

EEG Signal Classification using Principal Component Analysis with Neural Network in Brain Computer Interface Applications

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Abstract - Brain Computer Interface (BCI) is the method of communicating the human brain with an external device. People who are incapable to communicate conventionally due to spinal cord injury are in need of Brain Computer Interface. Brain Computer Interface uses the brain signals to take actions, control, actuate and communicate with the world directly using brain integration with peripheral devices and systems. Brain waves are in necessitating to eradicate noises and to extract the valuable features. Artificial Neural Network (ANN) is a functional pattern classification technique which is trained all the way through the error Back-Propagation algorithm. **In this paper in order to classify the mental tasks,** the brain signals are trained using neural network and also using Principal Component Analysis with Artificial Neural Network. Principal Component Analysis (PCA) is a dominant tool for analyzing data and finding patterns in it. In Principal Component Analysis, data compression is possible and it projects higher dimensional data to lower dimensional data. **By using Principal Component Analysis with Neural Network, the redundant data in the dataset is eliminated first and the obtained data is trained using Neural Network.** EEG data for five cognitive tasks from five subjects are taken from the Colorado University database. Pattern classification is applied for the data of all tasks of one subject using Neural Network and also using Principal Component Analysis with Neural Network. Finally it is observed that the correctly classified percentage of data is better in Principal Component Analysis with Neural Network compared to Neural Network alone.

Keywords: Artificial Neural Network (ANN), Brain Computer Interface (BCI), Electroencephalogram (EEG), Principal Component Analysis (PCA)

I. INTRODUCTION

The human brain is in fact a difficult system and exhibits prosperous spatiotemporal dynamics. EEG is the method of obtaining the electrical activity of the brain as analog signals using the instrument called Electroencephalogram available in hospitals laboratory. The brain signals are taken using the techniques like invasive, partially invasive or non-invasive. In most of the laboratory they are using the non-invasive technique to acquire the brain signals by placing the electrodes on the scalp using the conductive gel which improves the signal strength. The received EEG signal is in microvolt and is then amplified with the help of amplifiers. After amplification, the amplified signal is given to computer through analog to digital converter for further processing. Now the obtained signal is stored in the computer for doctor's advice. In hospitals the use of EEG signal is in diagnosis of epileptic disorder, coma, brain death and encephalopathies. EEG also used for the diagnosis of stroke, tumors and other main brain disorders, but this use has lowered with the arrival of anatomical imaging techniques with high spatial resolution such as Computer Tomography (CT) and Magnetic Resonance Imaging (MRI).

Worldwide there are people who have malfunction in their motor activities due to paralysis or having spinal injury because of accidents. They are incapable to perform their own activities. A normal human can interact with the computers using the peripherals like mouse, keyboard and etc. But the human with failed motor function needs an interface to communicate to others or to systems. For the patients having severe motor function failure has care assistants to help them for their regular

activities. Wide ranges of electronic device have been developed particularly to reduce the concern workload and the number of care assistants needed.

Functional Electrical Stimulation (FES) is one procedure for the restoration of lost movement functions [1]. Patients with spinal cord injury are incapable to perform movements because the brain signal proposed for progress of their extremities is not correctly transmitted to the peripheral nerves. If these control signals could be absolutely given to Functional Electrical Stimulation system, then the electric signals from the brain may be capable to stimulate the peripheral nerve and respect the command. Transmission of these signals to devices is essential but it is a time overwhelming work for severely paralyzed patients.

Brain-Computer Interfaces (BCIs) is the best feasible way of providing the communication between the human and the system by means of brain signals [2]. By using this BCI the patients can put across their views or needs by means of their brain signals just by thinking process. The signal classification module is composed of the obtained EEG signal features extraction and the transformation of these signals into device instructions. The EEG classification tactic depends on the inducement and, thereby, the reaction to detect motor imagery, event-related potentials, slow cortical potentials, or steady-state evoked potentials. The predicted EEG drives the classification to some precise feature extraction methods.

II. RELATED WORKS

Kenji Nakayama et al [3] introduced efficient pre-processing techniques in order to attain high probability of exact mental task classification. The preprocessing technique includes segmentation along time axis, amplitude of FFT of brain waves, reduction of samples by averaging and nonlinear normalization. Charles W. Anderson et al [4] applied PCA independently to little segments of data and the origin vectors themselves are used as features for classification. **In addition, time embedding the EEG by augmenting each sample with previous samples prior to PCA results in a representation that captures EEG variations in space and time.** The resulting features are classified into categories corresponding to which mental task a subject is performing in a brain-computer interface (BCI) paradigm. Jinyi Long et al [5] introduced a hybrid BCI that uses the motor imagery-based mu rhythm and the P300 potential to control a brain-actuated simulated or real wheelchair. The

user performs left- or right-hand motor imagery to direct a left or right movement and performs foot imagery or focuses on a flashing button to adjust the speed of the simulated or real wheelchair.

III. SOFT COMPUTING TECHNIQUES

Soft computing is the combination of methodologies (Neuro-Computing, Fuzzy Computing, Evolutionary and Genetic Computing and Probabilistic Computing) intended to model and make possible solutions to real world tribulations, which are not modeled or too complex for mathematical modeling. Its aspire is to utilize the tolerance for approximation (model features are similar to the real ones but not the same), uncertainty (not sure that the model features belief are the same as that of the entity), imprecision (model features quantities are not same as real ones but close to them) and partial truth in order to achieve close resemblance with human like decision making. The guiding theory of soft computing is to make use of these tolerance to achieve, robustness tractability and low solution cost. Human mind is the role model for soft computing. Some of the soft computing techniques are Artificial Neural Network (ANN), Fuzzy Logic (FL), Adaptive Neuro-Fuzzy Inference System (ANFIS), Principal Component Analysis (PCA) and evolutionary computation.

1. ARTIFICIAL NEURAL NETWORK (ANN)

A neural net is an artificial illustration of the human brain that tries to imitate its learning process. ANN is an interrelated group of artificial neurons that uses a mathematical model or computational model for information processing [6]. ANN is a network of simple processing elements which can demonstrate complex overall performance, determined by the connections between the processing elements and element parameters. ANN is an adaptive system that changes its structure based on external or internal information that flows through the network. ANN computing approach to information processing primarily involves a learning process with an ANN architecture that adaptively responds to inputs according to a learning rule. After the NN has learned, the trained network can be used to execute certain tasks depending on the exact purpose. **The talent to learn by example and simplify are the principal characteristics of ANN. Classification of signals is done by using this ANN to obtain the correct classification percentage.** ANN is learned using the backpropagation algorithm in which the

errors for the units of the hidden layer are determined by back propagating the errors of the units of the output layer. It is a systematic method of training multi-layer ANNs. It contains an input layer, at least one intermediate/hidden layer and an output layer in its network. Some of the ANN learning parameters are Threshold, Goal, Epoch, Sigmoidal function, Training type and Number of Hidden layers.

2. *PRINCIPAL COMPONENT ANALYSIS (PCA)*

The graphical representation for higher dimensional data is complex. PCA is an effective tool for analyzing data and finding patterns in it. It is a form of unsupervised learning and data compression is possible [7]. By projecting the data from higher dimensional into a lower dimensional space that precisely characterizes the state of the process, dimensionality reduction methods can significantly simplify and progress process monitoring procedures. **Principal Component Analysis is a dimensionality reduction technique and it produces a lower dimensional representation in a method that conserves the correlation structure between the process variables, and is best in terms of capturing the variability in the data. PCA projects high dimensional data to a lower dimension and it projects the data in the least square sense, it captures big inconsistency in the data and ignores small inconsistency.**

IV. EEG DATA ACQUISITION

In this paper, the EEG data used is collected from the Colorado state University website [8] and was formerly obtained by Keirn and Aunon using the following process. The subjects were seated in an sound controlled room with faint lighting. A non-invasive type electro-cap was wore to record signals from positions P3, P4, C3, C4, O1, and O2 electrodes defined by the international 10-20 system for electrode placement. **Data was recorded at a sampling rate of 250 Hz. Eye blinks were detected by placing a separate channel of data observed from two electrodes placed over and under the subject's left eye.**

V. MENTAL TASKS

There are five mental imaginary tasks taken from seven subjects. During the tasks the data was recorded for **10 seconds** which contains 2500 data (i.e. for 1 sec=250 data) and tasks are repeated for 10 trials [9]. The tasks are as follows.

- a) Baseline task
- b) Letter task
- c) Mathematical task
- d) Visual counting task
- e) Geometric figure rotation task

VI. IMPLEMENTATION AND RESULTS

1. *NEURAL NETWORK CLASSIFIER*

The brain signals taken from the above said seven electrodes which are all placed over the scalp are denoted as input layer for the neural network. [2] Here the five different mental tasks classification are the outputs and the output for baseline task is [1,0,0,0,0], for letter task is [0,1,0,0,0], for mathematical task is [0,0,1,0,0], for visual counting task is [0,0,0,1,0] and for geometric figure rotation task is [0,0,0,0,1]. After applying various values for the learning parameters like hidden layers, goal, threshold and epochs we found that the better classification is obtained for the learning parameters like number of hidden layers as 15, epochs as 1000, threshold as 0.5, goal as 0.01, sigmoidal function as logsig and training type as trainsecg. From the given dataset the data is taken from first trial of all tasks for one subject. Each trial we obtained 2500 data. Therefore for all first trials of all five tasks we obtained 12500 data. The data is shuffled well for mixing of data from all five tasks. Using the neural network with backpropagation algorithm the first 10000 data is trained well and then the next 2500 data is used for testing. After the training function the result gives the mean square error for testing and training, time taken for computation and the correctly classified percentage.

2. *PRINCIPAL COMPONENT ANALYSIS (PCA) WITH NEURAL NETWORK (NN) CLASSIFIER*

The signals obtained from the electrodes are given to Principal Component Analysis for dimensionality reduction to remove the redundant variables in the data and the classified using Neural Network classifier with backpropagation. In Principal Component Analysis the better classification of signals is obtained for the learning parameters like epochs as 1000, number of hidden layers as 3, goal as 0.01, sigmoidal function as tansig, threshold as 0.5 and training type as trainsecg.

The brain signals are trained using Neural Network and the training is shown in Fig.1. During the classification of the mental tasks using Neural Network classifier, the data is misclassified at the output i.e., the percentage of correct classification is low and is shown in

Fig.2. Similarly during the classification of the mental tasks using Principal Component Analysis with Neural Network classifier, the data is perfectly classified at the output i.e., the percentage of correct classification is good because of the reduction of the redundant variables in the dataset and is shown in Fig.3.

Table 1: Comparison results of Neural Network and Principal Component Analysis with Neural Network classifier.

S.NO.	PARAMETERS	NN	PCA WITH NN
1	Hidden layers	15	3
2	Epochs	1000	1000
3	Goal	0.01	0.01
4	Threshold	0.5	0.5
5	Sigmoidal function	Logsig	Tansig
6	Training type	Trainscg	Trainscg
7	MSE Training	0.1099	0.1467
8	MSE Testing	0.1651	0.1478
9	Processing Time in Seconds	179.2919	87.0798
10	Percentage Correctly Classified	28.84	100

The comparison of the results of Neural Network classifier and Principal Component Analysis with Neural Network classifier is tabulated in Table 1 to show the variation of mean square error during training, mean square error during testing, computation time and the percentage of correctly classified data for both type of classification.

VII. CONCLUSION

A Neural Network has been applied to the BCI problem. In order to improve accuracy of mental task classification, several kinds of pre-processing is done to generate the input data of the neural network. Compared with the Neural Network model, the probability of correct

classification has been increased by using the Principal Component Analysis with Neural Network. Further the same dataset can be classified by using other soft computing techniques like Fuzzy logic, ANFIS in future for better results.

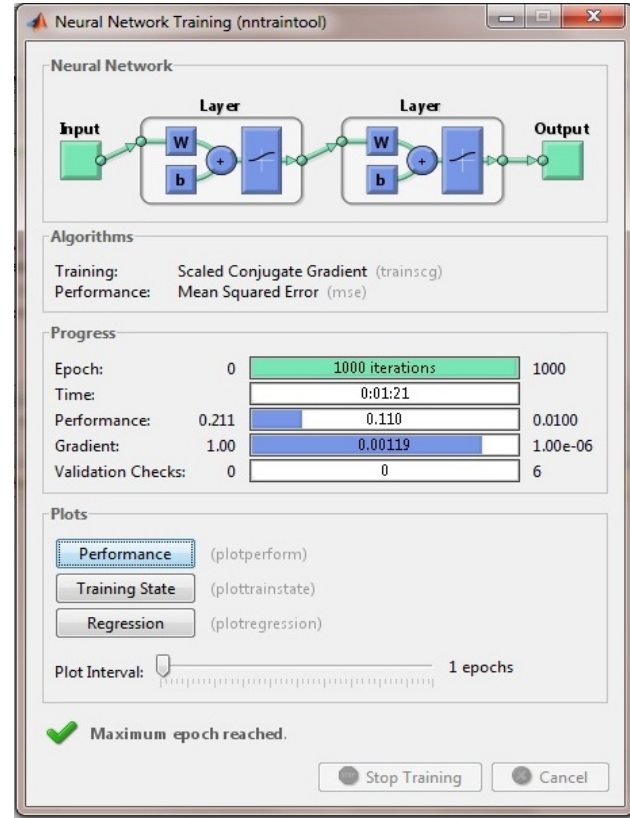


Fig.1: Neural Network Training

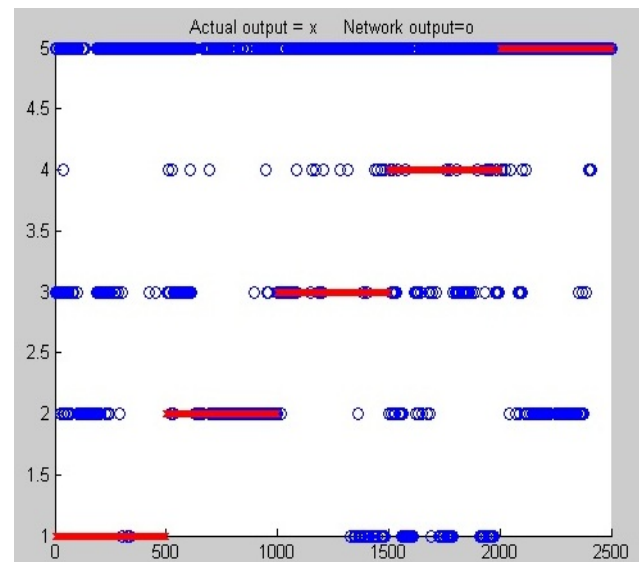


Fig.2: Neural Network Classification Output implies the classification of the mental tasks which are given as input to the Neural Network classifier

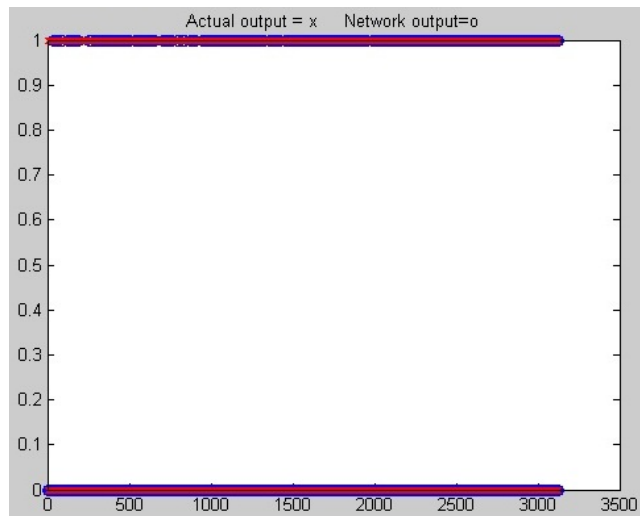


Fig.3: Principal Component Analysis with Neural Network Classification
Output implies the classification of the mental tasks which are given as input to the Principal Component Analysis with Neural Network classifier

VIII. ACKNOWLEDGMENT

We thank the Department of Instrumentation and Control Engineering of Kalasalingam University, (Kalasalingam Academy of Research and Education), Tamil Nadu, India for permitting to use the EEG setup and computational facilities available in Biomedical Laboratory which was setup with the support of the Department of Science and Technology (DST), New Delhi under FIST Program.

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