Motor Imagery Signal Classification for a Four State Brain Machine Interface

Hema C.R., Paulraj M.P., S. Yaacob, A. H. Adom, R Nagarajan

Abstract—Motor imagery classification provides an important basis for designing Brain Machine Interfaces [BMI]. A BMI captures and decodes brain EEG signals and transforms human thought into actions. The ability of an individual to control his EEG through imaginary mental tasks enables him to control devices through the BMI. This paper presents a method to design a four state BMI using EEG signals recorded from the C3 and C4 locations. Principle features extracted through principle component analysis of the segmented EEG are analyzed using two novel classification algorithms using Elman recurrent neural network and functional link neural network. Performance of both classifiers is evaluated using a particle swarm optimization training algorithm; results are also compared with the conventional back propagation training algorithm. EEG motor imagery recorded from two subjects is used in the offline analysis. From overall classification performance it is observed that the BP algorithm has higher average classification of 93.5%, while the PSO algorithm has better training time and maximum classification. The proposed methods promises to provide a useful alternative general procedure for motor imagery classification

Keywords—Motor Imagery, Brain Machine Interfaces, Neural Networks, Particle Swarm Optimization, EEG signal processing.

I. INTRODUCTION

BRAIN Machine Interface is a digital communication system, which connects the human brain directly to an external device bypassing the peripheral nervous system and muscular system. Thus a BMI opens up possibilities for a new communication channel for people with neuromuscular disorders. BMI can be designed by classifying the brain signals obtained through Electroencephalography (EEG). The spatio-temporal pattern changes in the EEG can be recognized and associated with subject's actual hand movements, imagined movements or observation of movements. The EEG electrodes are mainly chosen to be placed on the scalp overlying the sensorimotor cortex where the recorded EEG signals are sensitive to the movements. This paper

focuses on motor imagery which is the mental simulation of an imagined motor act. Motor imagery is a popular methodology employed in control BMI. 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. Motor imagery can modify the neuronal activity in the primary sensorimotor areas in a very similar way as observable with real executive movements [1]. Motor imagery refers to the active process by which humans experience sensations with or without external stimuli. It is active process during which a specific action is reproduced within working memory without any real movements. Motor imagery maybe seen as a motor act without any overt motor output. Sensory stimulation, motor behavior and mental imagery can change the functional connectivity within the cortex and results in amplitude suppression [event related desynchronization (ERD)] in amplitude enhancement [event related synchronization (ERS)] [1]. 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 communication or control signal [2].

Motor imagery has been under study to translate the EEG signal into left and right movement of a computer cursor. To analyze the EEG signals different methods have been proposed in the literature. Pfurtscheller et al [3] have compared an adaptive autoregressive model (ARR) and neural network model to show an improvement in the error rate using ARR. Pfurtscheller and Neuper [1] 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 orthosis. An accuracy of 65% was achieved after 28 training sessions. To analyze EEG signals different methods have been proposed by various researchers: autoregressive model [4], time-frequency analysis [5, 7, 8], neural networks [6], and Fuzzy [9].

Most literature focus on two states or three states BMI, this paper investigates the possibility of defining a four state BMI design using EEG signals recorded from two electrode positions C3 and C4. Our work presents a procedure for extracting PCA features from the EEG recorded from two subjects during motor imagery of hand movements. Neural networks are used to recognize four mental states from the

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EEG. Performances of four network models are compared to validate the methodology.

Chapter II of the paper presents the methods for feature extraction and classification while Chapter III discusses on the experimental procedure. Results and Discussion are presented in chapter IV and some conclusions are given in Chapter V.

II. METHODS

A. Feature Extraction

Feature extraction methods can be broadly grouped under four taxonomy namely Time, Space, Time-Space and Inverse models. Most common among the time methods is the autoregressive models [1, 4], band pass filtering and wavelets [12, 13]. Among the Space taxonomy, principle component analysis (PCA) [11], independent component analysis and common spatial patterns are the more popular feature extractors. PCA based methods are generally used to dimensionally reduce the original data to first n Eigen values or to reduce the numbers of channels, where the possibility of losing essential data is inevitable. This paper uses a modified approach in the application of PCA on the EEG segments to retain the principle features. Some researchers have used Time frequency analysis and spatial patterns of the EEG signals as feature descriptors [8].

PCA is a linear transformation from a high dimensional data space to a principle component feature space. The EEG signals collected from the ten sessions from two subjects are segmented into 0.5s windows with an overlap of 0.25s. PCA is applied to the window segments to extract principle features from the EEG signals this method decomposes and retains the data information of the two channels. As frequencies above 40 Hz convey little information related to motor imagery a band pass filter is applied to remove all signals below 0.5 Hz and above 40 Hz. The sequence of the feature extraction process uses the following procedure. 1. S = sample data for 10 seconds, 2. Apply band pass filtering 0.5 Hz to 40 Hz, 3. S is partitioned into 0.5 seconds windows with overlap 0.25s, 4. Do PCA on each window, 5. Repeat 1 to 4 for each trial. 39 features are extracted from the EEG signal per task per session. The features are extracted for the four tasks and for ten sessions from each subject.

B. Classification Procedures

Elman recurrent neural networks (ERNN) have feedback connections which add the ability to also learn the temporal characteristics of the data set. In this research Elman recurrent neural network architecture with three layers is used. The ERNN makes a copy of the hidden layer which is referred to as the context layer. The purpose of the context layer is to store the pervious state of the hidden layer at the previous pattern presentation [14].

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 functional link neural networks (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 [15, 16].

C. Particle Swarm Optimization Training Algorithm

The initial intent of the particle swarm concept was to graphically simulate the graceful and unpredictable choreography of a bird flock. In Particle Swarm Optimization (PSO) individuals referred to as particles are flown through hyper dimensional search space. Changes to the position of particles within the search space are based on the social-psychological tendency of individuals to emulate the success of other individuals. The changes to a particle within the swarm are therefore influenced by the experience or knowledge of its neighbors. The search behavior of the particle is thus affected by that of other particles within the swarm. The structure of the PSO is determined through the formation of neighborhoods. Individuals within the neighborhood can communicate with each other. Different neighborhood types have been defined and studied, namely star topology, ring topology and wheels topology [17].

A swarm consists of a set of 'N' particles where each particle represents a potential solution. Particles are then flown through the hyperspace, where the position of each particle is changed according to its own experience and that of its neighbors. In the original formulation of PSO [12], each particle is defined as a potential solution to the problem in a D- dimensional space. The particle i is represented in a D dimensional space as

$$X_i = (x_{i1}, x_{i2}, x_{i3}, ..., x_{iD})$$

and each particle maintains a memory of its previous best position. The best previous position of the ith particle can be represented as

$$P_i = (p_{i1}, p_{i2}, p_{i3}, ..., p_{iD})$$

and the velocity for the ith particle is represented as

$$V_i = (v_{i1}, v_{i2}, v_{i3}, ..., v_{iD})$$

The particle position with the highest fitness value for the entire run is called the global best. The global best particle among all the particles in the population is represented by

$$P_g = (p_{g1}, p_{g2}, p_{g3}, ..., p_{gD})$$

For each iteration the velocity vector of every particle is adjusted based on its best solution and the best solution of its neighbors. The position of the velocity adjustment made by the particle's previous best position is called the cognition component and the position of the velocity adjustments using the global best is called the social component. The updated PSO equations described in [11] are

$$v_{id}(t+1) = \omega v_{id}(t) + \eta_1 * rand() * (p_{id}(t) - x_{id}(t))$$
$$+ \eta_2 * rand() * (p_{gd}(t) - x_{gd}(t)) \tag{1}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t) \tag{2}$$

where ω is the inertia weight, η_1 and η_2 are positive acceleration constants. The velocity vector drives the optimization process and reflects socially exchanged information [18]. In this paper the global best algorithm is used which is as shown below.

1. Initialize the swarm $P(t)$, of particles such that the position $X_i(t)$ of each particle $P_i \in P(t)$ is random within the hyperspace , with $t = 0$.
2. Evaluate the performance $F X_i(t)$ of each particle, using its current position $X_i(t)$.
3. Compare the performance of each individual to its best performance thus far:
   if $F(X_i(t)) < p_{id}$ then

   (a) $p_{id} = F(X_i(t))$

   (b) $P_i = X_i(t)$
4. Compare the performance of each particle to the global best particle if $F(X_i(t)) < p_{gd}$ then
   (a) $p_{gd} = F(X_i(t))$

   (b) $P_g = X_i(t)$
5. Change the velocity vector for each:

   $$v_{id}(t+1) = \omega v_{id}(t) + \eta_1 * rand() * (p_{id}(t) - x_{id}(t))$$
   $$+ \eta_2 * rand() * (p_{gd}(t) - x_{gd}(t)) \tag{3}$$

   the second term in the above equation is referred to as the cognitive component, while the last term is the social component.
6. Move each particle to a new position.

   (a) $$x_{id}(t+1) = x_{id}(t) + v_{id}(t) \tag{4}$$

   (b) $t = t + 1$

7. Go to step 2 and repeat until convergence.

The further away a particle is from the global best position and its own best solution thus far, the larger the change in velocity to move the particle back toward the best solutions [18].

D. Back Propagation Training Algorithm

The back propagation (BP) training algorithm involves three stages [19] the feed forward of the input training pattern, the calculation and back propagation of the associated weight error and the weight adjustments. The training algorithm is as shown below.

1. Initialize the weights.
2. While sum squared error is greater than the tolerance, execute steps 3 to 8
3. For each training pair x: t, do steps 4 to 8
4. For each hidden layer neuron, compute the net weighted input signal.
5. Apply the activation function and compute the output of the hidden neuron and broadcast this output to the next layer.
6. For each output layer neuron, compute the net weighted input signal.
7. Apply the activation function and compute the output of the output neuron.
8. For each output neuron compute the error gradient and update the weights connected between the hidden to output neurons.
9. For each hidden neuron compute the error gradient and update the weights between the inputs to hidden neuron.
10. Compute the sum squared error.

III. EXPERIMENTS

A. Experimental Protocol

Two healthy subjects participated in the experiments. During the recordings the subjects are instructed not to make overt movements and keep their hands relaxed. The motor imagery task was cued by a visual stimulus presented on a computer monitor. Each trail is 10 s long, the subject performs four tasks namely, relax, forward, left and right, for the relax task a word 'RELAX' appears on the monitor, for forward, left and right tasks an arrow pointing to up, left and right respectively appears on the monitor.

Task 1 – Baseline Measurement
The subjects do not perform any specific task, but are asked to relax as much as possible and think of nothing in particular. This task is considered the baseline task for alpha wave production and used as a control measure of the EEG.

Task 2 – Forward
The subjects are requested to fixate on the monitor showing an upward arrow, the subjects are requested to imagine moving both hands in the direction of the arrow, and the subjects are 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 subjects are requested to imagine moving their left hand in the direction of the arrow, and the subjects are 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 subjects are requested to imagine moving their right hand in the direction of the arrow, and the subjects are requested to hold the thought for ten seconds. Each motor imagery task is recorded for 10 seconds; EEG is recorded from ten such sessions for each subject.

B. EEG Recording

An ADI 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 [20], 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 consisted of ten sessions per subject for each of the four tasks. All sessions were conducted on the same day. In this experiment two healthy subjects aged 15 and 46 participated, at the time of data recording the subjects are free from illness or medication. 40 EEG signals collected from C3 and C4 electrodes for the four motor imagery tasks are considered for classification. For this experiment artifacts such as eye blinks were not removed. EEG is recorded for 10seconds for each task per session
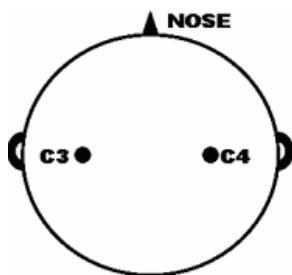

Fig. 1 Electrode positions for data collection

C. PSO Neural Network Models

The PSO ERNN classifier is modeled using 39 input neurons 15 hidden neurons and 4 output neurons. The numbers of hidden neurons are chosen experimentally. The ERNN is trained using the PSO algorithm discussed in section II. Thus for a 39-15-4 NN architecture (with bias) requires an optimization of 649 parameters. The problem is approached by using a particle swarm of 649 dimensional spaces. Training is conducted until the average error falls below 0.001 or reaches a maximum iteration limit of 1000. The PSO FLNN classifier is modeled with 39 input neurons and 4 output neurons. The input layer has 39 inputs from the features extracted and 77 inputs provided by the functional link (2n -1) applied on the input where n is the number of input neurons. Training is conducted until the average error falls below 0.1 or reaches a maximum iteration limit of 1000. The FLNN is trained using the PSO algorithm.

D. BP Neural Network Models

The BP ERNN classifier is modeled using 39 input neurons 6 hidden neurons and 4 output neurons. The numbers of hidden neurons are chosen experimentally. The ERNN is trained using the BP algorithm. Training is conducted until the average error falls below 0.001 or reaches a maximum iteration limit of 10000. The BP FLNN classifier is modeled with 39 input neurons, 4 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 (2n -1) applied on the input where n is the number of input neurons. Training is conducted until the average error falls below 0.001 or reaches a maximum iteration limit of 1000. The FLNN is trained using the BP algorithm.

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 [19]. Selection of the training and testing data is chosen randomly. All four classifiers are trained with 75% data samples and tested with 100% data samples for a testing error tolerance of 0.05.

IV. RESULTS AND DISCUSSION

Classification performance of the ERNN and the FLNN for both training algorithms are summarized in Table I and II respectively for the two subjects. In the testing phase 100% data samples were used. The classification of the motor imagery signals for the four states is shown in the tables as the minimum, 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 performance of the ERNN is comparatively better than the FLNN. No artifacts were removed from the EEG data, which shows the robustness of the algorithm. From the results it is also observed that the performance of the PSO algorithm is promising in terms of training time and maximum classification, average training of 5.93 seconds were observed in the PSO algorithm as against 17.76 seconds in the BP algorithm. Highest mean classification accuracy of 93.5% was observed for the BP ELMAN classifier while the BP FLNN had 93.25% accuracy. Figure 2 and 3 show the cumulative

error versus epoch plot for the BP ELMAN and BP FLNN classifiers respectively. Performance of subject 2 were comparatively better than subject 1. Designing a four state BMI using the motor imagery of the C3 and C4 locations proposed here provides a new procedure in designing BMIs using minimal electrodes.

TABLE I
CLASSIFICATION PERFORMANCE OF ERNN

Classification Performance	PSO Training		BP Training	
	Subject 1	Subject 2	Subject 1	Subject 2
Min Classification %	75	75	90	85
Ave Classification %	87.5	85	92.5	93.5
Max Classification %	100	100	97.5	100

TABLE II
CLASSIFICATION PERFORMANCE OF FLNN

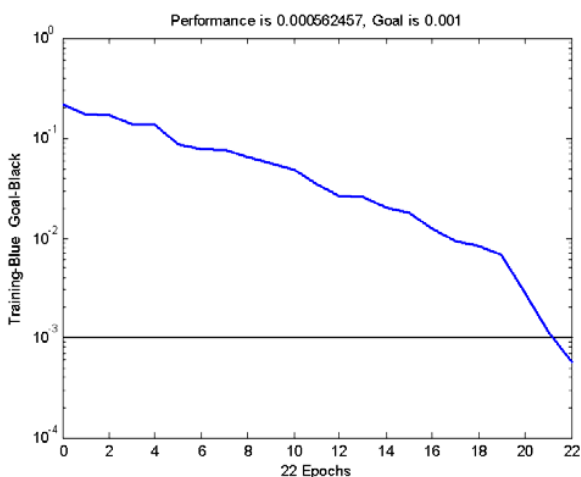| Classification Performance	PSO Training		BP Training	
	Subject 1	Subject 2	Subject 1	Subject 2
Min Classification %	75	75	85	90
Mean Classification %	82.1	80	91.25	93.25
Max Classification %	100	100	97.5	97.7

Fig. 2 Cumulative error vs. Epoch plot for BP ELMAN classifier
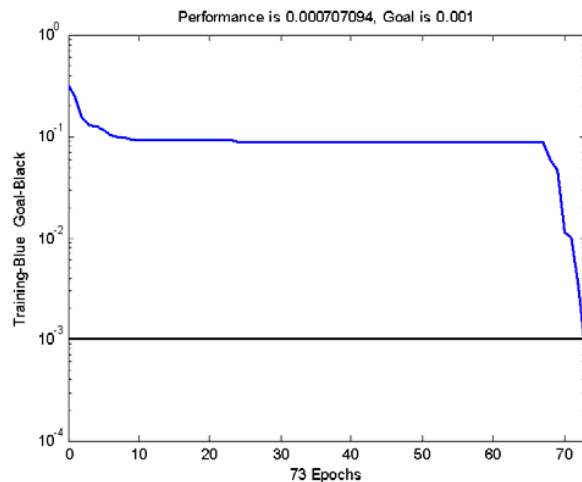

Fig. 3 Cumulative error vs. Epoch plot for BP FLNN classifier

V. CONCLUSION

A new protocol and four classification algorithms for a four state BMI design using motor imagery is presented. Data collected from the sensorimotor cortex regions for relax, forward, left and right tasks are classified.

PSO and BP training algorithm are used in the training process of the two classifiers presented. The PCA features of the segmented motor imagery signals are classified using an Elman and Functional Link Neural Classifiers. A comparison of the results is presented. Average scores of 93.5 % were observed using BP based classifiers, while PSO based classifiers had better training time and maximum classification of 100% with a testing error tolerance of 0.1. The ERNN was found to be more suitable for classification of motor imagery data. It should be noted that the EEG data were collected from ten 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 movement of devices such as prosthetic arms. However many issues need to be investigated before the practical utility of the method can be established. Features used in this work were obtained from 0.5 s window data, shorter time window has to be considered and analyzed before the method can be tested for real time scenarios. EEG signals have potential applicability beyond the restoration of lost movement and rehabilitation in paraplegics and would enable normal individuals to have direct brain control of external devices in their daily lives.

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