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Neuro-Fuzzy based Motor Imagery Classification for a Four Class Brain Machine Interface

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***Abstract*- Brain Machine Interface (BMI) provides a digital link between the brain and a device such as a computer, robot or wheelchair. This paper presents a BMI design using Neuro-Fuzzy classifiers for controlling a wheelchair using EEG signals. EEG signals during motor imagery (MI) of left and right hand movements are recorded noninvasively at the sensorimotor cortex. Four mental task signals are analyzed and classified to design a four class BMI. The proposed classifier has an average classification performance of 97%.**

***Keywords*- Brain Machine Interfaces, EEG Motor Imagery, EEG Band Power, Neuro-Fuzzy Classifiers**

I. INTRODUCTION

The brain uses the neuromuscular channels to communicate and control its external environment, however many disorders can disrupt these channels. Motor neuron disorders impair the neural pathways and completely paralyses the patient. This disorder affects nearly ten million people around the world. Sometimes the only option for restoring communicative functions to these patients is through a BMI. When biological communications channels are damaged, rehabilitation can be provided by digitally linking the brain to an electronic device. Electroencephalogram (EEG) and related methods, which have relatively short time constants, are found to be suitable in most environments and 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].

Studies show that imagination of movement activates similar cortical areas and shares similar temporal characteristics as the execution of the same movement [2].

Since motor imagery (MI) results in somatotopically organized activation patterns, mental imaginings of different movements can be an efficient strategy to operate a BMI. The challenge is to detect the imaginary-related changes in ongoing non-averaged EEG recordings.

MI is the most common methodology employed by majority BMI researchers. 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. MI can modify the neuronal activity in the primary sensorimotor areas in a very similar way as observable with real executive movements [3]. 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 [4].

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. MI is a dynamic state in which a subject mentally simulates a given action [4]. In this paper we investigate the usability of neuro-fuzzy classifiers for designing a four-class BMI for driving a wheelchair, the four states are relax, forward , left and right. The proposed classifier is tested with two features sets the conventional band power features and parseval features sets. The four MI tasks for the BMI are designed to drive a wheelchair in the forward direction, left and right turning and finally to stop the wheelchair. Our design approach is different from other BMI designs [5] where foot movement is used for forward movement; we propose only left and right hand movements for imagining the four states.

Chapter 2 provides background information on MI, chapter 3 discusses the data configuration, Neuro-Fuzzy classifier is explained in chapter 4 and results and conclusion are presented in chapter 5.

II. BACKGROUND

MI has been the basis of many brain-to-machine communication studies. An increase in cerebral blood flow has mainly been located in the supplementary motor area during imagination of sequential finger movements, a detailed review of MI and direct brain-computer communication is presented by Pfurtscheller and Neuper [3]. Cososchi et al [4] present a self organizing fuzzy neural network based time series prediction that performs feature extraction for MI signals. Methods based on power spectral density has always been a popular method for frequency based extracting and classifying EEG signals. However the power spectrum was not able to extract the distinguishing features.

Extraction of autoregressive (AR) coefficients [6, 7] from the c3 and c4 electrode signals is used in the classification. The results of AR based classification reveal that the method is not suitable as features for the data set used because the majority of AR analysis assumes the input data is linear and stationery. A time-frequency synthesis approach to accommodate individual difference and using the spatial patterns derived from the EEG rhythmic components as feature descriptors have been proposed in [8].

Auto-organizing fuzzy neural networks to classify MI signals are proposed in [4]. The network adapts itself to each individual's EEG signals so that very little subject knowledge or parameter selection is required. The proposed method has a maximum classification accuracy of 82.68%. The authors state that the proposed method is suitable for online adaptation because it can automatically add neurons to accommodate to the variations in the EEG data.

III. DATA CONFIGRATION

A. Motor Imagery Paradigm

In the synchronous experiments, the paradigm for the discrimination of the four mental states, the experimental task is to determine either left hand or right hand movement depending on the visual stimulus presented on a monitor. Subject is seated in a comfortable chair; the room is not acoustic proof but represents a normal room environment with less noise similar to home environments where patients are expected to use a wheelchair. The subject fixates on a computer 100 cm in front of him. During the recordings the subjects are instructed not to move and to keep their hands relaxed. 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 is collected for two sessions, each session has five trials per task, and each trial lasts for 10s.

MI 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 the baseline task and used as a stop control measure of the EEG.

MI Task 2 – Forward

The subject is requested to fixate on the monitor showing an up arrow, the subjects were 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 subject is requested to fixate on the monitor showing a left arrow, the subjects were requested to imagine moving his 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 are requested to imagine moving his right hand in the direction of the arrow, and the subject is requested to hold the thought for ten seconds.

B. Acquisition of EEG Data

In the EEG experiments 10 volunteer subjects participated. An ADI EEG Power Lab amplifier is used in this study. EEG is recorded using two gold plated cup electrodes placed at the C3 and C4 locations on the sensorimotor cortex area as per the international 10 -20 electrode placement system [9]. The EEG signals are amplified and sampled at 200 Hz. At the time of data recording the subjects are free from illness or medication, none of the subjects had previous experience with meditation.

The raw EEG signals are preprocessed using a band pass Chebyshev filter with a pass band of 0.5 Hz to 99 Hz. The filtered signals are segmented into 0.5s segments with an overlap of 0.25s. Figure 1 to 4 shows the motor imagery signals for the four tasks.

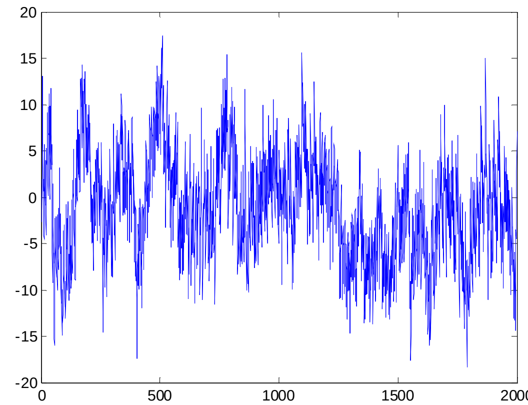

Fig. 1 MI signal for relax task

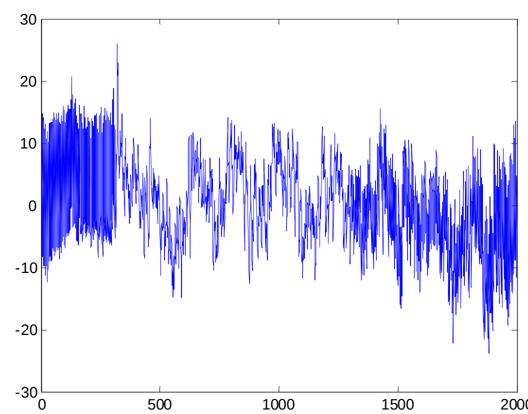

Fig.2 MI signal for forward task

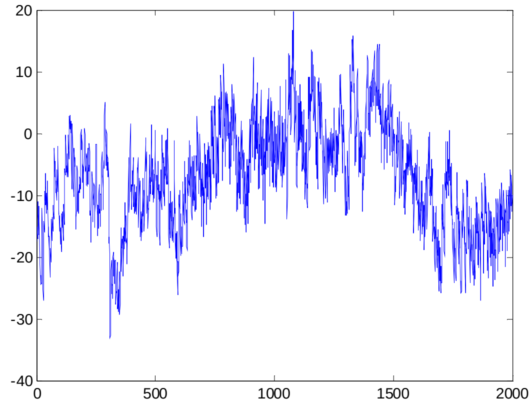

Fig. 3 MI signal for left task

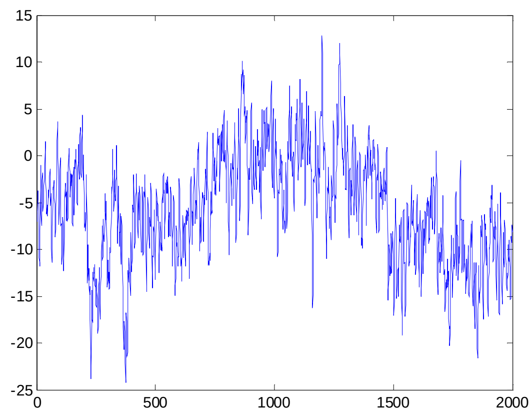

Fig.4 MI signal for right task

C. Band power features

The EEG is composed of different types of oscillatory activities whereby the oscillations in the mu and beta bands are particularly important to discriminate between different brain states during visual and motor imagery. One possibility to select parameters from the ongoing EEG is to estimate the short time band power for mu and beta bands. Power of five bands (8 Hz -10 Hz) (10 Hz -12 Hz) (13 Hz -15 Hz) (16 Hz -18Hz) (19 Hz -30 Hz) is estimated from each EEG segment. 195 features are extracted from each 10s EEG task signal.

D. Parseval Energy Features

The second feature set is also obtained from the 0.5s EEG segments, by extracting the energy density spectrum features using the Parseval theorem [10]. 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 two features sets are normalized using a binary normalization algorithm [11] and are used as input for the Neuro-Fuzzy classifier. Figures 5 to 8 show the spectral distribution of the EEG signal segment for the four tasks. The event related desynchronization is clearly visible in the 8 Hz to 30 Hz band range; the amplitude at the 50 Hz frequency indicates the noise due to power lines.

IV. Neuro-Fuzzy Classifier

A fuzzy inference system is a model that maps input characteristics to input membership functions, input membership function to rules, rules to a set of output characteristics, output characteristics to output membership functions, and the output membership function to a single-valued output or a decision associated with the output. Where membership functions are chosen arbitrarily and the rule structure is essentially predetermined by the user's interpretation of the characteristics of the variables in the model.

In some modeling situations, one cannot discern what the membership functions should look like simply from looking at data. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters could be chosen so as to tailor the membership functions to the input/output data in order to account for these types of variations in the data values. In such cases, a neuro-fuzzy learning technique can be used.

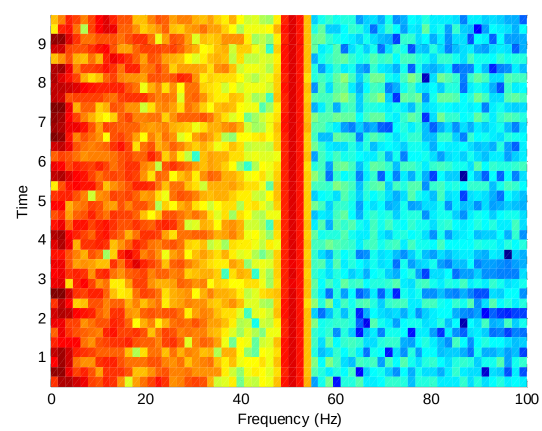

Fig. 5 Spectral distribution of the EEG signal for relax task

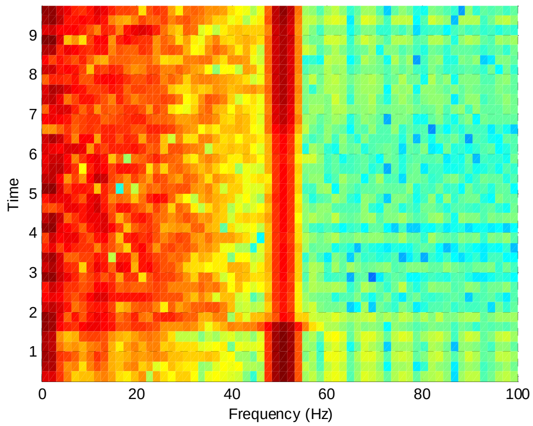

Fig. 6 Spectral distribution of the EEG signal for forward task

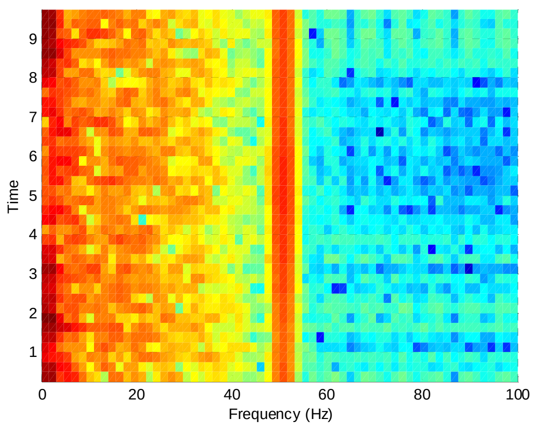

Fig. 7 Spectral distribution of the EEG signal for left task

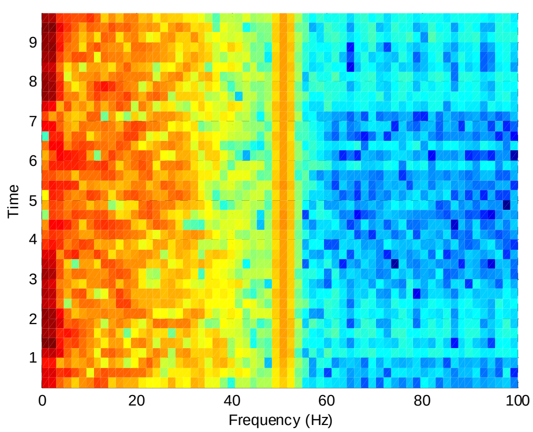

Fig. 8 Spectral distribution of the EEG signal for right task

The neuro-fuzzy learning method works similarly to that of neural networks. This learning technique provides a method for the fuzzy modeling procedure to learn information about a data set. Using a given input/output data set, a fuzzy inference system is constructed whose membership function parameters are adjusted using either a back propagation algorithm. This adjustment allows the fuzzy system to learn from the data that are modeled.

The parameters associated with the membership functions changes through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector. This gradient vector provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters [12]. When the gradient vector is obtained, any of several optimization routines can be applied in order to adjust the parameters to reduce some error measure. This error measure is usually defined by the sum of the squared difference between actual and desired outputs.

V. Results and Conclusion

Two classifier models for the two feature sets are modeled for each subject. The Neuro-Fuzzy classifier is trained with 80% data and tested with 100% data. The performances of the Neuro-Fuzzy models for each of the subjects are evaluated for 10 training rounds. The classification performances of the proposed Neuro-Fuzzy classifiers are shown in Table 1 for all ten subjects. The average classification performance for ten training rounds is shown for both the feature sets. The average performance of the classifier for band power features is 93.25%, while for the parseval features the performance is 97%. Figure 9 shows the membership functions for an input signal, Figure 10 and 11 shows the plot of the output data and output versus target data plots respectively.

From the results it is observed that the proposed Neuro-Fuzzy classifier provides good classification of the motor imagery EEG signals for a four class BMI. Maximum classification of 100% was observed for some subjects. The performance of the parseval features is observed to be better in comparison with band power features. Average classification efficiency of 97% is achievable from EEG data collected from only 10 trials. Artifacts were not removed from the EEG signal which shows the robustness of the proposed algorithm.

TABLE I
CLASSIFICATION PERFORMANCE OF HE NEURO-FUZZY CLASSIFIER FOR 10 SUBJECTS

Subject	**Classification Accuracy %**	
	Band Power Features	**Parseval Features**
1	97.5	97.5
2	82.5	95
3	92.5	97.5
4	97.5	95
5	87.5	100
6	97.5	100
7	97.5	100
8	90	97.5
9	90	97.5
10	100	90

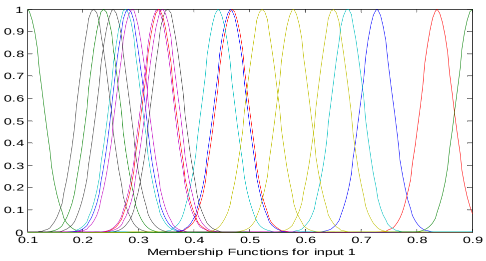

Fig.9 Membership function plot for input1 for subject1

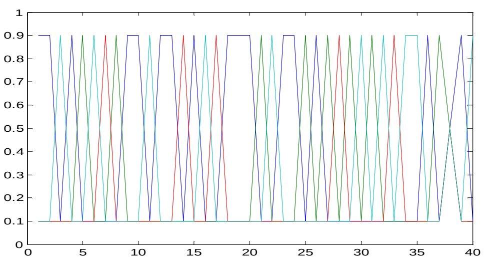

Fig.10. Plot of the output data for subject 1

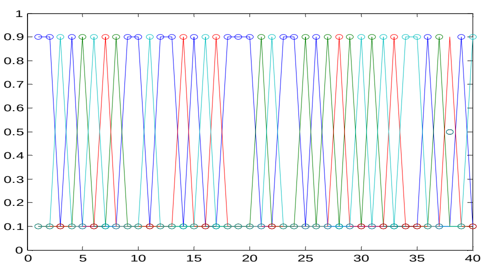

Fig.11. Plot of the output versus target for subject1

The results of the proposed Neuro-Fuzzy classifier are comparatively higher to [13] based on classification of mental tasks using a fuzzy classifier which has a maximum average classification accuracy of 85%.

Classification can be improved by training the subject to control the EEG signals. The output of the Neuro-Fuzzy classifier can be translated to control the movement of a wheelchair which is the focus of our future research. 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 0.5s 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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