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DESIGN OF MULTILAYER PERCEPTRON NEURAL NETWORK FOR MENTAL TASK RECOGNITION

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ABSTRACT

BCI (Brain Computer Interface) represents a direct communication between the neuron action of brain and a computer system. The main aim of the BCI is to translate brain activity into commands for the computer. Electroencephalogram (EEG) is used to captures the brain electrical signals. It is highly difficult to convert these measured brain electrical signals into commands. The steps involved to convert are signal Pre-processing, Feature Extraction, Classification. The output from the above steps is used to control the computer. In this paper it is mainly concentrated on the feature classification. It is adopted Multi Layer Perceptron Neural Network (MLP) with Back propagation training, dataset collected from the BCI Competition III 2008. The proposed Neural Network consists of 10 units in the input layer and hidden layers and with the output layer of one unit. This network is trained with the given dataset and obtained a low Mean Square Error (MSE) of 0.342, which is very low when compared to other Neural Network architectures. This proposed method worked with 100% training and 74% testing accuracy.

KEYWORDS: Brain Computer Interface, Multi Layer Perceptron Neural Network,

INTRODUCTION

Brain Computer Interface (BCI) represents a direct interface between the brain and a computer or any other system. BCI is a broad concept and comprehends any communication between the brain and a machine in both directions: effectively opening a completely new communication channel without the use of any peripheral nervous system or muscles. BCI has been rising as a major research area over the past decade, with its immense potential in Neural and Rehabilitation Engineering. Over the past 15 years the field of BCI has seen a rapidly increasing development rate and obtained the interest of many research groups all over the world.

Currently in BCI-research the main focus is on people with severe motor disabilities. This target group has little (other) means of communication and would be greatly assisted by a system that would allow control by merely thinking. Communication between the brain and computer involves four steps. First step, measuring the electrical activity generated by the neurons of the human brain when a thought was imagined, this step is called data acquisition. Electrical activity (fields) generated by the neurons is measured, there are many measuring methods like invasive and noninvasive. In invasive method electrodes are implanted in the brain scalp where as in non invasive method an electrode cap is placed on the brain scalp.

Many existing BCI system uses non invasive method in which EEG (Electroencephalography) is used for measuring the electrical activity. EEG is a non invasive technology which can be used to detect different characteristic signals and waves emitted from the brain. These measured signals are taken as input to the further steps. These input signals are then processed using signal pre-processing step, which include acquiring usable signal by amplifying, applying filters and reducing noise & artifacts of the input signals. Next step is feature extraction in which it extracts the most valuable signals from the processed input. Last step is the feature classification, which tries to classify the features into usable output. The output, from the classification is used as a control signal for various applications.

In the present work, we mainly concentrated on the classification step. Several algorithms and techniques have been developed to improve the efficiency of classification of datasets. This includes Fisher Discriminant analysis, Support vector machine etc. The major criteria for deciding the efficiency of an algorithm in the BCI scenario are three-fold: capability to extract and self train the data, computational speed and intensity, and classification accuracy. To achieve this criterion, It is designed the Multilayer (MLP) perceptron with back propagation algorithm to perform the classification task.

RELATED WORK

Neural networks (NN) are, together with linear classifiers, the category of classifiers mostly used in BCI research [1, 2]). The Neural network is an assembly of several artificial neurons which enables us to produce nonlinear decision boundaries [3]. An MLP is composed of several layers of neurons: an input layer, possibly one or several hidden layers and an output layer. MLP, which are the most popular NN used in classification, have been applied to almost all BCI problems such as binary [4] or multiclass [2], synchronous [5] or asynchronous [6] BCI. However, the fact that MLP are universal approximators makes these classifiers sensitive to overtraining, especially with such noisy and non-stationary data as EEG [7]. Therefore, careful architecture selection and regularization is required. A multilayer perceptron without hidden layers is known as a perceptron. A perceptron is equivalent to LDA and, as such, has been sometimes used for BCI applications [8, 9].

Other types of NN architectures are used in the field of BCI. Among them, one deserves a specific attention as it has been specifically created for BCI: the Gaussian classifier [10, 11]. Each unit of this NN is a Gaussian discriminate function representing a class prototype. This NN outperforms MLP on BCI data and can perform efficient rejection of uncertain samples [10]. As a consequence, this classifier has been applied with success to motor imagery [11] and mental task classification [10], particularly during asynchronous experiments [10, 9]. Besides the Gaussian classifier, several other NN have been applied to BCI purposes, in a more marginal way.

1. Learning vector quantization (LVQ) neural network [15, 14];
2. Fuzzy ARTMAP neural network [10,11];
3. Dynamic neural networks such as the finite impulse response neural network (FIRNN) [16],
4. Time-delay neural network (TDNN) or gamma dynamic neural network (GDNN) [17];

5. RBF neural network [14,12];
6. Bayesian logistic regression neural network (BLRNN)[12];
7. Adaptive logic network (ALN) [13];
8. Probability estimating guarded neural classifier (PeGNC) [17].

When compared with Probabilistic Neural Network, MLP and support vector machine, the MLP showed a good classifier output. Use of sigmoid function for adopting MLP, which makes MLP network capable of nonlinearly mapping and capturing dynamics of signals [10]. Four classification methods PNN Delta Band Method (PNN-DB), Ensemble of MLP Neural Networks with Driven Pattern Replication (MLP-DPR), Modular Multi-Net System (MMN), and Hierarchical Model (HM), MMN & HM show high average hit rate [3].

Multi Layer Perceptron Neural Network (MLP) and Fuzzy C-means analysis for classifying: accuracy, that is, percentage of correct classifications, training time and size of the training dataset for comparison. The results show that even if the accuracies of the two classifiers are quite similar, the MLP classifier needs a smaller training set to reach them with respect to the Fuzzy one. But finally MLP is used for the classification of mental tasks in Brain Computer Interface protocols [12].

PROBLEM SPECIFICATION

Presently classification of BCI problem contains number of classifiers which classify the mental task. But the issue here is the percentage of the classifier. Many papers have been published based on the improvement of classification percentage. This classification percentage achieved is 60-70 % up to now. Many neural network classifiers are also developed for the classification of BCI data; these networks classifier percentage can be improved by some efficient signal preprocessing methods. In the present project thesis, our problem includes the development of efficient techniques for signal preprocessing and construction of a Neural Network architecture which provide high percentage of classification.

PROPOSED METHOD

Multi-Layer Perceptron (MLP) Neural Network made of three layers: one input, one hidden and one output. Each neuron is connected with a certain weight to every other neuron in the previous layer. At each time step, the input is propagated through layer. The input layer has 10 neurons, one for each considered electrode. For each trial input neurons receive the relative powers of electrodes. At this point, the information is fed to the first hidden layer through weighted connections. Hidden layer has 10 neurons. All the neurons (excluding the input layer) have a sigmoid activation function scaled in the range of 1 to -1.

Sigmoid was preferred due to its independent and fundamental space division properties as it models the frequency of action potentials of biological neurons in the brain. The output layer has 1 neuron, for mental task to be recognized. In case of a successful classification the output of the neuron corresponding to the classified task tends to 1 or -1. Every neuron, except for the input layer, was initialized with a random weight in the range,

Where n is the number of neurons connected by means of that weight. As commonly done it was assigned to the input layer a constant weight of 1. After the output presentation a learning rule was applied. It is used a supervised learning method called back propagation. The back propagation calculates the mean-squared error between actual and expected output. The error value is then propagated backwards through the network, and small changes are made to the weights in each layer. The weight changes are calculated in order to reduce the error signal. The whole process was then repeated for each trial, and the cycle was reiterated until the overall error value drops below some pre-determined threshold.

EXPERIMENTAL DESIGN

Data

The dataset is collected from the Berlin Brain Computer Interface. The data was recorded from one healthy subject. This data set contains only data from the 7 initial sessions without feedback. The first 3 sessions are given with labels as training set. Visual cues (letter presentation) indicated for 3.5 seconds which of the following 3 motor imageries the subject should perform: (L) left hand, (F) right foot, (Z) tongue (=Zunge in german).

SIGNAL PREPROCESSING

Channel Selection

For the development of Brain computer interface system, the selection of channels is very important. Selecting the best channels, which contribute most of the desired information and keeping the resulting feature vector as small as possible while retaining the most valuable data. This channel selection is based on the mental task recognition. As the brain mental activity is divided into different region, this channel selection has crucial role in the current BCI research. To select the consistent channels one should develop theoretical information regarding the brain nature and function. This selection leads to low computational load, best feature vector selection, easy normalization, efficient preprocessing and correct mental task recognition.

Frequency Filtering

To decrease the dimensionality of the data, frequency filtering is required. We are applying the signal averaging technique, the alpha band frequency is selected i.e., 8-13Hz by using the FIR filters of EEG Lab.

classification

For classification Multilayer perceptron Neural Network is used. MLP is composed of several layers of neurons: an input layer, possibly one or several hidden layers and an output layer. Each neuron's input is connected with the output of the previous layer's neurons whereas the neurons of the output layer determine the class of the input feature vector. Neural networks and thus MLP are universal approximators, i.e., when composed of enough neurons and layers, they can approximate any continuous function. Added to the fact that they can classify any number of classes, this makes NN very flexible classifiers that can adapt to a great variety of problems, Consequently, MLP, which are the most popular NN used in classification, have been applied to almost all BCI problems such as binary or multiclass, synchronous or asynchronous BCI. However, the fact that MLP are universal approximators makes these classifiers sensitive to overtraining, especially with such noisy and nonstationary data as EEG. Therefore, careful architecture selection and regularization is required.

Neural network tool box (nntool) of MAT Lab R2008a is used for the construction of the network. Feed-forward Back propagation network type is selected, training function taken is TRAINLM (Levenberg-Marquardt back propagation), adoptive learning function used is LEARNGDM, transfer function selected is TRANSIG and performance function is MSE (Mean Square Error). Training parameters considered are epochs=1000, goal=0.000000000000001, max_fail=50 and min_grad=1e-010, rest we have taken the default parameters.

EXPERIMENTAL RESULTS AND ANALYSIS

The MLP architecture consists of input (10 nodes), hidden layer and output layer (1 node). The data was trained and run with different number of units in the hidden layer, and the MSE was observed at every secession. The number of hidden neurons was adjusted till a range until the relatively high performance (low MSE value) was obtained. 10 units in the hidden layer got the Mean Square error of **0.342**. This method worked with 100% training and 74% testing accuracy. The code used Mat lab Toolbox (nntool) only. After achieving the high performance trained network, then the network is simulated with test values and the outputs of the test values are recorded. The performance of the NN is increased by efficient preprocessing techniques like signal averaging using FIR filters. Correct Channel selection also plays a major role the NN architecture development. It is also observed that the number of hidden units must be in-between $l < n > 2l$, where l is the number of inputs. If the units exceeding $2l$, network lock is occurring. Performance of the net number of units should be considered in between the above mentioned range.

CONCLUSIONS

This paper has explored based on the features of the work that have been performed on the Berlin Brain-Computer interface data. The attractive features of the algorithm used include computational ease and speed; preprocessing efficiency and classification accuracy. The proposed method worked with **100%** training and **74%** testing accuracy. This work presents the possibility of the building BCI applications with faster and less intensive algorithms, thus making them capable of application in practical scenario. MLP neural network needs a reduced number of trials for training purposes; in the present work we have taken 16381 samples which is a huge training data. This is of fundamental importance because; training is a critical step since it is done a huge number of times in a

BCI system life. And so, the less a classifier is time demanding in the training phase, the more the patient is comfortable with it, being part of the communication load dramatically reduced.

FUTURE WORK

Future directions for this work includes exploration of classification algorithms like Radial Basic Function (RBF) Networks, or hybrid classification algorithms, one for feature extraction and other for training purposes. Using efficient preprocessing techniques like Independent Component Analysis (ICA) algorithm to add more relevant dimensions to the data. Adjusting the layers and inner options of the MLP algorithm and modifying the training technique is another method. The testing accuracy can be improved using various methods. Whatever be the direction, any further work should aim at reduction of computational complexity and memory dependency, as this is indispensable during the design of actual application interface.

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