Comparison of Static and Dynamic Neural Network Classifiers for Brain-Machine Interfaces

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Abstract— **neural network classifiers are one among the popular modes in the design of brain machine interface (BMI). In this study two novel dynamic neural network classifier designs for a four-state BMI are presented. Dynamic neural network based design for a four-state BMI to drive a wheelchair is analyzed. Motor imagery signals recorded noninvasively at the sensorimotor cortex region using two bipolar electrodes is used in the study. The performances of the proposed algorithms are compared with a static feed forward neural classifier. Average classification performance of 97.7% was achievable. Experiment results show that the distributed time delay neural network model out performs the layered recurrent and feed forward neural classifiers for a four-state BMI design.**

***Index Terms*—Brain Machine Interfaces, Dynamic Neural Networks, EEG Signal Processing**

I. INTRODUCTION

BMI systems help individuals to send commands to electronic devices only by means of brain activity. Such interfaces can be considered as being the only means of communication for people with motor disabilities [1]. BMI systems should be able to identify the different brain activity patterns produced by the user. This identification relies on a classification algorithm.

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Classification algorithms should deal with some critical feature properties such as poor signal to noise ratio, high dimensionality, time variation of specific brain patterns, non-stationary signals and small training sets. Many classifiers have been verified in BMI design; classifier taxonomy can be broadly grouped as, generative versus discriminative; static versus dynamic; stable versus unstable and regularized [2].

In this paper we present two classification algorithms using dynamic neural networks which overcome the drawback of the multilayer perceptrons where temporal information of the EEG is not considered for classification.

The first algorithm uses layered recurrent neural network architecture, while the second algorithm uses a distributed time delay neural network. The performances of the proposed algorithms are compared with a static feed forward neural classifier to validate the suitability of the classifiers in BMI design.

A synchronous experiment is used in this study, to analyze translation of brain activity into control signals to drive a wheelchair. Subject's motor imagery of left and right hand movements are recorded noninvasively for four mental tasks to design a four-state BMI. Two features sets are extracted from the EEG. The goal is to determine best classification algorithm and the optimal feature set.

A. Related Work

Classifiers used in BMI research can be divided into five categories: linear classifiers, neural networks, nonlinear Bayesian classifier, nearest neighbor classifiers and combination of classifiers [2]. Here our focus is on neural network classifiers. Linear classifiers and neural networks are the most used classifiers in BMI.

Among several architectures the multilayer perceptron (MLP) is the most widely used in BMI design based on EEG. 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 MLP very flexible classifier, consequently MLP has been used to almost all BMI problems such as binary or multiclass, synchronous or asynchronous BMI. However the fact that MLP are universal approximators makes these classifiers sensitive to overtraining, especially with such noisy and non-stationary data as EEG. Therefore careful architecture selection and regularization is required [2].

A Gaussian classifier specifically created for BMI is reported in [3]. Each unit of this NN is a Gaussian discriminant function representing a class prototype. The classifier is embedded in a portable brain computer interface called ABI, the classifier recognizes three mental tasks , relax, left and right the correct recognition is around 70%, one subject after five days of training achieved 93% , 61 % and 85% for relax, left hand and right hand movements respectively.

Other neural networks used marginally are learning vector quantization neural network with 60% for MI based three class BCI(Brain computer interface)[4], fuzzy art map neural network with 94.43% performance for five mental task based classifier [5], finite impulse response neural network with 87.4 % performance for MI based two class synchronous BCI[6], time delay neural network with 90% performance for movement intension based BCI, RBF neural network with 77.8 % performance for five mental task based BCI [7]and Recurrent neural networks with 80% for three mental task based BCI [8]. A detailed comparison of the above neural network based BCI are given in [2].

II. METHODS

A. *Experiment Paradigm*

BMI signals are recorded using a synchronous protocol, from 10 voluntary subjects. The subject is seated in a comfortable chair in front of a computer monitor. During the recording the subject is instructed not to move and to keep his hands relaxed. The MI tasks are cued by a visual stimulus presented on the monitor. The subject performs four tasks namely, relax, forward, left and right; the relax task is the baseline measurement task; for forward, left and right tasks an arrow appears on the monitor. Data are collected for two sessions, each session has five trials per task, and each task data is recorded for 10s. The imagination involves hand movements and not finger movements as in some BCI paradigms. The protocols for the four MI tasks are detailed below:

Task 1 – Relax: The subject is asked not to perform any specific task, but to relax as much as possible and think of nothing in particular. This task is considered as the baseline task and used as a stop control.

Task 2 – Forward: The subject is requested to fixate on the monitor showing an ‘up arrow’, the subject is requested to imagine moving both arms in a forward direction and the subject is requested to hold the thought for ten seconds. This is similar to using a games joystick for forward direction.

Task 3 – Left: The subject is requested to fixate on the monitor showing a left arrow, the subject is requested to imagine moving their left hand in the direction of the arrow and the subject is requested to hold the thought for ten seconds.

Task 4 – Right: The subject is requested to fixate on the monitor showing a right arrow, the subject is requested to imagine moving their right hand in the direction of the arrow, and the subject is requested to hold the thought for ten seconds.

B. *EEG Recording*.

An AD Instuments Power Lab amplifier is used in this experimentation. EEG is recorded using two gold plated cup bipolar electrodes placed at the C3 and C4 locations on the sensorimotor cortex area as per the International 10-20 Electrode Placement System [9], Figure 1 shows the electrode placement locations. A digital band pass filter (0.5 Hz to 100 Hz) is applied to the raw signal. The EEG signals are amplified and sampled at 200 Hz. The experiment consists of ten trials per task. Each trial lasts for 10 seconds. The subjects take breaks for 10 minutes between trials. All trials for a single subject were conducted on the same day. 10 healthy subjects aged between 16 and 46 participated in the study, at the time of data recording the subjects are free from illness or medication. 40 MI signals are collected from C3 and C4 electrodes for the four motor imagery tasks from each subject. For this experiment artifacts such as eye blinks are not removed.

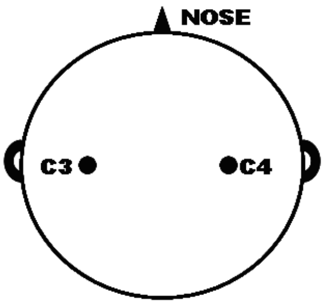

Fig.1. Electrode positions for data collection

To train and test classifiers a feature set is required to characterize the EEG. The EEG motor imagery is characterized using band power and parseval energy density methods; the two methods use the EEG time series to determine the features to classify the signals into the four mental states.

C. Feature Extraction.

We chose two feature sets to test the neural networks. The first one is the more conventional band power features of the mu and beta rhythms, and the other is the extraction of energy density spectrum using the parseval theorem. To extract the band power features, the raw EEG signals are segmented into 0.5s windows with an overlap of 0.25s. Segmented data are band pass filtered between 8 Hz and 30 Hz to obtain the mu and beta frequencies. A logarithmic transform is performed on the band power data. 195 features from five frequency components (8-10Hz, 10-12Hz, 13-15Hz, 16-18Hz and 19-30Hz) are extracted from the 10 second signals.

The second feature set is also obtained from the 0.5s segmented signals, by extracting the energy density spectrum features using the Parseval theorem [10] for each segment. The theorem states that the consumptive energy of discrete signal is equal to the square sum of the spectrum coefficients of the Fourier transform in the frequency domain. 39 features are extracted from a single task signal.

The features are normalized using a binary normalization algorithm [11] and are used as input for the neural classifier which is trained to classify the signals into one of the four mental states of the BMI.

III. Dynamic Neural Networks

Neural networks can be classified into dynamic and static categories. Static (feed forward) networks have no feedback elements and contain no delays; the output is calculated directly from the input through feed forward connections. In dynamic networks, the output depends not only on the current input to the network, but also on the current or previous inputs, outputs, or states of the network. The dynamic network has memory. Its response at any given time depends not only on the current input, but on the history of the input sequence. If the network does not have any feedback connections, then only a finite amount of history will affect the response.

A. Feed forward architecture

The topology of feed forward networks consists of a set of neurons connected by links in a number of layers. The basic configuration usually consists of an input layer, a hidden layer and an output layer. Feed forward networks implant fixed weight mapping from the input space to the output space. The weights of a feed forward network are fixed after training, so the state of any neuron is solely determined by the input-output pattern and not the initial and past states of the neuron, that is there is no dynamics; consequently such networks are classified as static neural network. The advantage of the static-feed forward neural network is that the network can be easily built with simple optimizing algorithm and is the most popular architecture in use today [12]. One important drawback of these networks is that the network cannot cope well with major changes that were never learned in the training phase.

B. Feedback architecture

Neural networks with feedback architecture, which has feedback connections from the output layer to the input layer or from the hidden layer to the input layer. Since neurons have one or more feedback link whose state varies with time, the feedback architecture is called a dynamic neural network. The presence of a feedback link has a profound impact on the learning capability of the network and on its performance. Because these networks have adjustable weights the state of its neuron depends not only on the current input signal but also on the previous state of the neuron.

The advantage of the dynamic neural network is that it can effectively decrease the network's input dimension and therefore the training time. Dynamic networks are generally more powerful than static networks (although somewhat more difficult to train), because dynamic networks have memory, they can be trained to learn sequential or time-varying patterns [12].

C. Layered recurrent neural network (LRNN)

This network is a modified version of an Elman network. In the LRNN, there is a feedback loop, with a single delay, around each layer of the network except for the last layer. The LRNN has an arbitrary number of layers and to have arbitrary transfer functions in each layer. The network is trained by a Bayesian regulation back propagation algorithm [13].

D. *DISTRIBUTED TIME DELAY NEURAL NETWORK (DTDNN).*

The DTDNN distributes the tapped delay lines throughout the network i.e. the first layer has weights coming from the input with the specified input delays. Each subsequent layer has a weight coming from the previous layer and specified layer delays. All layers have biases. The last layer is the network output. The network is trained by a resilient back propagation training algorithm [13].

E. Feed forward Neural Network (FFNN).

A static three layered FFNN is modeled to compare the performance of the dynamic neural networks. The training of the FFNN is accomplished by using Levenberg-Marquardt back propagation algorithm. Back propagation involves two phases [11, 14].

Forward Phase. During this phase the free parameters of the network are fixed and the input signal is propagated through the network layer by layer. The forward phase finishes with the computation of an error signal.

$$e_i = d_i - y_i \qquad (1)$$

where d_i is the desired response and y_i is the actual output produced by the network in response to the input x_i.

Backward Phase. During this second phase, the error signal e_i is propagated through the network in the backward direction. It is during this phase that adjustments are applied to the free parameters of the network so as to minimize the error e_i in a statistical sense.

DI. EXPERIMENTS

Four dynamic neural networks are modeled using the band power and parseval feature data. Two static neural networks are also modeled using the same data sets. For the band power features the classifiers are modeled using 195 input neurons 4 hidden neurons and 4 output neurons to indicate the four MI tasks. The numbers of hidden neurons are chosen experimentally. Training is conducted until the average error falls below 0.01 or reaches a maximum iteration limit of 1000. The parseval feature based classifiers are modeled with 39 input neurons, 4 hidden neurons and 4 output neurons. Training is conducted until the average error falls below 0.01 or reaches a maximum iteration limit of 1000.

In all the six classifiers, mean square error is used as a stopping criterion. 400 data samples are employed in this experiment. The training and testing samples is normalized by adopting a binary normalization algorithm [11]. Selection of the training and testing data is chosen randomly. All four classifier models are trained with 80% data samples and tested with 20% data samples for a testing error tolerance of 0.1.

DII. Results and Discussion

The dynamic and static architectures, training methods and training rates were determined using a trial and error approach. Several attempts were made until the proper learning rate; number of neurons in each hidden layer was reached. A training approach which combines adaptive learning with momentum training as the learning rate and four neurons in the hidden layer were selected. The network architecture selected after these attempts has produced the minimal error in both training and testing data.

The Classification performance of the proposed dynamic and static models for a four state BMI are shown in Tables 1 to 3. Table 1 shows the performance of the LRNN model for band power and Parseval features as the test data. The minimum, mean and maximum recognition accuracies are tabulated for all the 10 subjects. Similarly Table 2 and 3 shows the performance of the DTDNN and FFNN respectively. Table 4 shows the comparison of the training and testing time for the LRNN, DTDNN and FFNN classifier models.

The average classification results of the LRNN are 93% and 94% for the band power and parseval features respectively, the DTDNN average classification results are much higher at 97.65% and 97.7% for the band power and parseval features respectively. Examining the performance of all the network models it is seen that performance of the static FFNN models is inferior to that of the dynamic networks with average classification rates at 89.4% and 92.7% for the band power and parseval features respectively. The parseval features outperform the band power features in terms of average classification and training time. The DTDNN with parseval features is found to be the best classifier model among the six models designed for a four state BMI, with average efficiency of 97.7% and training time of 2.9s.

DIII. Conclusion

Six neural network classifiers for a four-state BMI to drive a wheelchair are proposed. Both static and dynamic network models are analyzed for four motor imagery tasks acquired from the motor cortex area. Network models were designed using two feature sets. Data from ten subjects were used in the experimentation. Comparisons of the performance of static and dynamic network model results are presented. First both static and dynamic network models yield a good classification with average classification performance ranging from 89.4% to 97.7%. This was achievable from EEG data collected from 10 trails only. Dynamic network models perform better than static models. Of the two features sets used the parseval features are found to be more suitable than band power features. The results suggest that the DTDNN network model with parseval features is best suited for a four state BMI design. The results obtained are comparatively better in comparison to Elman recurrent networks and functional link network proposed for MI signals in our earlier work in [15].

The experiment results also validate that the proposed algorithms have the ability of recognizing four mental states from the MI data collected with only two electrodes. No artifacts were removed from the EEG data, which shows the robustness of the algorithm. The output of the classifiers can be translated to control the navigation of a power wheelchair for three directional movements and to stop the wheelchair. However real-time experiments are to be conducted to verify the applicability of the proposed algorithms for actual navigational control of a wheelchair. This is an area of our current research. BMI has potential applications beyond rehabilitation and can be used by normal individuals to control their environment

TABLE 1
CLASSIFICATION PERFORMANCE OF THE LRNN

Subject	Recognition Accuracy in %					
	Band Power Features			Parseval Features		
	Min	Mean	Max	Min	Mean	Max
1	97.5	97.5	97.5	90	90	90
2	82.5	82.5	82.5	95	95	95
3	92.5	92.5	92.5	97.5	97.5	97.5
4	97.5	97.5	97.5	90	90	90
5	87.5	87.5	87.5	97.5	97.5	97.5
6	97.5	97.5	97.5	97.5	97.5	97.5
7	97.5	97.5	97.5	92.5	92.5	92.5
8	90	90	90	95	95	95
9	87.5	87.5	87.5	97.5	97.5	97.5
10	100	100	100	87.5	87.5	87.5

TABLE 2
CLASSIFICATION PERFORMANCE OF THE DTDNN

Subject	Recognition Accuracy %					
	Band Power Features			Parseval Features		
	Min	Mean	Max	Min	Mean	Max
1	90	96.75	100	97.5	99.75	100
2	85	96.75	100	92.5	97	100
3	97.5	99.5	100	92.5	97.75	100
4	87.5	98	100	97.5	99.75	100
5	95	99.25	100	92.5	98.5	100
6	65	95	100	80	94.75	100
7	97.5	99.75	100	87.5	96.25	100
8	95	99	100	95	98.5	100
9	90	97.5	100	92.5	97.75	100
10	85	95	100	87.5	97	100

TABLE 3
CLASSIFICATION PERFORMANCE OF THE FFNN

Subject	Recognition Accuracy %					
	Band Power Features			Parseval Features		
	Min	Mean	Max	Min	Mean	Max
1	60	95.31	97.5	90	90	90
2	82.5	83	85	47.5	89.75	97.5
3	92.5	93.25	95	97.5	97.5	97.5
4	30	89.5	97.5	42.5	85.25	90
5	87.5	88.5	90	97.5	97.5	97.5
6	52.5	84	97.5	97.5	97.5	97.5
7	45	90.25	97.5	92.5	93	95
8	90	90	90	95	95.75	100
9	87.5	87.75	90	57.5	92	97.5
10	25	92.5	100	87.5	89.5	92.5

TABLE 4
TRAINING AND TESTING TIME FOR THE SIX NEURAL CLASSIFIER MODELS

Subject	LRNN				FFNN				DTDNN			
	Band Power Features		Parseval Features		Band Power Features		Parseval Features		Band Power Features		Parseval Features	
	Train Time	Test Time	Train Time	Test Time	Train Time	Test Time	Train Time	Test Time	Train Time	Test Time	Train Time	Test Time
1	21.53	0.11	7.96	0.11	38.56	2.38	4.86	1.74	3.7	0.13	2.92	0.12
2	22.88	0.11	9.21	0.11	9.93	2.25	12.96	2.3	3.37	0.12	2.82	0.12
3	30.79	0.11	5.34	0.11	11.87	2.12	4.0	1.76	3.37	0.12	3.84	0.10
4	18.11	0.11	10.69	0.11	22.6	1.23	6.65	1.91	3.10	0.10	2.77	0.10
5	21.03	0.12	5.54	0.11	61.74	1.31	1.74	1.11	3.08	0.11	2.97	0.11
6	22.61	0.11	7.58	0.11	72.03	1.22	7.42	1.22	2.92	0.10	3.09	0.10
7	24.52	0.11	9.59	0.10	83.31	1.18	2.73	1.12	10.3	0.11	2.85	0.10
8	20.21	0.12	7.58	0.11	10.10	1.23	1.92	1.17	3.34	0.10	2.82	0.10
9	39.3	0.10	7.05	0.11	5.10	1.19	39.72	1.12	2.89	0.11	3.05	0.11
10	24.1	0.12	5.48	0.11	39.71	1.2	2.35	1.15	3.10	0.11	2.85	0.12

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