Brain Machine Interfaces: Recognition of Mental Tasks using Neural Networks and PSO Learning Algorithms

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Abstract— **Brain machine interface (BMI) provides a digital channel for communication in the absence of the biological channels. BMIs are used to rehabilitate patients with neurodegenerative diseases, a condition in which all motor movements are impaired including speech leaving the patients totally locked-in. BMIs are designed using the electrical activity of the brain detected by scalp EEG electrodes. Classification of EEG signals extracted during mental tasks is a technique for designing a BMI. In this paper five different mental tasks from two subjects were studied, combinations of two tasks are studied for each subject. Two neural network architectures using a novel particle swarm optimization (PSO) learning algorithm is studied. Band power features of the EEG signals are used for the classification. The classification performance of the functional link network is seen to be higher than an Elman network. Baseline and Math tasks were found to be more suitable in designing the BMI. The results obtained validate the performance of the PSONN algorithm for mental task classification.**

Index Terms— **Brain Machine Interfaces, EEG Signals, Mental Tasks, Neural Networks, Particle Swarm Optimization Training.**

I. Introduction

BMI provides a direct communication link between the brain and an external device in the absence of the biological communication channels. Neuromuscular disorders like amyotrophic lateral sclerosis can temporarily or permanently impair spoken and physical communication. Those most severely affected may lose all voluntary muscle control and may be completely locked-in to their bodies, unable to communicate in any way. However sensory and cognitive abilities often remain intact. Using the cognitive abilities is sometimes the only way to restore communication for conveying messages and commands to the external world. At present, only EEG and related methods, which have relatively short time constants, can function in most environments, they also require relatively simple and inexpensive equipment. Through training, subjects can learn to control their brain activity in a predetermined fashion that is classified by a pattern recognition algorithm [1].The EEG is measured directly from the cortical surface. When brain cells or neurons are activated, local current flows are produced. EEG measures mostly the currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. The highest influence of EEG comes from electric activity of cerebral cortex due to its surface position [2].

In this paper two neural networks namely Elman Recurrent Neural Networks (ERNN) and Functional Link Neural Networks (FLNN) are proposed to classify five mental task signals using a PSO learning algorithm. Band power features extracted from the mental task signals are used as input features. Features are extracted from EEG signals, recorded during five mental tasks, namely baseline–resting, mathematical multiplication, geometric figure rotation, letter composing and visual counting. The features are used by the neural nets to classify different combinations of two mental tasks. The output of the BMI interface could be used with some translation schemes for left or right movement, or as a Morse code [3] for two way movement control for a device. This serves as the communication or control channel for the paralyzed patients with motor impairments.

II. Background

Autoregressive models are one of the common feature extraction techniques in analyzing EEG signals. Huan et al [3] use fixed and adaptive autoregressive models of EEG signals for classification of mental tasks. EEG data collected by Keirn and Aunon [4] has been used in this study. Four different features extractions methods are proposed to extract features from the EEG signals. Fixed AR coefficients computed with Burg's algorithm using 125 data points without segmentation and with segmentation of 25 data

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points. Adaptive AR coefficients computed with Least–Mean-Square Algorithm using 125 data points without segmentation and with segmentation of 25 data points. Multilayer Perceptrons trained by BP algorithm is used to classify these features. The FAR without segmentation was found to be the best among the four methods with an average classification of 74.09% followed by FAR with segmentation with an average classification of 72.04%.

Work reported in this article uses the data collected by Keirn and Aunon [4]. In their study they investigated the classification of five different mental tasks. Data were recorded from seven subjects using six channels. Features were first extracted from spectral estimates, calculated from both the Fourier transform of the windowed autocorrelation function and a scalar AR model. Features extracted were asymmetry ratios and power values for each channel from the four frequency bands, delta, theta, alpha and beta. Asymmetry ratios were taken across all right to left combinations of leads defined by (R - L)/(R + L). A second set of features were generated from the AR coefficients themselves concatenated together from all channels. The classifier in this case was a quadratic Bayesian classifier. Average results of 84.6 % were obtained using AR coefficients as the features.

Multivariate Autoregressive models for classification for spontaneous EEG signals during mental tasks are proposed by Anderson et al [5]. EEG signals from four subjects were recorded while they performed two mental tasks. Quarter second windows of six channels EEG were transformed into four different representations: scalar AR model coefficients, multivariate AR coefficients, and Eigen values of a correlation matrix and the Karhunen-Loeve transform of the multivariate AR coefficients. Feature vectors defined by these representations were classified with a FFNN. Multivariate AR coefficients were found to perform slightly better than the other methods with an average accuracy of 91.4% on novel untrained data.

In one of our previous studies Hema et al [6], EEG data collected from five subjects for five mental tasks were studied, the power of the four spectral bands namely alpha, beta, delta and theta were extracted and summed. A logarithmic transform was performed on the summed values to extract the features. 28 features were used to classify a mental task. A simple FFNN was used for classification. Average classification of 90.4 % was achieved.

Wavelet is another common feature used in EEG signal analysis. Bostanov [7] introduced a continuous wavelet transform to detect event related potentials (ERP) for classification of single trial ERP. The classifier used was a classical linear discriminant analysis. The classification had 17.4% errors.

Anderson et al [8] suggest a generalized singular value decomposition to separate multichannel EEG into components found by optimizing a signal to noise ration quotient. These components are used to filter out artifacts. Short time principal component analysis of time delay embedded EEG is used to represent windowed EEG data to classify EEG according to five mental tasks [4] using a K-means clustering. 75% classification was obtained first four tasks and 60% for the fifth task.

III. Methods

A. Experimental Data

Data used in this study, was collected by Keirn and Aunon [4]. The EEG electrodes were connected through a bank of Graz amplifiers whose band pass analog filters were set at 0.1 -100Hz. and the amplified EEG traces were sampled and stored at 250 samples per second. The data collected from two subjects were used in this study. The subjects execute five different mental tasks while remaining in a totally passive state. No overt movements were made during the performance of the tasks. Subjects are seated comfortably in a sound controlled booth with dim lighting. Subjects were aged between 21 and 48. EEG signals are obtained from two subjects using six electrodes placed at the O_1, O_2 , P_3 , P_4, C_3 and C_4 locations of the international 10 -20 system [9],

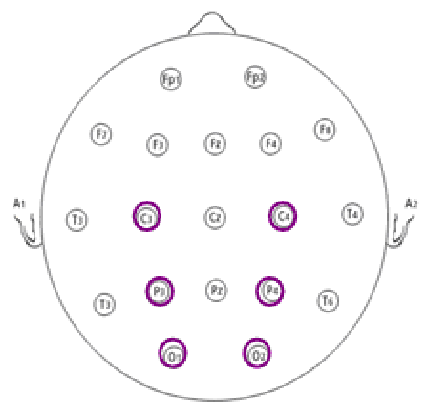

Fig. 1. . Electrode positions for Data Collection

Fig.1 shows the electrode placement locations. The subjects were requested to perform five mental tasks and data from all the six electrodes were reordered for 10s during a given task and each

task was repeated five times per session. Data from two sessions is collected. The sampling frequency is 250Hz. Following is the description of the tasks performed by each subject.

Task 1 – Baseline Measurement

No mental task is performed, subjects are told to relax and try to thing of nothing in particular. This task is used as a baseline measure of the EEG.

Task 2 – Complex Problem Solving

The Subject is given a nontrivial multiplication problem to be solved mentally without vocalization and overt movements.

Task 3 – Geometric Figure Rotation

Subject is shown a 3D block figure drawing of an object after which the drawing is removed and the subject is instructed to visualize the rotation of the object about an axis.

Task 4 – Mental Letter Composing.

The subject is instructed to mentally compose a letter to a friend without vocalizing.

Task 5 – Visual Counting

The subject is instructed to imagine a blackboard and to visualize numbers being written on a board sequentially with the previous number being erased before the next number is written, the subject is also asked to count the numbers.

Keirn and Aunon [4] chose these tasks since they involve hemispheric brainwave asymmetry (except for the baseline task).

B. Feature Extraction

In the experimental study a combination of two tasks for each subject is used for classification. In this paper band power features of four EEG bands are extracted from the mental task signals. Previous researchers [3, 4] have used fixed autoregressive and adaptive autoregressive models to extract features on the same data set. Anderson et al [9] suggest a Time-delay embedding; PCA based method for classification of EEG signals using a K-means clustering. Other researchers have used Common Spatial Patterns and PCA on left and right motor EEG imagery to extract features [8]. Time frequency analysis and spatial patterns of the EEG signals are used as feature descriptors by Wang et al [10]. PCA based methods are generally used to dimensionally reduce the original data to first *n* eigenvalues [11], or to reduce the numbers of channels, where the possibility of losing essential data is inevitable. Others have used wavelet transforms as a feature extractor for EEG signals [7]. In this paper the EEG signals collected from six electrodes for five mental tasks are considered. For this experiment artifacts such as eye blinks were not removed. EEG is recorded for 10seconds at 250 Hz. The proposed algorithm uses the four frequency bands of the EEG signal to extract the EEG features. It has been suggested by Keirn and Aunon [4] that alpha band asymmetry ratios alone would yield poor classification results, hence all the four frequency bands namely delta (0-3 Hz), theta (4-7 Hz), alpha (8 – 13 Hz) and beta (14- 20 Hz) are considered in creating the feature set .The feature extraction algorithm consists of three steps:

1) Band pass filters are applied to extract the four frequency band signals.
2) Sum of the power values are extracted and
3) A logarithmic transform is performed on the summed power value.

28 features are extracted for each subject per task combination. The features are extracted for ten such trials and are used to train and test the two neural networks.

IV. PARTICLE SWARM OPTIMIZATION NEURAL NETWORKS

Multilayer Elman and Functional Link neural networks with one hidden layer are trained using the PSO algorithm. The PSO algorithm is a population based search algorithm based on social behavior of birds within a flock. PSO requires only primitive mathematical operators and is computationally inexpensive in terms of both memory requirements and speed. The features that drive PSO are social interaction. Individuals (particles) within the swarm learn from each other and based on the knowledge obtained move to become more similar to their better neighbors. 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 [12].

A. The Particle Swarm Optimization Algorithm

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 [13], 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

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

and each particle maintains a memory of its previous best position. The best previous position of the i^{th} particle can be represented *as*

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

and the velocity for the i^{th} particle is represented as

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

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

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

At 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 [14] are

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

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

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 [12]. 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 $\boldsymbol{X_i(t)}$ of each particle $\boldsymbol{P_i} \in \boldsymbol{P(t)}$ is random within the hyperspace , with $t = 0$.
2. Evaluate the performance $F\ \boldsymbol{X_i(t)}$ of each particle, using its current position $\boldsymbol{X_i(t)}$.
3. Compare the performance of each individual to its best performance thus far:
   if $F\ (\boldsymbol{X_i(t)}) < p_{id}$ then
   (a) $p_{id} = F\ (\boldsymbol{X_i(t)})$
   (b) $\boldsymbol{P_i} = \boldsymbol{X_i}$(t)
4. Compare the performance of each particle to the global best particle if $F\ (\boldsymbol{X_i}(\mathrm{t})) < p_{gd}$ then
   (a) $p_{gd} = F\ (\boldsymbol{X_i(t)})$
   (b) $\boldsymbol{P_g} = \boldsymbol{X_i(t)}$
5. Change the velocity vector for each:

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

where the second term above is referred to as the cognitive component, while the last term is the social component.

6. Move each particle to a new position.

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

(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 [14].

A. ELMAN Neural Networks

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 [12].

An ERNN with 28 input neurons and one output neuron is considered to classify the EEG features. The numbers of hidden neurons are chosen experimentally. By experimental study it is observed that the performance of the network is better when five hidden neurons and ten hidden neuron were chosen and there is no significant improvement in the network performance if the numbers of hidden neurons are fixed more than 10. The input layer has 28 nodes The NN is trained with one hidden layer with five neuron and ten neurons respectively. Thus for a 28-1-1 NN architecture (with bias) requires an optimization of 29 parameters. The problem is approached by using a particle swarm of 29 dimensional spaces. Mean square error is used as a stopping criterion. 400 data samples are used in this experiment. The NN is trained with 50% data sets for all 10 combination pairs of mental task. The training and testing samples are normalized between 0 to 1 using binary normalization algorithm [15]. Selection of the training data is chosen randomly. Training is conducted until the average error falls below 0.1 or reaches a maximum iteration limit of 10000. The NN is trained with 10 data samples for each task pair and tested with 20 data samples per task pair.

C. Functional Link Neural Networks

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 network (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 separability becomes possible in the enhanced space, thus both the training and the training error of the network can be improved [16].

The FLNN architecture in this study consists of the input layer with a functional link and the output layer. The input layer has 28 inputs from the features extracted and 55 inputs provided by the function (2n -1) applied on the input where n is the number of input neurons, the output layer has 1 node to classify into either one of the tasks, 0 indicating task 1 and 1 indicating task 2. 400 data samples are used in this experiment. The FLNN is trained with 50% data sets for all 10 combination pairs of mental task. The training and testing samples are normalized from 0 to 1 using binary normalization algorithm [15]. Selection of the training data is chosen randomly. The FLNN is trained using the proposed PSO algorithm. Training is conducted until the average error falls below 0.001 or reaches a maximum iteration limit of 100. The FLNN is trained with 20 data samples for each task pair, the network is trained with 10 task pairs for each subject. The FLNN is tested with an error tolerance of 0.1.

V. Results and Conclusion

The results of the PSO ERNN and PSO FLNN classification are shown in Table I and II respectively, for different training sets with two hidden layer neuron configurations. In Table I the classification accuracies were found to be good for baseline based task pairs. Results are displayed for two hidden neuron configurations. The best combinations for subject 1 are Baseline-Math and Baseline - Letter, while for subject 2 the best combination is Baseline-Math. Though the classification accuracies for both subjects reached a max of 100% for some task pairs the average accuracies remained in the range of 79.5% to 91%. Average testing time varied from .02s to .03s. As observed from Table II, the classification performance is significantly better using the FLNN , maximum efficiency of 100% were achievable with a testing error tolerance of 0.1 for most task combinations. For subject 1 Baseline-Rotation task combination is found to be more suitable while for subject 2, again the Baseline –Math task combination is found to be more suitable. The average classification accuracy was seen in the range between 80% to 100%. Test results validate the performance of a PSO based learning algorithm for classification of mental tasks. Further studies are being conducted to implement the PSO training algorithm on other network architectures.

In this paper a PSO ERNN and PSO FLNN network based classification of EEG features recorded during mental tasks is proposed. The results indicate the feasibility of classifying EEG patterns related to mental tasks. The results show that mental tasks classifications vary from subject to subject. Average classification accuracies of 100% are obtainable for combination of tasks like Baseline-Math. Future works will consider improving the classification rates through other feature extraction techniques. 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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TABLE I
RESULTS OF PSO ERNN CLASSIFICATION ACCURACIES

Mental Task Combinations	Subject 1				Subject 2			
	Hidden Neuron 5		Hidden Neurons 10		Hidden Neuron 5		Hidden Neurons 10	
	Ave %	Max %	Ave %	Max %	Ave %	Max %	Ave %	Max %
Baseline, Math	90	95	87	95	88	95	91	100
Baseline , Rotation	85.5	95	86.5	100	84.5	95	84.5	95
Baseline, Letter	88	95	89	100	83	95	83	90
Baseline , Count	83.5	90	83.5	90	82	90	79.5	90
Math, Rotation	87	90	86	95	84	90	83	90
Math, Letter	89.5	95	84	90	82.5	90	87.5	95
Math, Count	82.5	90	86.5	95	85.5	100	84.5	95
Rotation, Letter	84	90	84	95	80.5	85	80.5	85
Rotation , Count	82.5	90	86.5	95	85.8	90	83.7	90
Letter, Count	84.5	90	88.5	95	81	85	83.7	85
Best Combination	Baseline, Math		Baseline, Letter		Baseline, Math		Baseline, Math	

TABLE II
RESULTS OF PSO FLNN CLASSIFICATION

Mental Task Combinations	Subject 1				Subject 2			
	Hidden Neuron 1		Hidden Neurons 2		Hidden Neuron 1		Hidden Neurons 2	
	Ave %	Max %	Ave %	Max %	Ave %	Max %	Ave %	Max %
Baseline, Math	97.5	100	97	100	100	100	99.5	100
Baseline , Rotation	99.5	100	99	100	91	100	95.5	100
Baseline, Letter	96.5	100	93	100	90.5	100	91	100
Baseline , Count	89.5	90	86	90	95	100	95.5	100
Math, Rotation	97.5	100	97.5	100	92	100	93.5	100
Math, Letter	92	100	92.5	100	94	95	96.5	100
Math, Count	86.5	90	89.5	95	80.5	85	80	80
Rotation, Letter	95.5	100	94.5	100	80	80	93.5	100
Rotation , Count	83	90	87.5	95	92.5	95	94	95
Letter, Count	90	100	91.5	100	85	85	84.50	85
Best Combination	Baseline , Rotation		Baseline , Rotation		Baseline, Math		Baseline, Math	