

[#1, *2]Department of Electronics & Telecommunication Engineering,

VES Institute of Technology, University of Mumbai, India.

***Abstract*— This paper presents the results obtained by the experiments carried out in the project which aims to classify EEG signal for motor imagery into right hand movement and left hand movement in Brain Computer Interface (BCI) applications. In this project the feature extraction of the EEG signal has been carried out using Discrete Wavelet Transform (DWT). The wavelet coefficients as features has been classified using Support Vector Machine (SVM), k-Nearest Neighbor (k-NN) and Backpropagation Neural Network (BPNN). The maximum classification accuracy obtained using SVM is 78.57%, using k-NN is 72% and using BPNN is 80%.**

***Keywords*— Brain Computer Interface (BCI), Motor Imagery, Electroencephalography (EEG), k-nearest Neighbor (k-NN), Support Vector Machine (SVM), Backpropagation Neural Network (BPNN).**

I. INTRODUCTION

Diseases like Amyotrophic Lateral Sclerosis (ALS), brainstem stroke, brain, spinal cord injury and other such diseases make people locked in their body. Such people are not able to communicate with the external world due to loss of their voluntary muscle controls and has to completely dependent on the caretakers. To improve the life of such people for certain extent need to have a device which translates the brain signal proportional to user's intent into device commands. Such device is called as Brain Computer Interface (BCI). A BCI is defined as a system that measures and analyzes brain signals and converts them in real-time into outputs that do not depend on the normal output pathways of peripheral nerves and muscles [1], [2].

Electroencephalography (EEG) is a method used in measuring the electrical activity of the brain. The EEG signal can be picked up with electrodes either from scalp or directly from the cerebral cortex [4].

Sensorimotor rhythms are recorded from somatosensory and motor areas of the cortex. The preparation of movement or imagination of movement changes the sensorimotor rhythms (SMR) which comprises mu and beta rhythms. The frequency band most important for the motor imagery are mu and beta (12-30 Hz) activity [14]. Mu activity is the alpha rhythm(8-12 Hz) recorded from the somatosensory and motor areas[1]. Event-related desynchronization (ERD)/ Event-related synchronization (ERS) patterns can be produced by motor imagery. The imagery right hand and left hand movement activity is most prominent over electrode C3 and C4 of EEG signal.

In this project the EEG signal of electrodes C3 and C4 have been classified into imagined left and right hand movement. The feature extraction of this signal has been done using discrete wavelet transform. The wavelet coefficients were used as features for classification. These features were fed to support vector machine, k-nearest neighbor and backpropagation neural network classifiers.

II. METHODOLOGY

A. Discrete Wavelet Transform

The EEG signal is decomposed into a coarse approximation and detail information performing multiresolution analysis.The decomposition of the signal into different frequency bands is obtained by successive high-pass and low-pass filtering of the time domain signal [8]. These decomposed bands are called as sub bands. The low-pass filter output gives the approximation coefficients, while the high pass filter output gives the detail coefficients.

In this project the C3 and C4 electrode signals were decomposed upto level 4. After decomposition each level detail coefficients Cd_1, Cd_2, Cd_3, Cd_4 and 4th level approximation coefficients Ca_4 were obtained. The detail coefficients Cd_2 and Cd_3 were considered for classification, since these coefficients lies in the mu and beta band. The statistical parameters of these coefficients like maximum of wavelet coefficients of each sub band, minimum of wavelet coefficients of each sub band, mean of wavelet coefficients of each sub band and standard deviation of wavelet coefficients of each band were also considered as features. The Daubechies 2 (db2) wavelet function were used for this implementation.

B. Support Vector Machine

Support Vector Machines are supervised learning machines based on statistical learning theory which can be used for pattern recognition and regression [7]. In this implementation support vector machine with radial basis function kernel has been used as one of the classifier. The classifier was trained using training data and the C and γ parameters of SVM were set using 5 fold cross validation process. The C and γ parameter of the case which gives best cross validation accuracy were selected. Then, the testing data was applied to the classifier and classification accuracy was determined as a performance measure parameter of the classifier.

C. k-Nearest Neighbor (k-NN)

k-nearest neighbor, the simplest machine learning algorithms for classification has been used as the second classifier in this implementation. Different feature set fed to the k-NN and the classification accuracy has been determined. The number of neighbors (k) for each feature set were varied and the classification accuracy has been estimated.

D. Backpropagation Neural Network (BPNN)

The number of types of ANNs and their uses is very high. An ANN which learns using the back propagation algorithm for learning the appropriate weights, is one of the most common models used in NNs, and many others are based on it. The backpropagation algorithm is used in layered feed-forward ANNs. This means that the artificial neurons are organized in layers, and send their signals "forward", and then the errors are propagated backwards. The backpropagation algorithm uses supervised learning, which means that if the inputs to the algorithm and outputs of the network are provided and then the error (difference between actual and expected results) is calculated. The idea of the backpropagation algorithm is to reduce this error, until the ANN learns the training data. The activation function of the artificial neurons in ANNs implementing the backpropagation algorithm is a weighted sum (the sum of the inputs multiplied by their respective weights). The most commonly used activation function is sigmoidal function, since this allows a smooth transition between the low and high output of the neuron. The goal of the training process is to obtain a desired output when certain inputs are given. Since the error is the difference between the actual and the desired output, the error depends on the weights, and there is a need to adjust the weights in order to minimize the error. The backpropagation algorithm calculates how the error depends on the output, inputs, and weights. Then the weights can be adjusted using the method of gradient descent.

In this implementation, backpropagation neural network with gradient descent algorithm for error correction has been used. The classification accuracy of different feature sets as a features for different number of hidden layer neurons has been estimated. In this case for cross validation 70 % of training samples were used for training and remaining 30% samples of training were used for testing. The cross validation has been implemented for different number of hidden layer neurons. Further, the testing samples were fed to neural network to determine the classification accuracy. The activation functions used in each case were hyperbolic tangent sigmoid transfer function and logarithmic sigmoid transfer function.

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

This section presents the dataset used in this implementation and the results obtained using three classifiers.

A. Dataset

The Data set used in this project has been obtained from BCI Competition II, dataset III provided by Department of Medical Informatics, Institute for Biomedical Engineering, University of Technology Graz [9],[10],[11]. This dataset was recorded from a normal subject. The subject sat in a relaxing chair with armrests. The task was to control a feedback bar by means of imagined left or right hand movements. The order of left and right cues was random. Three bipolar EEG channels were measured over C3, Cz and C4.

The experiment consists of 7 runs with 40 trials each. Each trial is of 9s length. The first 2s was quite, at t=2s an acoustic stimulus indicates the beginning of the trial and a cross "+" was displayed for 1s; then at t=3s, an arrow (left or right) was displayed as cue. At the same time the subject was asked to move a bar into the direction of the cue. The EEG was sampled with 128Hz. The trials for training and testing were randomly selected.

B. Results

The wavelet coefficients and their statistical parameters were used as features for classification. Different feature set formed were fed to the support vector machine, k-nearest neighbor and backpropagation neural network classifiers for classification. In case of SVM the values of C and γ were selected using 5-fold cross validation. The maximum cross validation accuracy obtained was 78%. The maximum testing classification accuracy obtained was 78.57%.

In case of k-NN classifier the classification accuracy was obtained for different values of number of neighbor, k. The maximum classification accuracy estimated here is 72%.

The third classifier used was BPNN. In this case the number of hiddenlayer neurons were varied and also the hyperbolic tangent sigmoid transfer function and logarithmic sigmoid transfer function as activation function has been used.

For analysis different wavelet coefficients has been used and hence total twelve feature set has been formed. Fig.1 shows the plot of classification accuracy for different values of number of neighbors using k-NN classifier. For backpropagation neural network the plot of cross validation

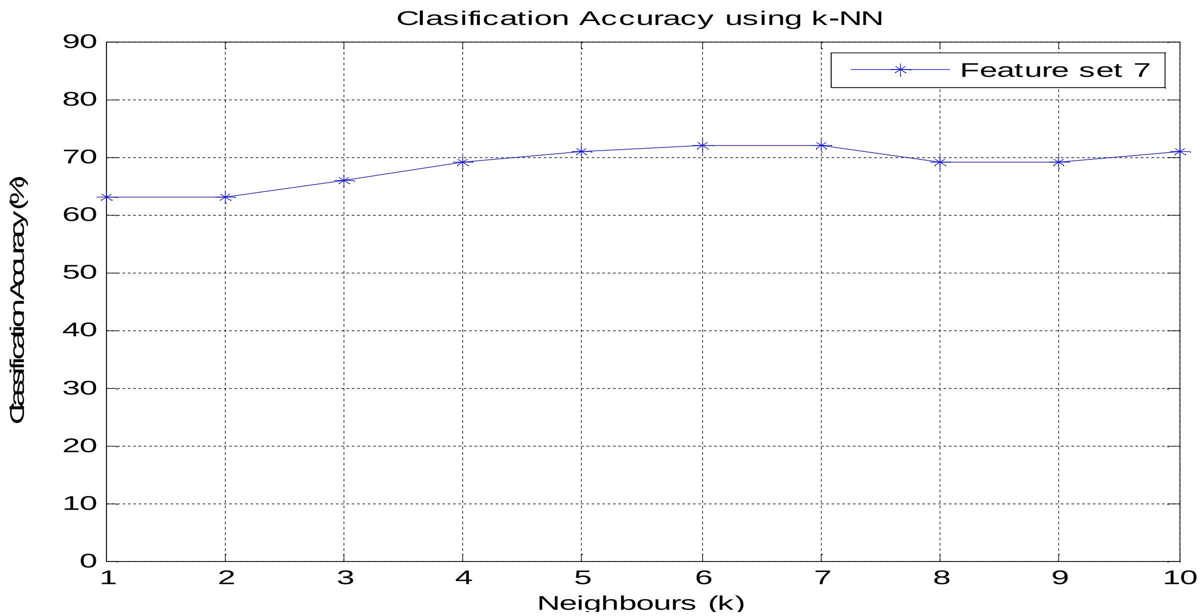

Fig.1 Classification accuracy for feature set 7 using k-NN

TABLE I
COMPARISON OF CLASSIFICATION ACCURACY OF SVM, K-NN AND BPNN

Feature	Description	Classification Accuracy using SVM (%)	Classification Accuracy using k-NN (%)	Classification Accuracy using BPNN (%)
Feature set 1	Wavelet coefficients Cd3 and Cd2	68.57	67	66
Feature set 2	Statistical parameters of Cd3 and Cd2 (mu and beta)	71.4	64	75
Feature set 3	Wavelet coefficients- Cd2 (Beta)	70.7	64	66
Feature set 4	Statistical parameters of wavelet coefficients- Cd2 (beta)	65.7	58	75
Feature set 5	Wavelet coefficients-Cd3(mu)	66.42	71	71
Feature set 6	Statistical parameters of wavelet coefficients- Cd3 (mu)	70	69	75
Feature set 7	Few coefficients from Cd3	78.57	71	74
Feature set 8	Statistical parameters of feature set 7	72.24	69	78
Feature set 9	Few coefficients from Cd2	74.28	67	71
Feature set 10	Statistical parameters of feature set 9	72.14	74	80
Feature set 11	Combining feature set 7 and 9	77.14	71	77
Feature set 12	Statistical parameters of feature set 11	77.14	71	79

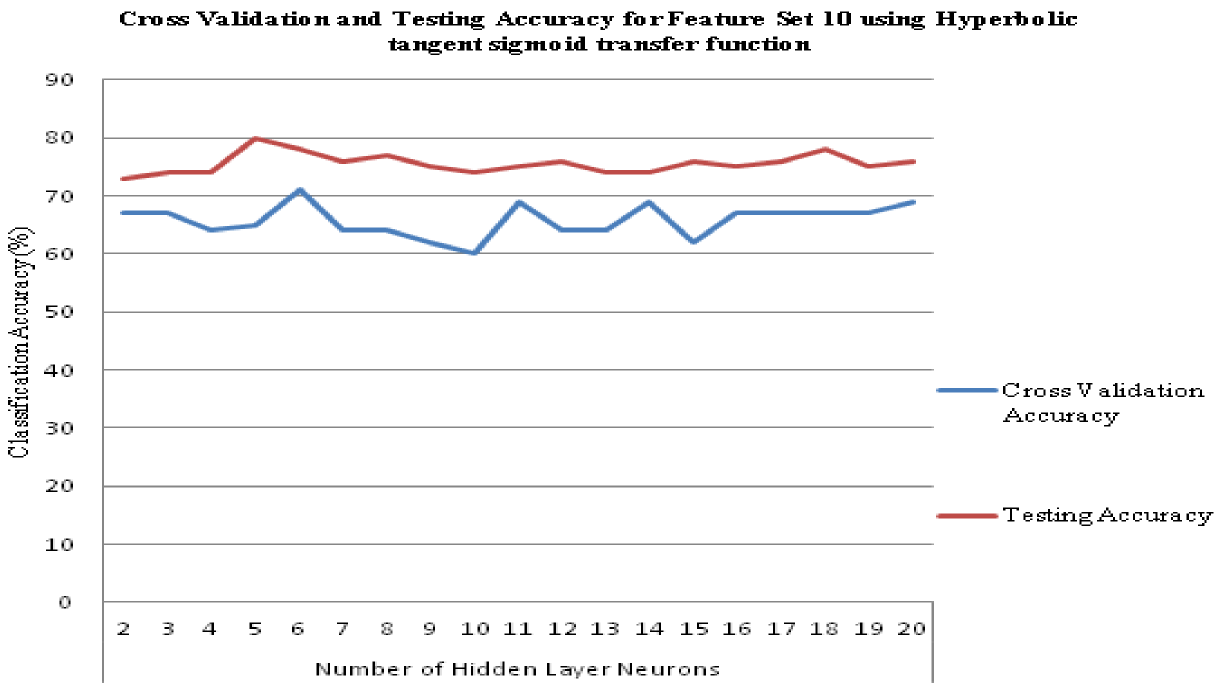

Fig 2. Cross validation and testing accuracy for feature set 10 using hyperbolic tangent sigmoid transfer function

accuracy and testing accuracy for different feature set and hyperbolic tangent sigmoid transfer function and logarithmic sigmoid transfer as activation function has been obtained. The plot of cross validation accuracy and testing accuracy for feature set 10 is shown in fig 2.

The classification accuracy for different feature set using SVM, k-NN and BPNN is summarized in table 1.

IV. CONCLUSION

This project aims to classify the EEG signal into imagined left and right hand movements for BCI applications. Here, feature extraction of the signal were obtained using discrete wavelet transform. Different wavelet coefficients and their statistical parameters were used as the features for the classification. Since, mu and beta rhythms are associated with motor imagery, the wavelet coefficients whose frequency lies in this range were considered for the analysis. These coefficients are Cd2 and Cd3.

Imagined left and right hand movement are seen in only mu rhythms or only beta rhythms, hence the coefficients which lies in these bands were considered. Further, few coefficients from these bands were considered in which the motor imagery activity was seen more prominent.

Different feature sets were fed to the support vector machine for classification. The parameters of the SVM were selected using 5- fold cross validation method. The maximum classification accuracy estimated was 78.57 for feature set 7. Further, the feature set 11 and 12 also gives better classification accuracy.

Same feature sets were fed to the k-nearest neighbor for classification. The maximum classification accuracy was observed with feature set 7 for k=5 as 71%, with feature set 10 for k=1 as 74%, with feature set 11 for k=9 as 71% and feature set 12 for k=3 as 71%. When the classification accuracy using SVM and k-NN is compared it is found that SVM gives better classification accuracy.

Though the k-NN is very simple algorithm to understand and implement, but it is slower when compared with SVM. Unlike SVM, k-NN is lazy algorithm , it means it start learning when it see the testing data while SVM learns before it see the test data k-NN algorithms have fewer computational cost than SVM algorithms during training. In case of k-NN the computation cost is very high as there is a need to find the distances of each testing pattern to all training pattern.

The third classifier used in this analysis was back propagation neural network. Same feature sets were fed to the BPNN. The classification accuracy for the feature sets in which the statistical parameters of the coefficients were determined, was estimated high. The activation function for three layers used were tangent sigmoid transfer function and logarithmic sigmoid transfer function. For some feature sets tangent sigmoid transfer function gives better results and for some feature sets logarithmic sigmoid transfer function gives better results.

The maximum classification accuracy estimated was 78% for feature set 8, 80% for feature set 10, 77% for feature set 11 and 79% for feature set 12. The maximum classification accuracy was investigated using back propagation neural network and support vector machine.

Among these two classifiers, the maximum classification accuracy was obtained using back propagation neural network. This doesn't mean that the backpropagation neural network is the best classifier. Support vector machine also gives the good result in some cases. So it totally depends on the input data to be analyzed.

EEG signal for motor imagery is prominently seen in mu band. The motor imagery activity is also seen in beta band but not seen prominently. For motor imagery, if both mu and beta band coefficients are considered as features, this gives better classification using all classifiers.

The maximum classification accuracy obtained is 78% to 80%. Still there is a scope for improvement in the classification accuracy. To improve the classification accuracy there is need to study more on the wavelet coefficients and find the best features which maximizes the classification accuracy.

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