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EEG CLASSIFICATION USING ADAPTIVE RESONANCE THEORY

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ABSTRACT

In the recent times, increasingly more number of research activities is being conducted about the different methods that humans can communicate with computers. Despite the competence of various users, the normal model of keyboard and mouse may not be suitable to people having disabilities; it may prove a little clumsy as well. One possible way to enable interaction between human beings and computers is by using signals of Electroencephalogram (EEG) that does not demand much regarding physical abilities. When the computer is trained to identify and organize EEG signals, the users can maneuver the machine effectively by just thinking about the actions they want the machine to perform within some defined group of choices. The signals of Electroencephalogram (BCI) are the electrical signals gathered from scalp of humans. They are being used frequently in the interaction between brain and computer. One primary growing research in the field of medical science is diagnosis of brain's abnormalities. Electroencephalogram (EEG) can be used as a tool in measurement of activities of brain that reveal brain's conditions. In our proposed system our aim of this study is to classify the EEG signal for identify the difference brain thought or actions. It is proposed to develop an automated system for the classification of brain thoughts by ART (Adaptive Resonance Theory) and RBF (Radial Basis Function) algorithms. Finally we show the difference between the accuracy of two algorithms for identifying the EEG signal.

Keywords: EEG, linear discriminant analysis, ART (Adaptive Resonance Theory), RBF (Radial Basis Function).

1. INTRODUCTION

BCI is one scheme that connects the activities of the brain pertaining to the user with a computer. It allows manipulating different devices using the assistance of brain's signal along, without having to use any muscular functions [1] [2]. During the recent past, mental assignments have been widely analyzed by a number of researchers with their results showing the usefulness of BCI in the case of individuals who are physically challenged. Those individuals having their entire voluntary actions lost can rely only upon certain cognitive actions for interacting with other people. BCI is found to be very useful for such individuals. [3]. Electroencephalogram (EEG) signals offer information rich with the human brains electrical activities. EEG signal may be summarized from human beings scalp. EEG happens to be the electrical signals recording. BCI is the scheme that connects the activities of a user with a computer. BCI permits manipulating different devices using the brain signal while not involving any muscular functions [1] [2]. In the recent past, a number of researchers have studied about the mental tasks with their results proving the usefulness of BCI for individuals who are physically challenged. Those individuals having their intended actions entirely lost have to depend only on cognitive actions of theirs for communicating with other people. BCI is found to be very useful for such people [3]. Electroencephalogram (EEG) signals offer information rich with electrical activities of the human brain. EEG signal may be gathered from human beings scalp. EEG is registering of the electrical signal generated along the length of the scalp. It is the method of evaluating the electrical variation throughout the scalp. Mental activity [4] is the cause of this variation. EEG signals go through alterations in both frequency and amplitude when varied mental functions are accomplished [5]. EEG-oriented BCI is found to be useful in the categorization of mental functions [6]. In such functions, signal corresponding to varied mental functions are gathered and categorized. EEG has been used for identifying diseases in the brain by several researchers. Their study has been helpful to control electronic devices. An abnormal state which impacts an organism's body is called as a disease. A characteristic group of signs and symptoms denote any deviation away from normal structure relating to an organ or body part. The Electroencephalogram is helpful in detection of diseases in brain. Electrical functions of brain along the human scalp are recorded in the Electroencephalogram. It assesses the fluctuations in voltage resulting out of ionic flows of current within the brains neurons. Diagnostic exercises focus normally on the spectral element of EEG which is the kind of swings that are noticed in the EEGE signals. EEG which is harmless and painless does not involve passing any sort of electricity into the body or brain of humans. EEG signals can be normally divided into five sub-bands of EEG: theta, alpha, beta, delta, and gamma. The alpha waves which are rhythmic have a frequency range between 8 and 13 Hz. The alpha waves amplitude is low. Every area in the brain supposedly has alpha characteristics but it is predominantly registered out of the parietal and occipital regions. In relaxed and awaken stage with closed eyes, it swings from adult. Beta waves whose range of frequency is normally upward of 13Hz are irregular. Beta waves amplitude is normally very low. Mostly it is registered from frontal and temporal lobe. It swings from the time of deep sleep; mental function is related to remembering. Delta waves, whose range of frequency is between 4 and 7 Hz, are rhythmic. The delta wave has high amplitude. It swings from children in the sleeping state, adults in drowsy condition and emotionally distressed occipital lobe. The frequency of these waves is below 3.5 Hz and they are slow. The theta waves amplitude is normally low-medium. It swings from grown-ups and common sleep rhythm. The Gamma waves have the fastest frequency of brainwave and their range of frequency is between 31 and 100, having the least amplitude. In our suggested study, EEG signals normally are fed as input for pre-processing. Noises are removed in the pre-processing procedure and EEG signals get disintegrated as five auxiliary-band signals. Non linear specifications (frequency and time) were derived from each one of six EEGE signals (actual EEG, theta, alpha, beta, delta, and gamma). Just after the derivation procedure, the linear discriminant analysis grader helps in classifying whether the particular EEG signal is abnormal or normal.

2. RELATED WORK

The process of acquiring brain signals can be performed with the aid of different non-invasive approaches such as Close Infra-Red Spectrography (NIRS), Operational Magnetic Sonority Imaging (fMRI), Electro Encephalography (EEG), Electro Encephalography (EEG), and Magneto Encephalography (MEG).

A. EEG

EEG had been registered by Richard Caton on the brain of animals during 1875. Hans Berger first recorded it on the human brain in 1929 [4]. EEG has got high temporal resolve, security, and offers ease in usage. In the process of EEG signal acquiring, a placement of 10-12 standard electrodes is used. EEG which happens to be non-stationary with regard to character has a low spatial resolve. EEG signal is vulnerable to erroneous observations that may be caused due to blinking of eyes, movement of eyes, muscular functions, heartbeat, and power line conclusions [6].

B. fMRI

fMRI technology is generally being used by clinical labs. fMRI uses the hemoglobin level and is called the Blood Oxygen Impregnation Rank Dependent (BOLD). Further cost of set up is needed. It has got high spatial and temporal resolution. There is possibility of occurrence of time delay during the process of data acquisition [7].

C. NIRS

NIRS is a technology with Low temporal resolution; this even might obstruct the rate of transformation. For improving the rate of transformation, NIRS may be connected with EEG forming Hybrid BCI. The NIRS makes use of BOLD as well, for estimating the accuracies of classification. Although it is not expensive, it exhibits very poor performance when compared with EEG-oriented BCI [8].

D. MEG

Magnetic signals generated due to electrical functions are taken over by using MEG technology. This particular method offers wider range of frequency and also exemplary spatiotemporal resolve, but it needs heavy-sized and expensive equipment [9].

Post signal-acquiring stage, the signals have to undergo feature extraction, pre-processing, feature selection and classification. Certain literature study has been found to focus on feature extraction, pre-processing of EEG signals, feature selection and classification strategies. Siuly [7, 1] has introduced a cross interrelationship-oriented LS-SVM [8, 4] [9, 6] to improve the categorization accuracy of the signals of EEG. Sabeti M [10, 2] employs discrete wavelet change to process [8, 4] [11, 9] and the genetic algorithm that may be adopted for selecting the best aspects from the derived features. Two classifiers LDA and SVM [8, 4] are used for classifying abnormalities of the EEG signal. Svenson N J [12, 3] has established an automated ranking method for the particular EEG abnormality pertaining to neonates. Manifold linear discriminant categorizer is being used for classifying abnormality in EEG in the case of neonates having HIE. Marcus [13 5] has promoted time-frequency range of the signals of EEG. In this, SVM are employed for classifying epilepsy out of signals of EEG. Nandish M [14, 7] has introduced EEG signals classification founded on neural network systems. Salih Gunes [8] has described that in Fast Fourier Change for the process involving pre-processing the combined Decision tree and KNN classifiers for classifying signals of EEG. Umut Orhan [11, 9] focused a neural network of multi layer perceptron for the categorization of EEG signal. Parvinnia E [15, 10] has proposed an adaptive strategy called weighted span nearest bystander algorithm that is being used for classifying EEG signal.

3. PROPOSED WORK

The primary objective of the suggested work is analysis of EEG signal toward detecting thoughts of the brain. This scheme involves processes like EEG data set training, dimensionality reduction and classification.

The initial module is dealing with EEG set training. It is normally training the data sets by pairing with expected output. The second module reduce the dimensionality of data for minimize the input variance. Here the dimensionality reduction is achieved by feature selection. The philosophy behind feature selection is that not all the features are useful for learning. Hence it aims to select a subset of most informative or discriminative features from the original feature set. Third module process the input data with trained data for identifying the brain thoughts. Here we use ART and RBF methods for classification the output.

3.1 Training the EEG data

In this system we are using data sets with different brain thoughts. This data set will be trained for identifying the different brain thoughts. Normally, a training set is a collection of data used to identify the possibly predictive relationship. These training sets are used in machine learning, genetic programming and statistics. Basically data sets have correct and expected

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outputs. Once we trained the EEG signal data sets then we assigns it into classes.

3.2 Architecture

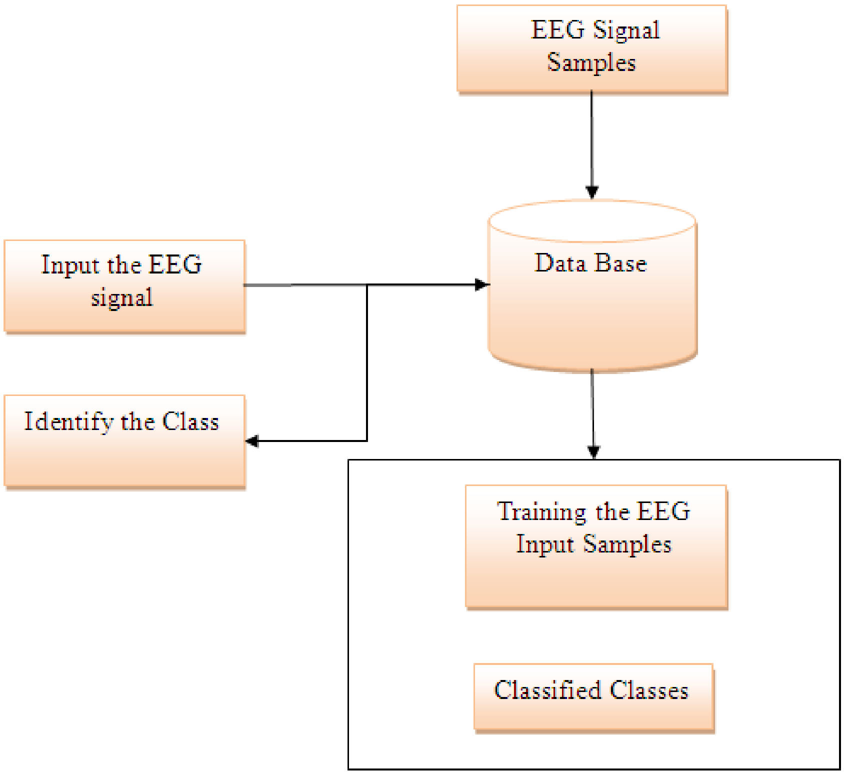

Figure-1. Overall architecture.

3.3 Dimensionality reduction by LDA

Generally speaking about the reduction of dimensionality can be done by subspace learning and feature selection. The concept take the place in feature selection is that not all features are related to learning. Thus it focus to select a most informative subset or discriminative feature from the original set of feature. Selection of feature is the procedure of selecting the relevant aspects done by elimination of features with only a little or with no prognostic information. For finding a feature auxiliary set which generates higher categorization accuracy and adopted for reducing the time of training. GA is the procedure for selecting relevant features. It begins with the individuals' primary population that depicts a probable solution for optimization-related problems. Evolution process is controlled by choice, mutation, and crossover rules. Crossover and mutation operators maintain the population's diversity. GA is efficient at dealing with huge search space. Normally training data sets have more dimensionality, but it is not possible for all words or data relevant for classifying and clustering inputs. For that we use LDA for dimensionality reduction. The Linear Indiscriminant Analysis (LDA) packs objects as mutually exclusive sets depending on their characteristics. Selecting the best possible discriminant operation which distinguishes the sets (or groups) is the objective of this test. The function will be a line, in case the number representing the groups happens to be 2, it is a plane in the case of 3 groups, and above 3 groups, the discriminant operation will be hyper-plane. Making use of these discriminant operations, it becomes possible to reduces the dimensionality of the trained data sets.

3.4 Classification

Classification happens to be one technique of data mining which affixes data in one group of target classes and genres. Classification aims at accurately predicting labels for all the classes in the relevant data. In our suggested scheme, the chosen features are fed as inputs for the ART (Adaptive resonance theory) and RBF (Radio Basis Function). Here we using these techniques for identifying the classes and compare the results of these classes. Normally trained data sets only contain input patterns. So learn to these samples from classes we have use classification methods.

ART is a unsupervised learning model. In this unsupervised learning the cost and data function are provided. The ANN is trained to reduce the function of cost by finding suitable input and output connection. ART uses the two layers for processing the input data. First is the Feature layer and next is output layer. Using this layer's it performs the classification on classes. Our proposed when EEG input is given to the ART models it includes new data by finding for similarity between this new data and already learned data. If there is a close

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ARPN Journal of Engineering and Applied Sciences

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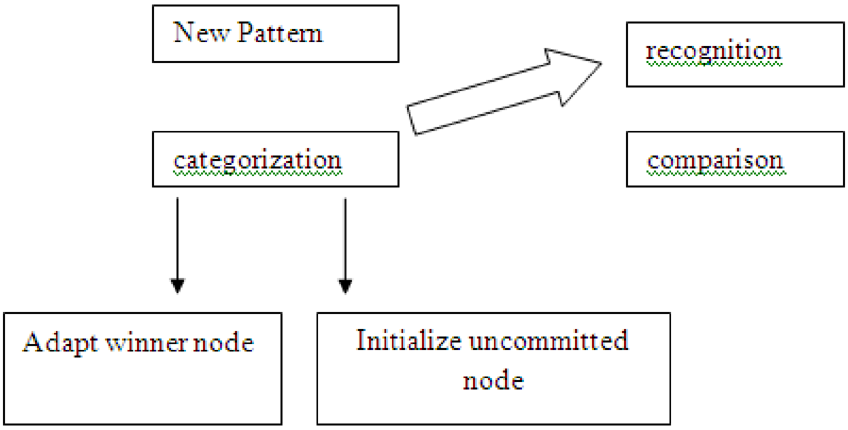
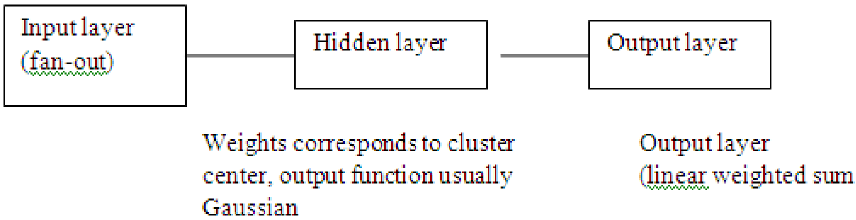
enough matches with input data, the new data is learned and it recognizes the class. So using this output we can identify the brain thoughts. If the given EEG input is not similar with already learned data, this new data is stored as a "new memory".

The below steps explains ART algorithm how to match the given input with trained data sets.



- Incoming pattern matched with stored cluster templates.
- If close enough to stored template joins best matching cluster, weights adapted
- If not, a new cluster is initialised with pattern as template

The RBF (Radial Basis Function) is a special type of neural networks with more different features. This is one of neural network concept with diverse application and is main rival to multi layered perceptron. More inspiration for RBF networks has come from traditional statistical pattern classification techniques.



A RBF network contains three layers, namely the input, hidden and output layer. The input layer is simply a fan-out layer and does no processing. The second or hidden layer performs a non-linear mapping from the input space into a (usually) higher dimensional space in which the patterns become linearly separable. The final layer performs a simple weighted sum with a linear output. When the EEG input is given to the RBF function, First input layer transmit the input vector coordinates to each units in the hidden layer. In hidden layer each then produces an activation base on the Related RBF (Radial Base Function). In this layer it checks the corresponding weights to cluster centre with the given input. The final layer performs a simple weighted sum with a linear output. Based on the output we can identify the related brain thoughts. The important feature of the RBF is the process performance in hidden layer. The thing is that the pattern in the input space cluster. If these cluster centres are known, then the distance from cluster centre can be estimated. Moreover, this distance estimates are made non-linear, so that if a pattern is in an area that is close to a cluster centre, it gives a value close to 1.

In our system we use the ART and RBF function for classification and finally compare the outputs of these two classification methods. In out experimental results shows ART performs better than the RBF method.

4. RESULT AND DISCUSSIONS

Recognition of brain's signals has been difficult as computers are found not to be efficient at this task. As the signals may be too long, is becomes tough to detect the minute fluctuations in signals. As of now, the field of recognition of brain signal has been limited to finding certain brain diseases like tumor, sleep disorders, encephalitis, and epilepsy by making use of hardware such as Electroencephalogram (EEG). In the suggested study, we are making use of linear discriminate analysis method for choosing between groups illustrated by EEG signals. This is one effective categorization method in linear classification.

ARPN Journal of Engineering and Applied Sciences

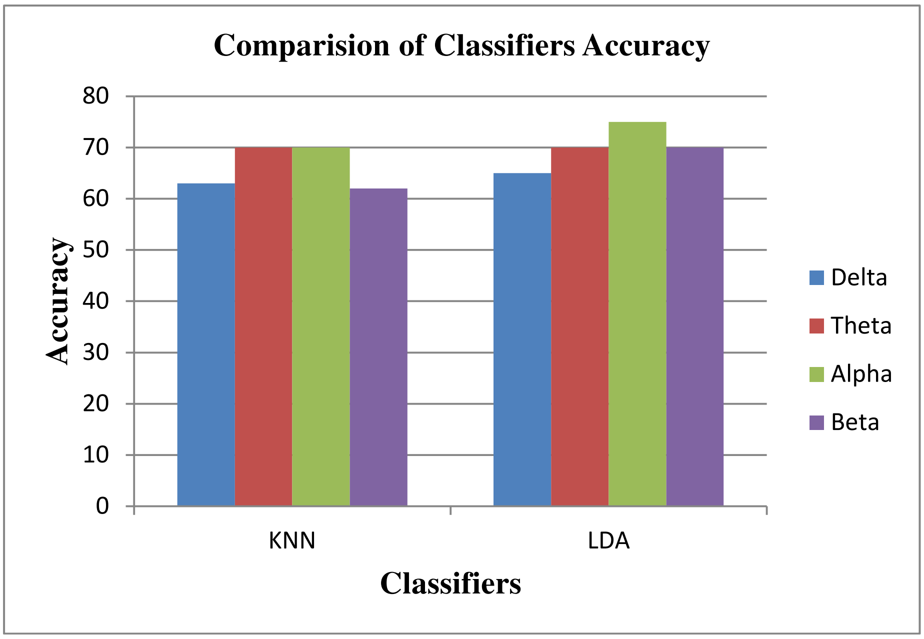


Figure-2. Comparison of classifiers accuracy.

The above Figure-2 shows the comparison of KNN classifiers and LDA Classifiers. Compare to the KNN our proposed method of LDA provides a better result to Classify EEG signal. In the final stage of classification it identifies brain abnormalities by the extracted EEG signal.

Here we show the output screen of existing system. In existing system it used the SVM algorithm for classify the input of eeg samples. It shows experimental result of the system with some eeg input samples.

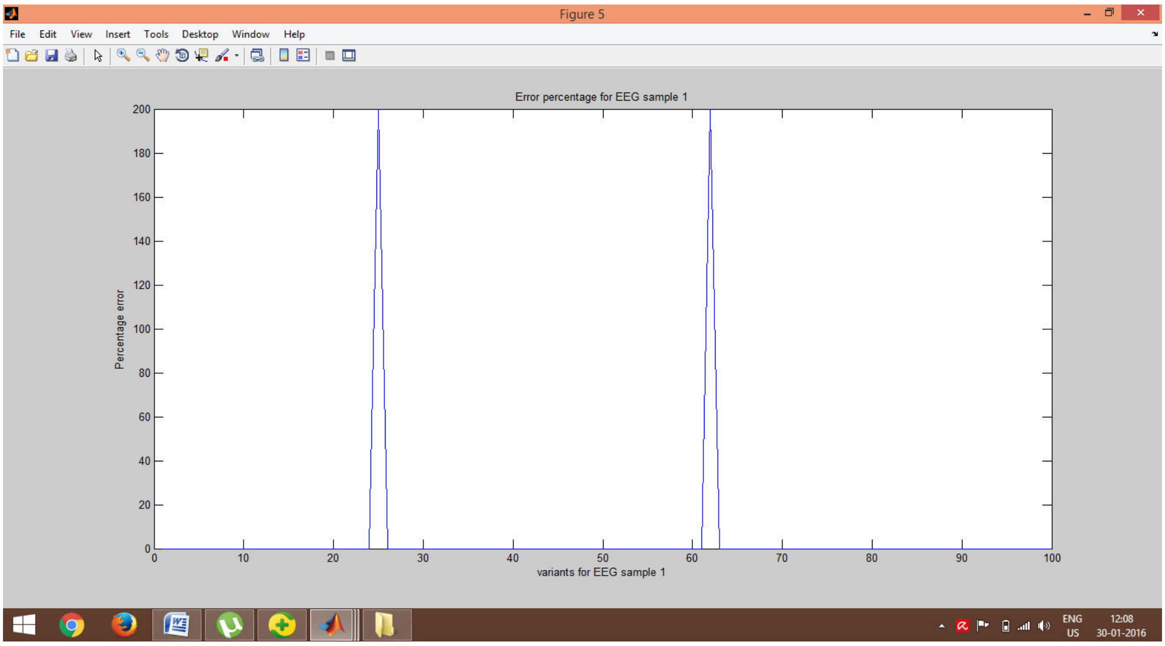


Figure-3. Error percentage for EEG sample 1 in SVM.

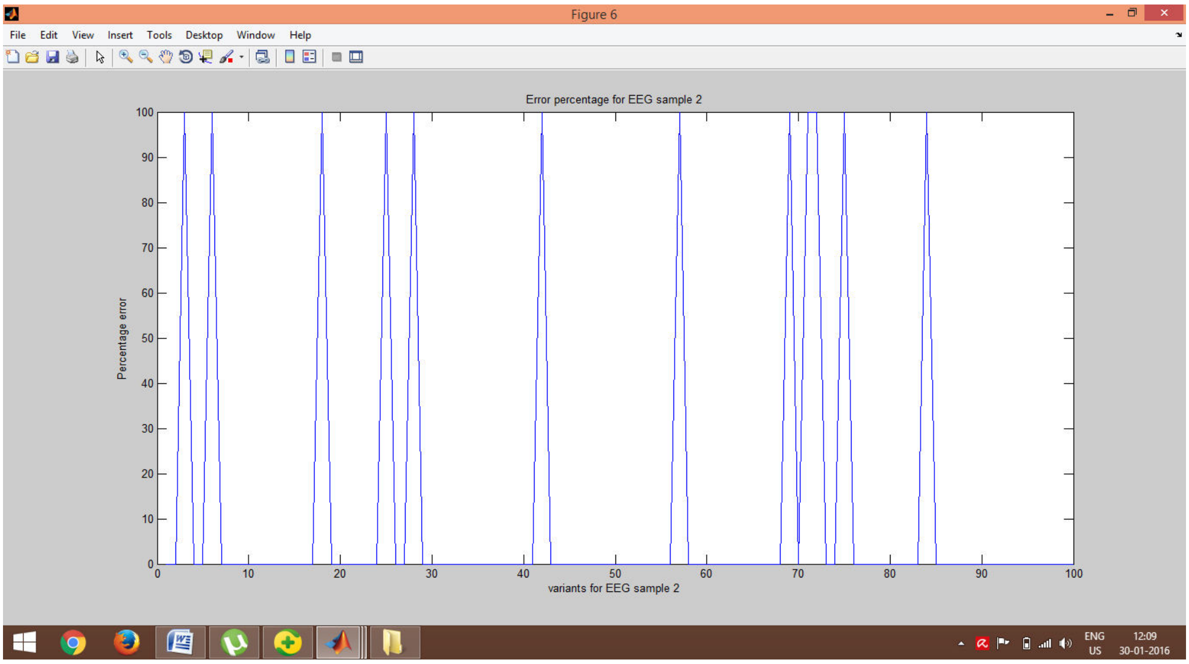


Figure-4. Error percentage for EEG sample2 in SVM.

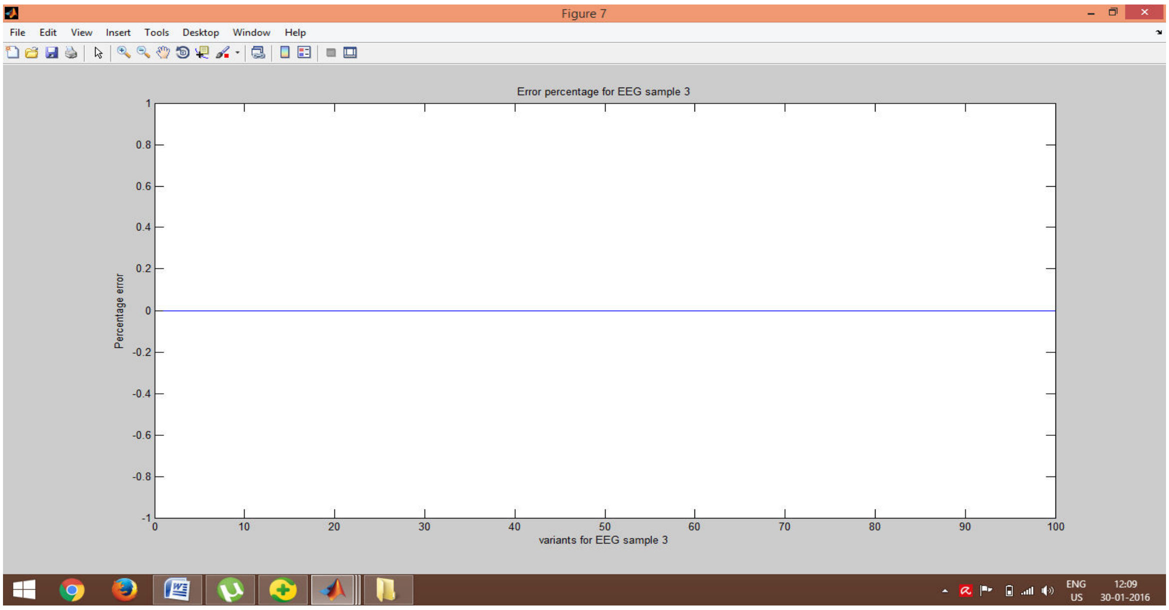


Figure-5. Error percentage for EEG sample3 in SVM.

ARPN Journal of Engineering and Applied Sciences

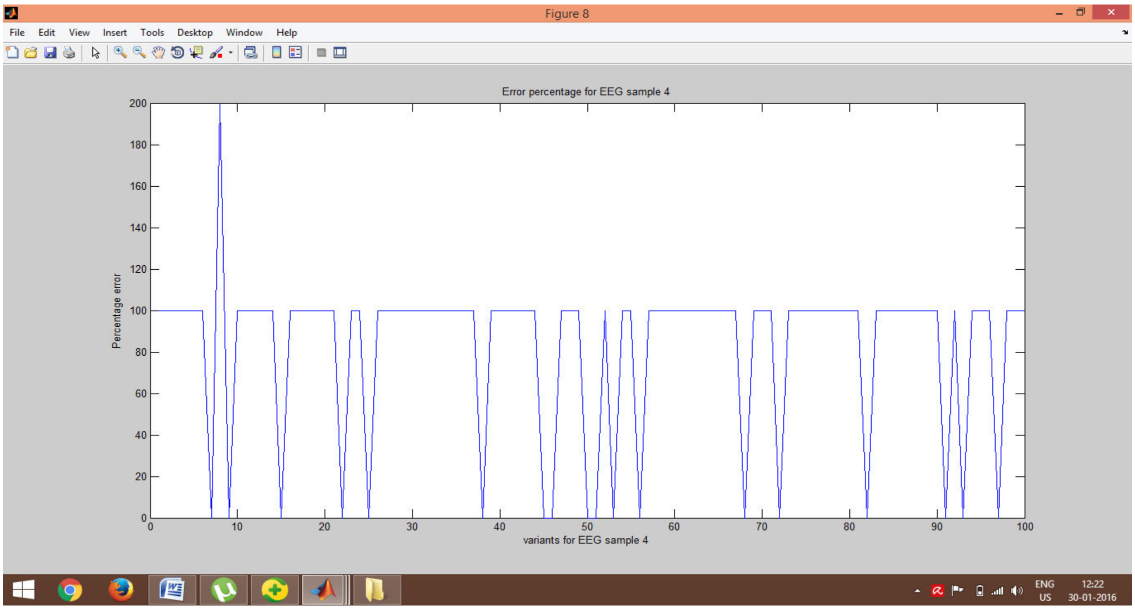


Figure-6. Error percentage for EEG sample4 in SVM.

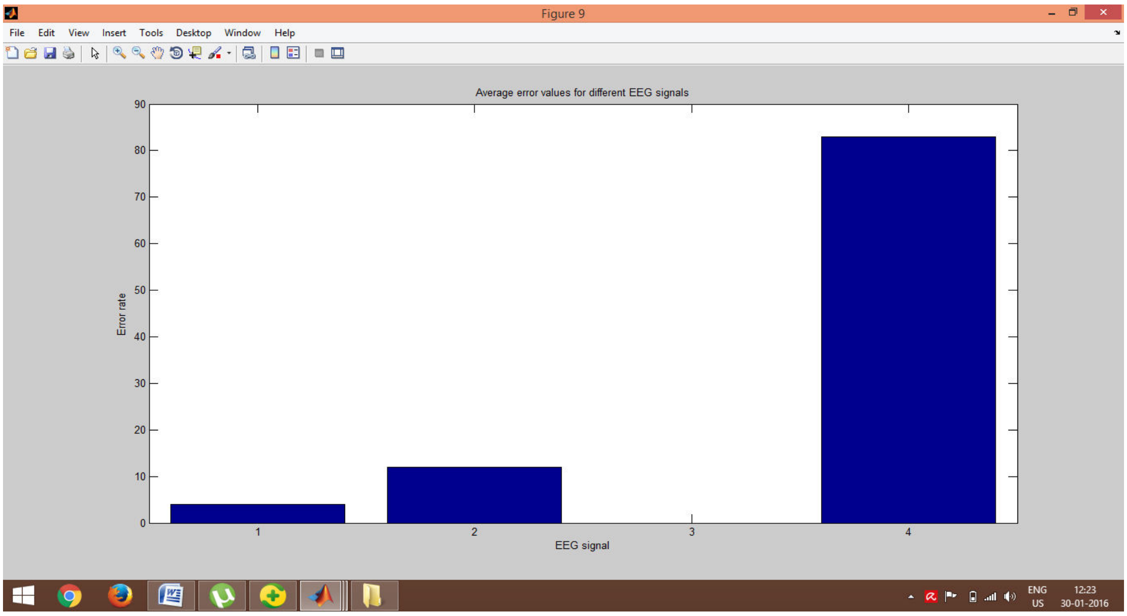


Figure-7. Average error values for different EEG signals in SVM.

VOL. 11, NO. 11, JUNE 2016 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

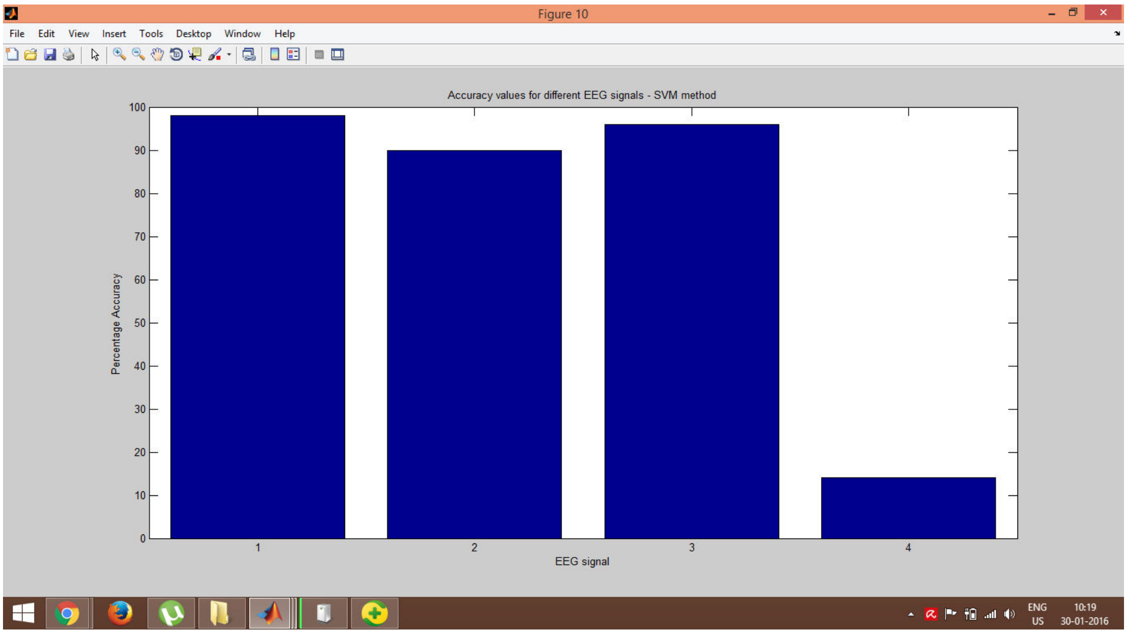


Figure-8. Accuracy for SVM method (existing work).

The above Figures shows the Error percentage values of existing system with different input of eeg samples. Each input produces various output error signals. Finally it shows the average error value and accuracy of SVM method.

The below screen explains the proposed system work with some EEG input samples. Here we show the advantages of proposed system than existing system. In our proposed we use Adaptive Resonance Theory (ART) and Radial Basis Function (RBF) algorithms for identifying the brain thoughts with different EEG input samples and also test and compare these two algorithms for determine best algorithms.

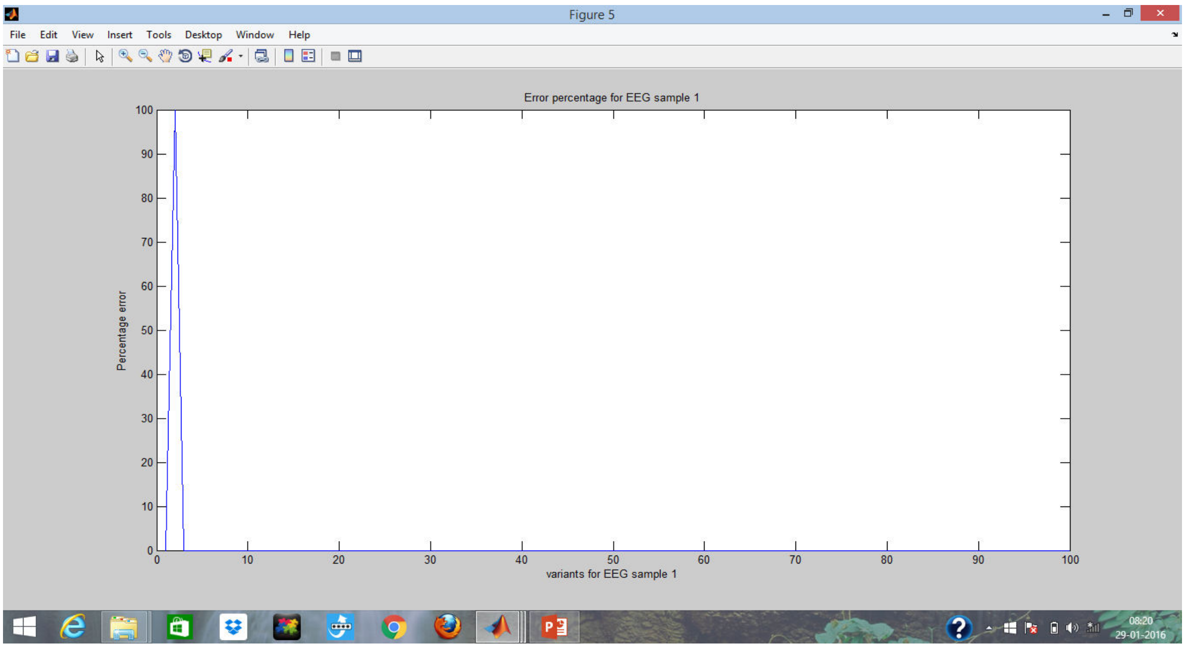


Figure-9. Error percentage for EEG sample 1 in ART.

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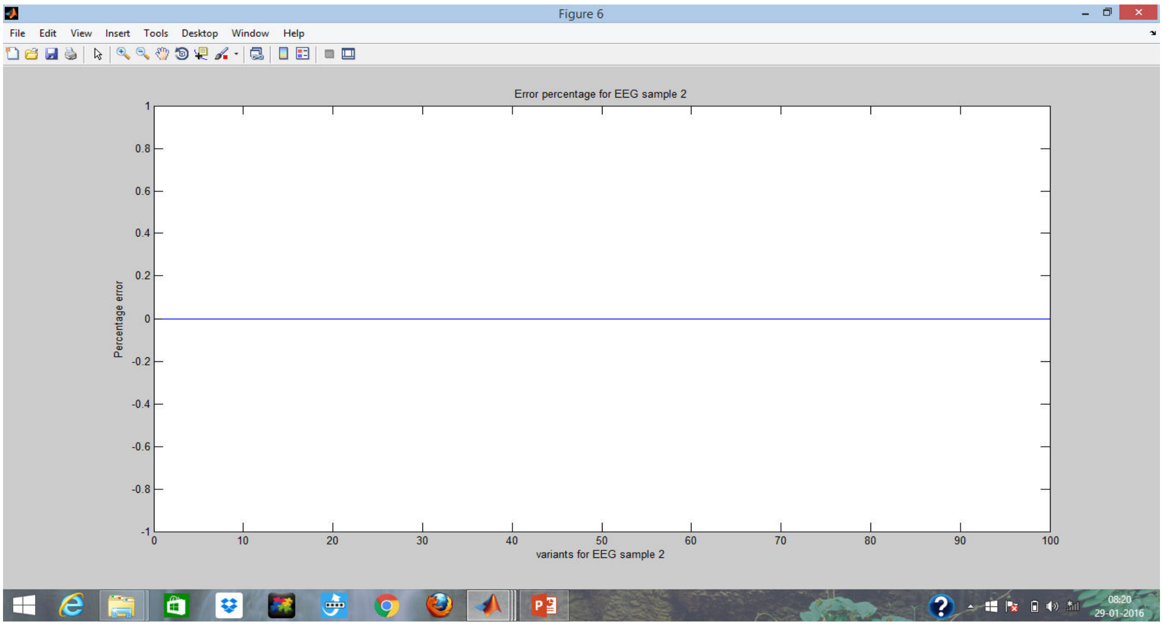

Figure-10. Error percentage for EEG sample 2 in ART.

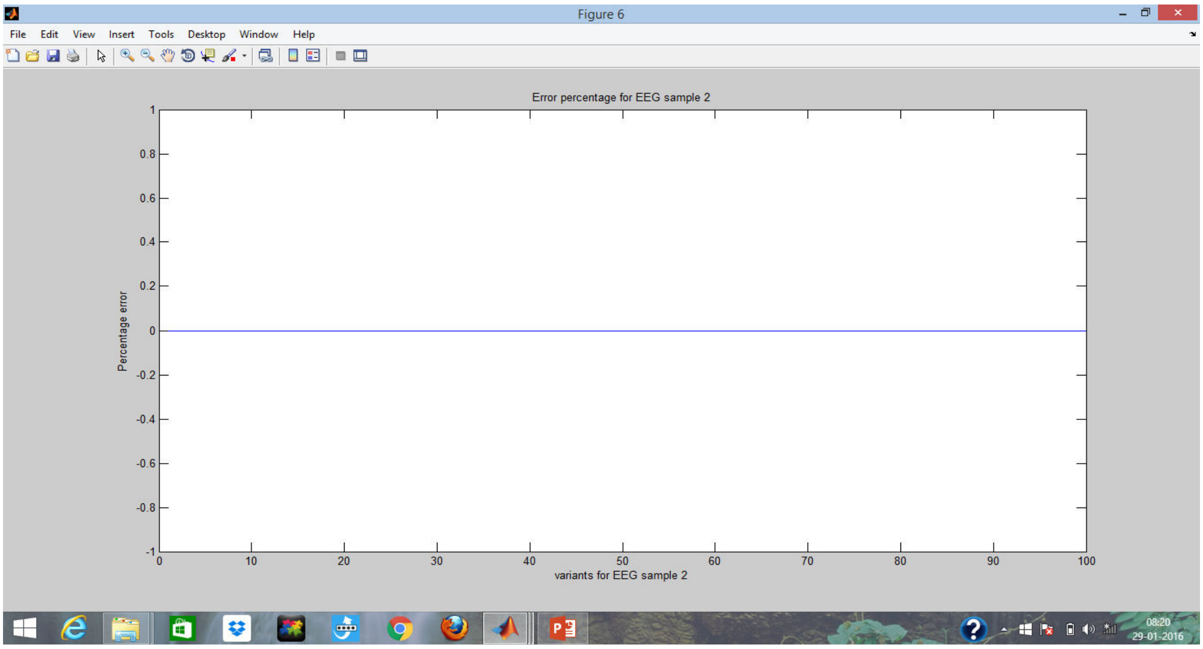

Figure-11. Error percentage for EEG sample 3 in ART.

VOL. 11, NO. 11, JUNE 2016 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

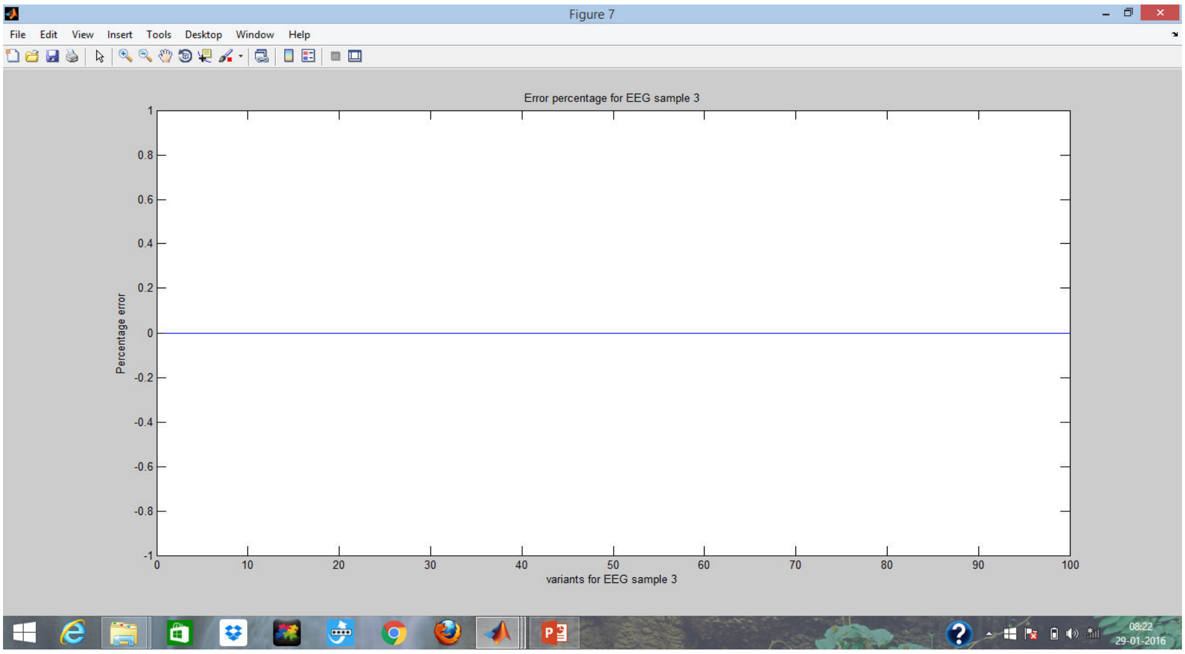

Figure-12. Error percentage for EEG sample 4 in ART.

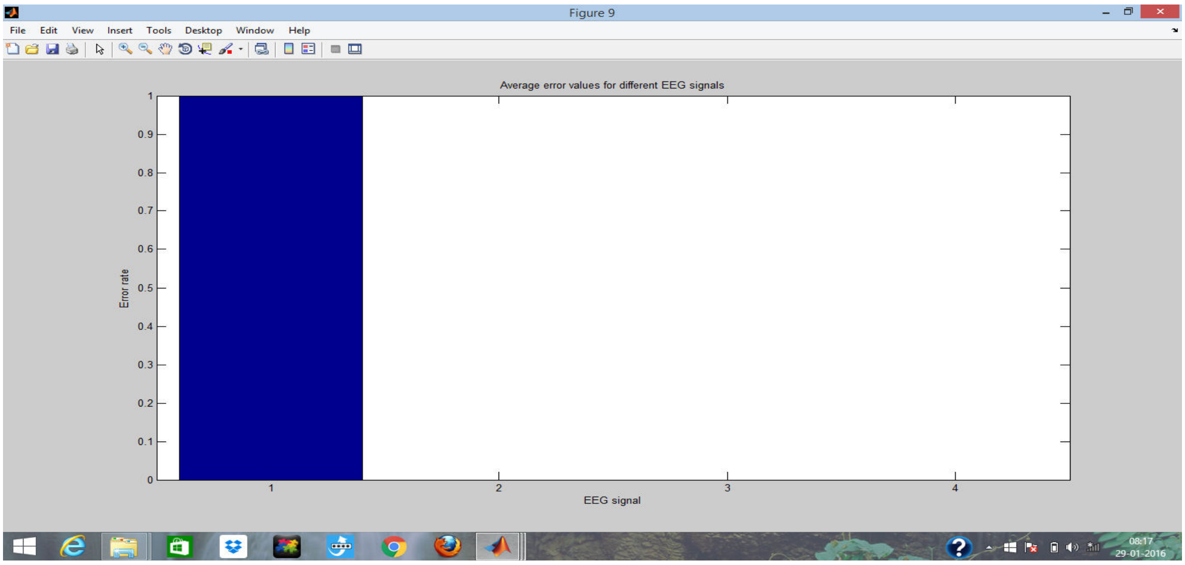

Figure-13. Average error values for different EEG signals in ART.

The above experimental results shows the process of ART algorithm with EEG samples. The ART algorithm provides different error rate for different input of EEG samples. ART provides minimum error rate compare to RBF algorithm.

VOL. 11, NO. 11, JUNE 2016 ISSN 1819-6608
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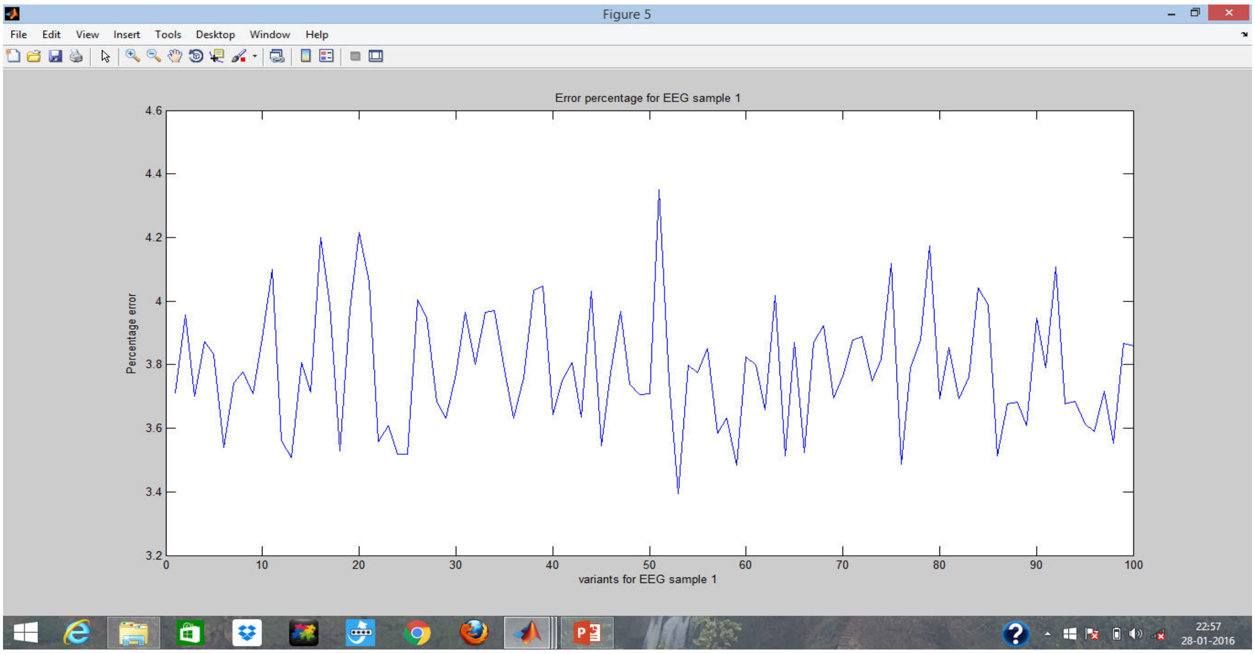

Figure-14. Error percentage for EEG sample 1 in RBF.

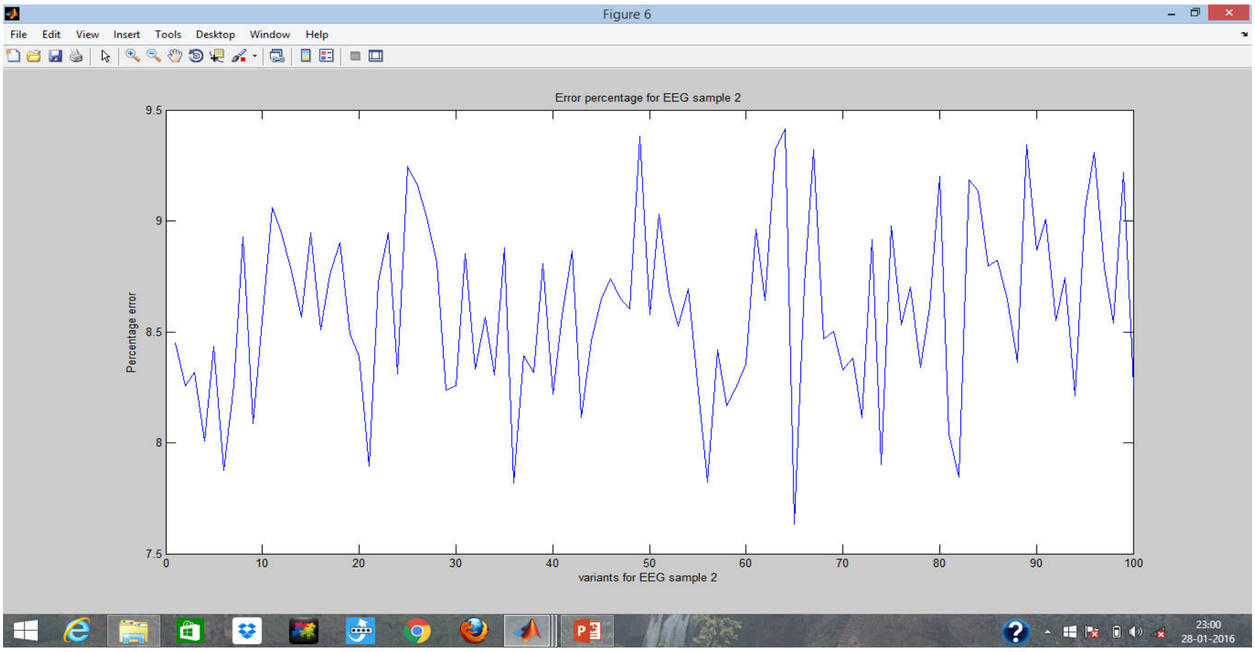

Figure-15. Error percentage for EEG sample 2 in RBF.

VOL. 11, NO. 11, JUNE 2016 ISSN 1819-6608
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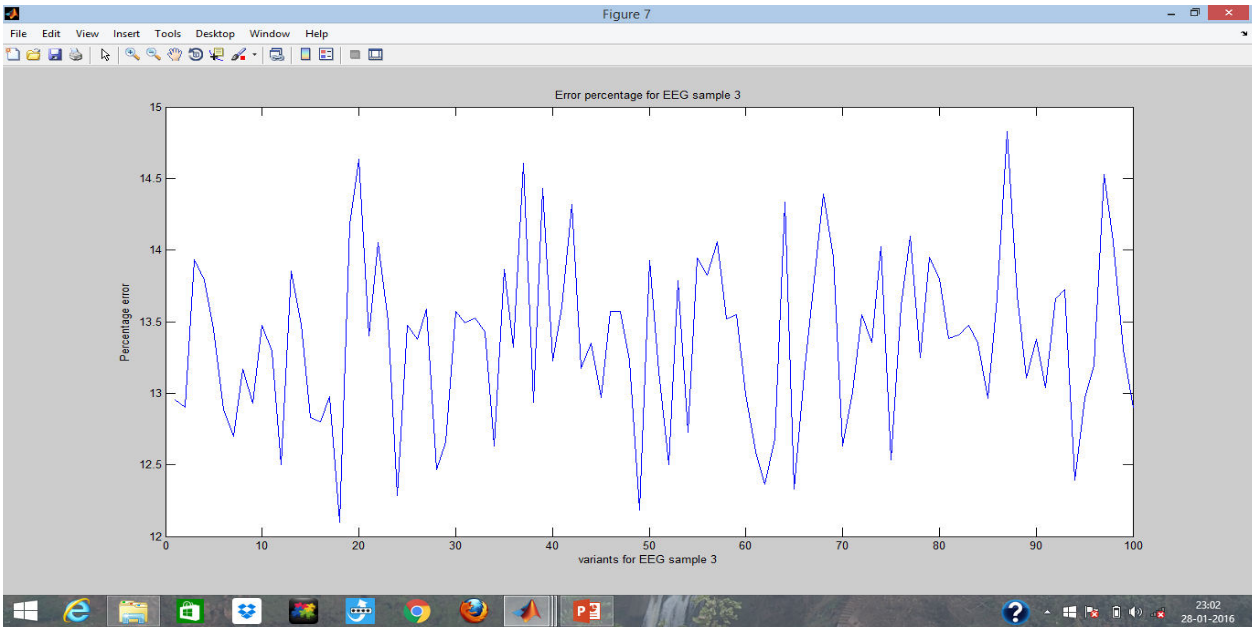

Figure-16. Error percentage for EEG sample 3 in RBF.

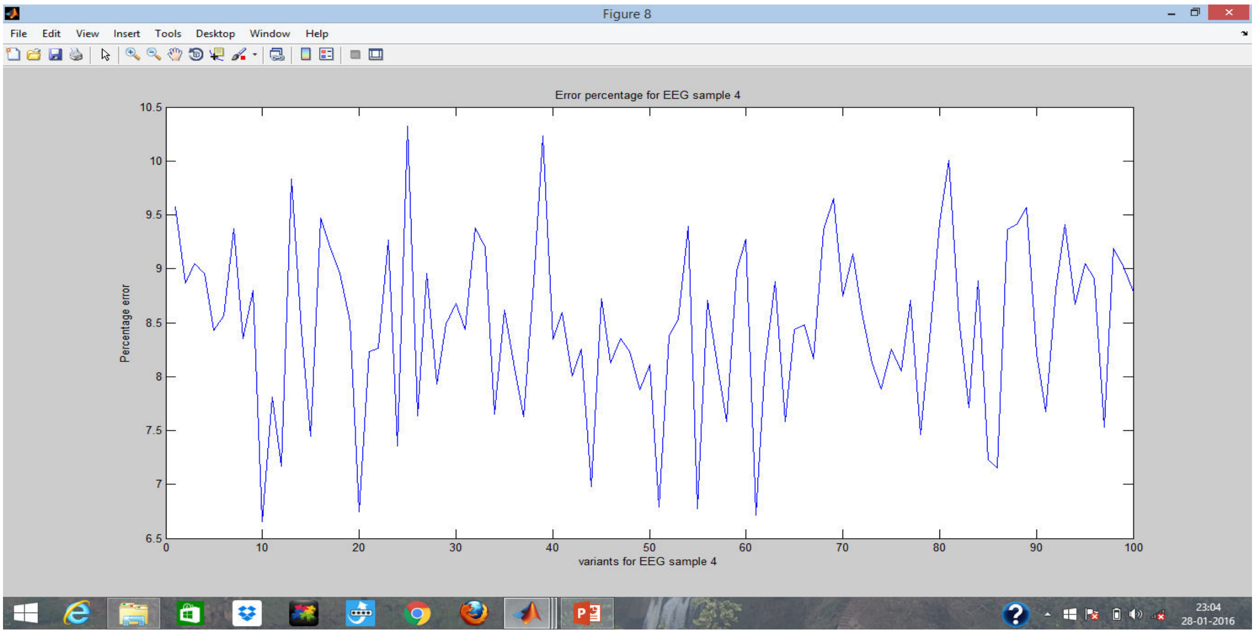

Figure-17. Error percentage for EEG sample 4 in RBF.

ARPN Journal of Engineering and Applied Sciences

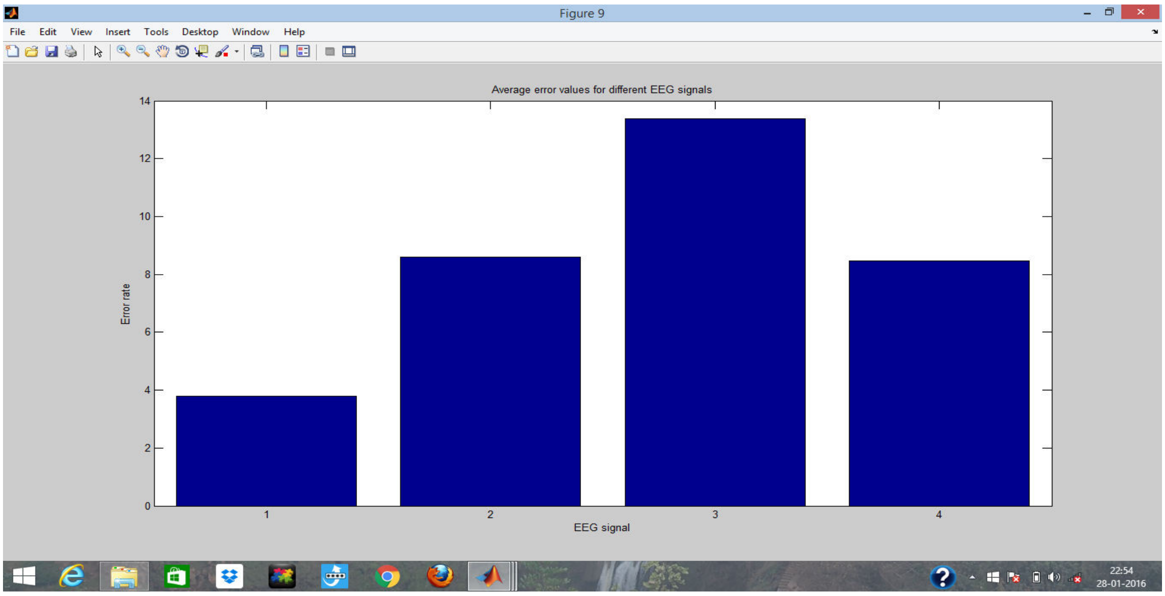

Figure-18. Average error values for different EEG signals RBF.

The above results shows the expermental result of RBF algorithm. Compare to ART method this RBF provides more error average for EEG input samples.

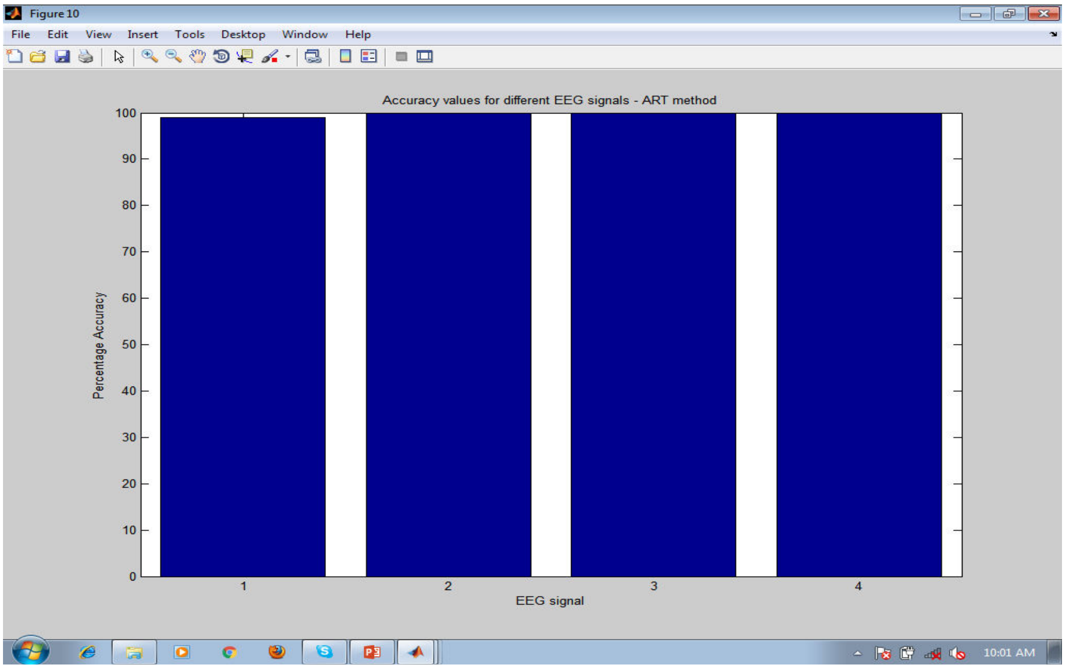

Figure-19. Accuracy for ART method.

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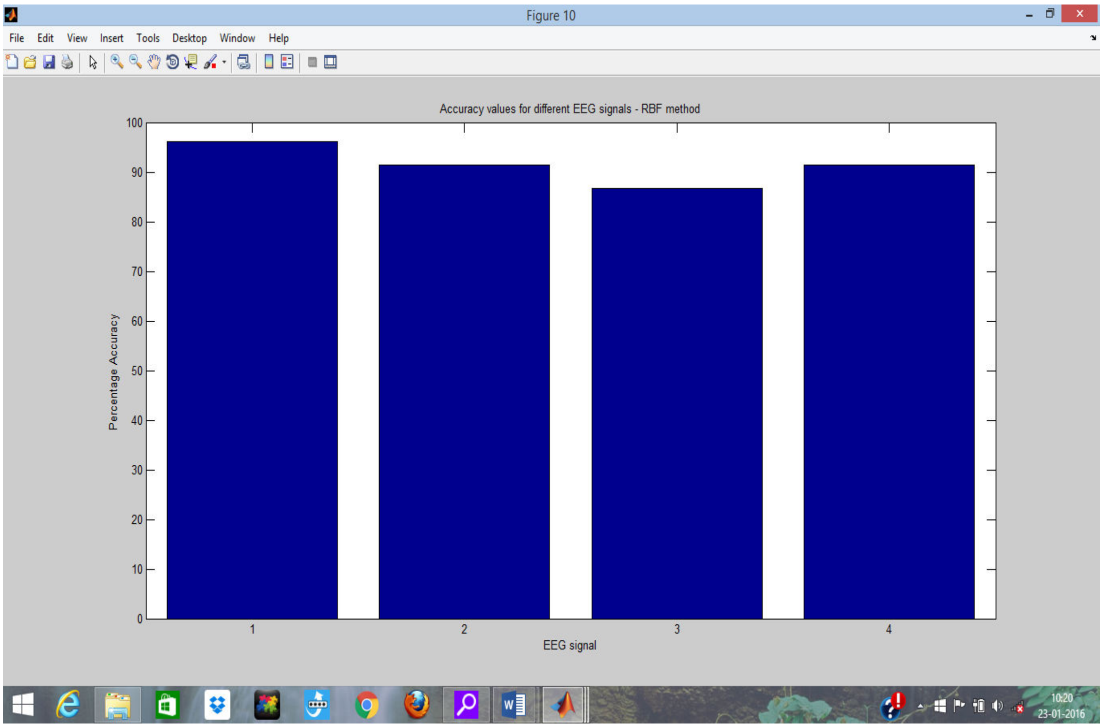

Figure-20. Accuracy for RBF method.

These screens are shows the accuracy percentage of both algorithm. Here this resutls are shown by different input sample. ART identify more exact brain thoughts in trained samples than RBF algorthm.

5. CONCLUSIONS

For accurate functioning of brain-computer interfaces (BCIs) that are founded on natural Electroencephalogram (EEG) signals, perfect categorization of the multichannel EEG is required. In the mean while, in medical science discipline, Electroencephalogram (EEG) is employed to identify activity of brain and the abnormalities that reflect the conditions of human brain. EEG is one helpful tool with regard to understanding the brains difficulty. Testing EEG signal toward detecting abnormalities in brain is one difficult task. The aim of our proposed is system to identify brain thoughts based on the trained samples. Hence, a computer-based automated method is required for detecting thoughts of brain. This work proposed by us assists a lot in analysis of brain thoughts. Linear Discriminate Analysis has been employed for reduction dimensionality of training data. ART and RBF are used for classifying the classes from trined samples based on the user input. By that various brain thoughts can be identified. Finally the comparison result of these two classification was shown. Experiments conducted have proved the possibility of identifying the thoughts of brain with the assistance of EEG signal.

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