Four State Brain Machine Interface Design using Functional Link Networks

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Abstract— **The ability of an individual to control his EEG through imaginary motor tasks enables him to control devices through a brain machine interface [BMI]. BMI provides a direct link between the human brain and devices such as wheelchair and hand prosthesis bypassing the biological channels (peripheral nerves) for control. BMI are essentially designed to provide mobility to people with severe motor disabilities. This paper presents a four-state BMI design for controlling a power wheelchair. Electroencephalogram [EEG] signals acquired during motor imagery for left and right hand movements are used to classify the four controls. The BMI is designed using a Functional Link Neural Classifier [FLNN]. The performance of the four-state BMI is tested with three feature sets. From the results it is observed that the performance of the BMI is better for the FLNN model using MEIG features with an average efficiency of 93%.**

I. Introduction

EEG phenomena such as slow cortical potentials, P300 potentials, motor imagery, mu and beta rhythm control can provide rehabilitation for the severely disabled individuals to interact and communicate with their environment [1]. Motor imagery is the most common methodology employed by majority BMI researchers [1-5]. This can be attributed primarily to the purely cognitive nature of these methods as opposed to the requirement of stimulus in the P300 and evoked EEG- potential methods.

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Motor imagery can modify the neuronal activity in the primary sensorimotor areas in a very similar way as observable with real executive movements [2]. Sensory stimulation, motor behavior and mental imagery can change the functional connectivity within the cortex and results in amplitude suppression or event related desynchronization. With proper training and motivation, majority of the subjects can learn to control the intensities of specific frequency bands, which can be used as a control signal [3]. Pfurtscheller et al [4] have compared an adaptive autoregressive model (ARR) and neural network model to show an improvement in the error rate using ARR. Pfurtscheller and Neuper [2] present an ARR and Linear Discrimination approach to classify EEG signals for left and right movement from electrode positions C3, C4 and Cz, collected from a tetraplegic patient to control a hand.

The processing of the EEG within the motor imagery still shows open directions; most studies have relied on subjective evaluation and not objective confirmation of task performance. Motor imagery is a dynamic state in which a subject mentally simulates a given action [3]. In our earlier work [6] we observed that the performance of neural classifiers were comparatively better than fuzzy classifier for BMI design. In this work we propose a new algorithm using a FLNN classifier to classify the four-states of the BMI for a wheelchair control. Data recorded from two subjects involving motor imagery of hand movements is analyzed in this study.

II. METHODS

A. Experimental Paradigm

Motor imagery signals are recorded using a synchronous protocol, from 2 voluntary subjects. The subject is seated on a comfortable chair in front of a computer monitor. The room used for the experiments does not have any special acoustic control. 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 MI 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 protocols for the four MI tasks are detailed below:

Task 1 – Relax

The subjects are 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 for the wheelchair.

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.

Task 3 – Left: The subjects are 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 subjects are 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

EEG is recorded using and AD Instruments amplifier, two gold plated cup noninvasive electrodes are placed at the C3 and C4 locations on the sensorimotor cortex area and the earth electrode is placed at the Fp1 location ***as*** per the International 10-20 Electrode Placement System [8]. 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 twenty trials per task. Each trial lasts for 10 seconds. The subjects take breaks for 15 minutes between trials. All trials for a single subject were conducted on the same day. 2 healthy subjects aged 16 and 46 participated in the study, at the time of data recording the subjects are free from illness or medication. 80 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

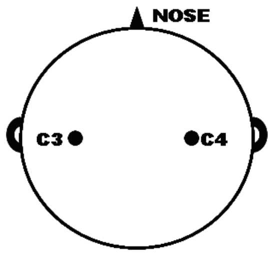

Fig. 1. Electrode positions for data collection

C. Feature Extraction

To train and test the classifier a feature set is required to characterize the EEG. The EEG motor imagery is characterized using three methods; the first two methods uses the EEG time signals to determine the features, while the second method uses the frequency content of the signals for classification. Some of the common feature extraction techniques are autoregressive models (AR), spectral density estimation, independent component analysis and principal component analysis (PCA).

Pfurtscheller et al [4] have used fixed autoregressive and adaptive autoregressive models to extract features from EEG data. Other researchers have used Common Spatial Patterns and PCA on left and right motor EEG imagery to extract features [5]. Time frequency analysis and spatial patterns of the EEG signals are used as feature descriptors by Wang et al [7]. PCA based methods are proposed in [6] which are used to dimensionally reduce the original data to first *n* features. For this experiment artifacts such as eye blinks were not removed. A novel feature extraction algorithm based on modified Eigen vector approach is proposed, the FLNN is also tested with parseval features and the conventional band power features.

The EEG trials are portioned into 0.5s windows, with an overlap of 0.25s. The first method uses the modified Eigen vector features (MEIG) of window segments of the EEG motor imagery to extract the features. The feature extraction algorithm uses the following procedure:

.1. S = sample data for 10 seconds
2. Apply band pass filtering 0.5 Hz to 100 Hz
3. S is partitioned into 0.5 seconds windows with overlap 0.25s
4. E = segmented signal multiplied with its transpose
5. Extract Eigen vector of E;
6. Repeat 1 to 5 for each trial. 39 features are extracted from the EEG signal per task per trial.

The second method uses the parseval theorem [9] to extract the energy density features of the segmented signals. 39 features are extracted from the EEG signal per task per trial. In the third method band power of five frequency bands (8-10Hz), (10-12Hz), (13-15Hz), (16-18Hz) and (19-30Hz) from each segmented signal is extracted. 195 features are extracted from the EEG signal per task per trial. The FLNN is trained and tested with the three features sets.

D. *FLNN Classifier*

Since neural networks are used for identification and control, the learning capabilities of the networks can have significant effects on the performance of the system. If the information content of data input to the network can be modified in an appropriate way the network will be able to more easily extract the salient features of the data. This is the motivation behind the FLNN. Functional links basically expand the original input space into higher dimensions in an attempt to reduce the burden on the training phase of the neural network. In one sense no new ad hoc information has been inserted into the process, nonetheless, the representation has definitely been enhanced and separatibility becomes possible in the enhanced space, thus both the training and the training error of the network can be improved [10, 11].

For the first two feature sets the FLNN classifiers are modeled with 39 input neurons, 5 hidden neurons and 4 output neurons. The functional link is applied to the input layer. The input layer has 39 inputs from the features extracted and 77 inputs provided by the functional link (f_n) in eqn (1), applied on the input where *n* is the number of input neurons.

$$f_n = (2n - 1) \tag{1}$$

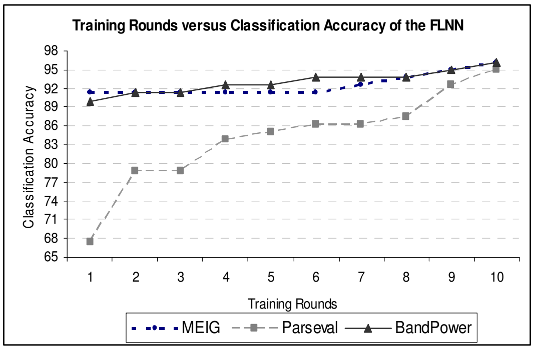

Fig.2. Training round versus Classifications Accuracy for all three FLNN models for Subject 1.

The third FLNN model has 195 input neurons, 389 unctional link neurons, 4 hidden neurons and 4 output neurons. Hidden neurons in all three NN models are chosen experimentally. Training is conducted until the average error falls below 0.01 or reaches a maximum iteration limit of 1000.

The FLNN models are trained using the back propagation algorithm [12].

In all classifiers mean square error is used as a stopping criterion. 80 data samples are used in this experiment. The training and testing samples is normalized using binary normalization algorithm [12]. Selection of the training and testing data is chosen randomly. All four classifiers are trained with 80% data samples and tested with 20% data samples for a testing error tolerance of 0.1.

III. Results and Discussion

Classification performance of the three FLNN models is summarized in Table I and II for subject 1 and subject 2 respectively. The classification of the motor imagery signals for the four states is shown in the tables as the mean and maximum classification obtained from the 80 samples for subject 1 and subject 2. Subject 2 is a right handed person, while subject 1 can write using both left and right hands. From Table I and II it is observed that the proposed FLNN using MEIG features has good performance for subject 1; while for subject 2 the FLNN with parseval features has good performance. Fig.2 shows the training rounds versus classification accuracy for all three FLNN models for subject 1.

TABLE I
CLASSIFICATION PERFORMANCE OF THE FLNN FOR SUBJECT 1

MEIG		Parseval		Band Power	
Mean %	Max %	Mean %	Max %	Mean %	Max %
93	96.25	92.5	96.25	84.12	95

TABLE II
CLASSIFICATION PERFORMANCE OF THE FLNN FOR SUBJECT 2

MEIG		Parseval		Band Power	
Mean %	Max %	Mean %	Max %	Mean %	Max %
91	92.5	92.38	95	86	91.25

From the results it is also observed that the performance FLNN with MEIG features has the shortest average testing time of 0.05s which makes it ideal for real time experiments.

IV. Conclusion

A novel classification algorithm for a four state BMI design for a wheelchair control using motor imagery is presented. Data collected from the sensorimotor cortex regions for relax, forward; left and right tasks are classified. Three FLNN models with different feature sets are trained and tested with motor imagery data. Average performance of 93% was observed for the proposed MEIG features. It should be noted that the EEG data were collected from twenty trails only. Classification could be improved by training the subjects to control the EEG signals. Artifacts were not removed which improves the robustness of the proposed method.

The output of the classifier can be translated to control the directional movements of a power wheelchair. However many issues need to be investigated before the practical utility of the method can be established. BMIs have potential applicability beyond the restoration of mobility in paraplegics and would enable normal individuals to have direct brain control of external devices in their daily lives.

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