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# Comparison of LDA and RBF-NN in EEG Features Classification for Motor Imagery

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**Abstract – This paper presents an approach that uses self-organizing fuzzy neural network based time series prediction to extract the EEG features in time domain. EEG signals from two electrodes placed on the scalp over the motor cortex are predicted by a single fuzzy neural network. Features derived from the mean squared error of the predictions and from the mean squared of the predicted signals are extracted from EEG data within a sliding window using two auto-organizing fuzzy neural networks with multi inputs and a single output. The features are classified by linear discriminant analysis and radial-basis function neural network.**
**Keywords: EEG, neurofuzzy network, prediction, auto adaptation, LDA, RBF-NN**

## I. INTRODUCTION

Motor imagery is the mental simulation of a motor act that includes preparation for movement, passive observations of action and mental operations of motor representations implicitly or explicitly. Motor imagery as preparation for immediate movement likely involves the motor executive brain regions. Implicit mental operations of motor representations are considered to underlie cognitive functions. Another problem concerning neuro - imaging studies on motor imagery is that the performance of imagination is very difficult to control. The ability of an individual to control its EEG may enable him to communicate without being able to control their voluntary muscles. Communication based on EEG signals does not require neuromuscular control and the individuals who have neuromuscular disorders and who may have no more control over any of their conventional communication abilities may still be able to communicate through a direct brain-computer interface. A brain-computer interface replaces the use of nerves and muscles and the movements they produce with electrophysiological signals and is coupled with the hardware and software that translate those signals into physical actions. One of the most important components of a brain-computer interface is the EEG feature extraction procedure.

The Motor imagery is by far the commonest methodology employed by majority of BCI research groups. This can be attributed primarily to the 'purely cognitive' nature of these methods (as opposed to the requirement for a stimulus in BCIs based on P300 and steady state (SS) visually evoked EEG-potentials (VEP)). Motor imagery (like motor action) has been reported to produce an Event Related Desynchronization (ERD) [1]. This is characterized by a transient reduction in the power of the alpha and beta bands of the EEG. By cleverly employing different strategies for motor imagery, one can generate ERDs in different spatial locations overlying the bilateral motor homunculus. With proper training and motivation, majority of subjects can learn to control the intensities (and spatial location) of specific frequency bands in their EEG, which can then be used as a communication and control signal. A Canadian research group has studied the effect of mental imagery at the corticospinal level when hand movements are performed [2]. In their study, the influence of imitation of hand actions on the cortical level was analyzed. The hand movements were studied by an American research group which established that the specific cortical pattern associated with the variation of the motor control parameters during execution and imagery are the same [3]. Recently, the researchers have studied the interference between action observation and action execution [4], in order to contribute to the analysis of the observation, trying to explain the process by which the representation of an observed movement is converted into the representation of a goal-directed action. To analyze the EEG signals different methods have been proposed in the literature: autoregressive model [5], [6], neural networks [7], mixture of densities approach [8], independent component analysis [9], time-frequency analysis [10] and statistical methods [11]. The processing of the EEG within the motor imagery shows still opened directions. This year, the researchers have tried to elucidate the difference in processing the biological and non-biological movements in man [4], to detect the cognitive abilities of the unresponsive patients [12] and to improve the EEG analysis in the framework of motor imagery application [13]. Most studies have relied on subjective evaluation and not objective confirmation, of task performance. Motor

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imagery is a dynamic state in which a subject mentally simulates a given action. Our work presents a procedure for extracting features from the electroencephalogram (EEG) recorded from subjects involving motor imagery. Two auto-organizing fuzzy neural networks are used to perform prediction tasks for the EEG data, as proposed by Coyle and his coworkers [6]. Features are taken from the mean squared error in prediction and from the mean squared of the predicted signals. Linear analysis is used for classification of signals. This extraction procedure is tested offline on two subjects leading to classification accuracy rates near 83% with information transfer rates near 8 bits/min. This approach shows good potential for online feature extraction and autonomous system adaptation. The architecture of the two auto-organizing fuzzy neural networks is a network with multi inputs and single output. The use of auto-organizing fuzzy neural networks is convenient for applications because the auto-organizing fuzzy neural network can adapt itself to each individual's EEG signals so that very little subject specific knowledge or parameter selection is required. It can perform online learning thus has potential for continous learning and continuous adaptation to the dynamics of each individual's EEG signals. Chapter II of the paper presents the data configuration. Chapter III gives the results and some conclusions.

## II. DATA CONFIGURATION

### A. *Acquisition of EEG data*

The data is recorded from two subjects in a timed experimental recording procedure where the subject is instructed to imagine moving the left and right hand in accordance to a directional cue displayed on a monitor. In each recording session a number of EEG patterns correlated to the imagined right or left arm movement are produced by a subject over a number of trials. Recorded EEG signals are filtered between 0.5 and 30Hz and then are sampled at 120Hz [14].

### B. *Configuration of EEG data*

The EEG data recorded from each electrode is configured so that the measurements from time instants $t$ - 5 to $t$ - 1 are used to make a prediction of the measurement at time $t$. Each training data input exemplar contains five measurements from the data recorded from either the C3 or C4 electrode. The training data output contains every subsequent measurement $t$ from each of the input data vectors. The extracted input-output data vector for the time series at the electrodes C3 and C4 are in (1) and (2).

$$\left[c_3(t-5); c_3(t-4); c_3(t-3); c_3(t-2); c_3(t-1); c_3(t)\right] \quad (1)$$

$$\left[c_4(t-5); c_4(t-4); c_4(t-3); c_4(t-2); c_4(t-1); c_4(t)\right] \quad (2)$$

Every trial has 5 seconds of task related data. The data is recorded from two subjects, S1 and S2. There were 300 trials recorded for subject S1 and 300 trials recorded for subject S2, an equal number of trials for each type of movement imagery. Each trial consists of 600 samples (5 s x 120 Hz = 600). There are 595 training data pairs for each trial, samples 595 to 599 are used to predict the sample 600.

### C. *Neurofuzzy architecture*

Two auto-organizing fuzzy neural networks are used to perform prediction. One auto-organizing fuzzy neural network is trained for the left EEG data and the other one auto-organizing fuzzy neural network for right EEG data. By using separate auto-organizing fuzzy neural networks for each type of data, it is desired that each trained auto-organizing fuzzy neural networks develop certain uniqueness, in that it is more apposite to each type of time series data [14].

The advantage of using a self-organizing structure, like that of the auto-organizing fuzzy neural networks, is that the problem of specifying the network's architecture does not have to be considered [15].

For the neural networks, finding the optimum architecture for a particular task can be very problematic and does have a significant effect on the performances. Auto-organizing fuzzy neural networks are hybrid systems that combine the theories of fuzzy logic and neural networks. In hybrid systems like the self-organizing fuzzy neural networks, the fuzzy techniques are used to create or improve certain aspects of the neural network's performance. An important advantage of the auto-organizing fuzzy neural network is the generation of a model from observations of complex systems where little insufficient expert knowledge is available to describe the behavior, as is the case for EEG data [16].

The auto-organizing fuzzy neural networks can deal with characteristics of EEG such as large dimensions and noise to provide a model that can be used for interpretation of the EEG. This is another advantage of using an auto-organizing fuzzy neural network for EEG analysis. The auto-organizing fuzzy neural network is designed to approximate a fuzzy process of fuzzy inference through the structure of neural network and thus create an interpretable hybrid model of neural network using the superior learning ability of neural networks and easy interpretability of fuzzy systems.

The dynamic adaptation of the structure of the hybrid network captures the underlying behavior of a nonlinear time-varying complex system more easily and accurately. The online learning algorithm, based on a hybrid recursive least squares estimator, and an autonomous neuron adding and pruning structure based on the optimal brain surgeon technique, provide a truly online learning algorithm for modeling/predicting the highly non-stationary EEG signal [14].

D. *EEG features extraction procedure*

Each self-organizing fuzzy neural network is a multi-input-single-output (MISO) network so only EEG data recorded from a single electrode can be predicted. The system is configured in three stages [14]. The first stage involves training of the two auto-organizing fuzzy neural networks separately to perform one-step-ahead prediction, using five previous measurements of each time series. The two auto-organizing fuzzy neural networks are named *L* for the left data-electrode C3 and *R* for right data electrode C4 corresponding to the type of EEG data on which they are trained, either left or right motor imagery. The second stage implies input of each type of training data, the same data used to train the auto-organizing fuzzy neural networks into each of the auto-organizing fuzzy neural networks. All the *L* training data is input to both the *L* and *R* networks, then all the *R* training data is input to both *L* and *R* network in a similar manner. Each auto-organizing fuzzy neural network provides a one-step-ahead prediction for the data in for each trial. When a trial is input to all of the two auto-organizing fuzzy neural networks, features are extracted by calculating the mean square error (MSE) of the prediction for a portion of the trial and the mean squared of the actual prediction (MSA). As these calculations gives predictions over a segment to a scalar value, EEG features based on the error and on predicted signal can be obtained as in (3).

$$f_k = \frac{1}{M}\left(\sum_{t=1}^{M}\left(y(t) - \hat{y}_k(t)\right)^2 + \sum_{t=1}^{M}\left(\hat{y}_k(t)\right)^2\right) \qquad (3)$$

Equation (3) is used for obtaining each feature, where $y(t)$ is the actual signal and $\hat{y}_k$ (t) is the predicted signal. The *k* index is used to show whether the signal is from left *l* or right *r* auto-organizing fuzzy neural network. *M* is the number of prediction samples used. The extracted features are in vector form, the feature vector $f_v$, is shown in Fig. 1.

For each trial a two elements feature vector is obtained and classes of features for right and left data can be obtained by entering all trials of training data into the auto-organizing fuzzy neural networks in Fig. 1. Normalizing the features (i.e. dividing each feature vector by the sum of the components within the vector) can reduce the intra class variance – a fundamental goal of any feature extraction procedure. Features can be extracted for every time point in a trial using a sliding window approach. To extract a new set of features for every time point in a trial using the sliding window approach, *t* ranges from $t = s$ to *M* where *s* and *M* are incremented before the next set of features is extracted (initially $s = 1$ and $M$ = window size). This means that data at the beginning of a trial is forgotten as the window slides away from the start of the trial. The advantage of using the sliding window for feature extraction is that the feature extraction procedure does not require knowledge about the point at which communication is initiated by the user and so online feature extraction can be realized [14].

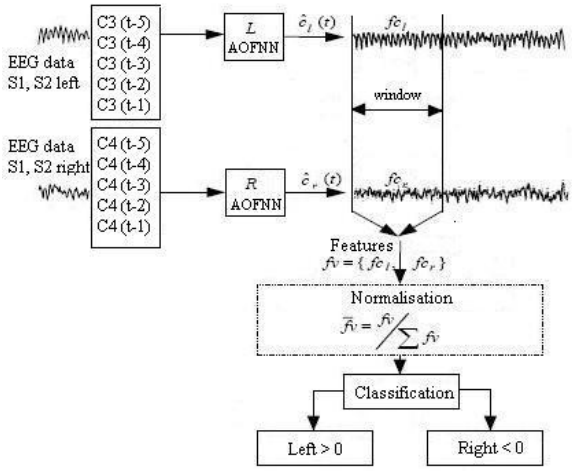


Fig. 1. EEG feature extraction procedure

## III. DATA CLASSIFICATION

The last step is the data classification performed using linear discriminant analysis (LDA), a classifier that works on the assumption that different classes of features can be separated linearly and alternatively using radial basis function network (RBF-NN) that uses a nonlinear function to map the input data into high-dimension space so that they are more likely to be linearly separable than in the low-dimension space.

A. *Linear discriminant analysis*

The principle of LDA is to seek a vector *w* so that two projected clusters of *R* and *L* feature vectors can be well separated from each other while keeping small variance of each cluster. This can be done by maximizing the Fisher's criterion. After *w* is obtained by means of the training data, we project the test samples on it, and then classify the projected points by the k-nearest-neighbor decision rule [17]. Linear classifiers are more reliable than the nonlinear ones because they have limited flexibility.
The idea of LDA is to seek a vector $\vec{w}$ so that two projected clusters of *R* and *L* feature vectors on $\vec{w}$ can be well separated from each other while keeping small variance of each cluster. This can be done by maximizing the Fisher's criterion

$$J(w) = \frac{w' S_b w}{w S_w w} \qquad (4)$$

where $S_b$ is the scatter matrix between classes:

$$S_b = (m_R - m_L)(m_R - m_L)^{\mathrm{T}} \qquad (5)$$

and $S_w$ is the scatter matrix within the class:

$$S_w = \sum_{\vec{x}\in R} (\vec{x} - m_R)(\vec{x} - m_R)^T + \\ + \sum_{\vec{x}\in L} (\vec{x} - m_L)(\vec{x} - m_L)^T \quad (6)$$

in which two summations run over all the training samples of classes R and L , respectively, and $m_R$ and $m_L$ represent the group mean of classes R and L, respectively. The optimal $\vec{w}$ is the eigenvector corresponding to the largest eigenvalue of $S_w^{-1} S_b$. After $\vec{w}$ is obtained by means of the training data. Experimentation involved extraction and classification of features at every time point in a trial, allowing selection of the optimum time points to perform feature extraction and classification for more effective deployment of the system. This approach allows features to be extracted at the rate of the sampling interval [14].

B. *Radial - basis function neural networks*

The radial - basis function neural network (RBF-NN) uses a nonlinear function to map the input data into high-dimension space so that they are more likely to be linearly separable than in the low-dimension space, as depicted in Fig. 2.

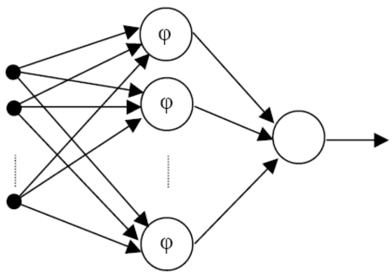


Fig. 2. RBF-NN architecture

The hierarchy of RBF-NN consists of one input layer, one hidden layer, and one output layer. Each RBF-NN is designed to have a nonlinear transformation from the input layer to the hidden layer, followed by a linear mapping from the hidden layer to the output layer. The mapping between the input and output space is expressed by:

$$F(\vec{x}) = \sum w_i \varphi(\|\vec{x} - \vec{x}_i\|) \quad (7)$$

where $\varphi(\|\vec{x} - \vec{x}_i\|) = e^{-\|\vec{x}-\vec{x}_i\|^2}$ and $w_i$ is the weighting from the $i$-th hidden neuron to output neuron and $\vec{x}_i$ represents the $i$-th known feature vector with dimension $N$.

Compared with other neural networks which uses gradient-based optimization process to estimate the weightings, for example, the back-propagation recurrent neural network, the RBF-NN solve for a set of linear equations to avoid trapping in a local minimum and greatly reduce the training time [17].

## IV. RESULTS AND CONCLUSIONS

A. *Results*

The system was tested on 150 for subject S1 and 150 for subject S2. The obtained results are shown in Table 1 and Table 2.

The first column specifies the subject. The second column specifies whether normalized features where used. Column three specifies the sliding window size. Column four indicates classification accuracy rate for LDA in Table 1 and respectively for RBF-NN in Table 2. Column five shows the time elapsed for classification and column six shows the information transfer (IT) rates.

All results in bold specify the best results obtained for each type of performance quantifier. All IT rates were calculated using the time interval between communication start meaning the second 4 of timing scheme and the point that maximum classification accuracy was obtained. This provides good indication about the maximum IT rate a system can achieve whilst system accuracy is optimal. IT rates can be much higher if calculated in the first second of a trial, even if classification accuracy is lower.

Irregular transients in the signals, caused by noise or artifacts did not have as much affect on the features because the auto-organizing fuzzy neural networks did not predict irregular transients in the signal that indicates that the auto-organizing fuzzy neural networks aided to the removal of artifacts and noise for subjects S1 and S2. Normalizing the features produces higher classification accuracy and IT rates that is because normalization reduces the intra-class variability. The number of neurons in each auto-organizing fuzzy neural network was different from its counterparts due to variations in the types of signals on which each auto-organizing fuzzy neural network was trained.

Table 1

| Sub | Norm | Wind Size | Classif Acc [%] LDA | Time [s] | Rate [bpm] |
|---|---|---|---|---|---|
| S1 | No | 310 | 76.34 | 3.43 | 6.89 |
| | Yes | 320 | **82.68** | 3.62 | 7.27 |
| S2 | No | 300 | 70.63 | **3.24** | 6.43 |
| | Yes | 340 | 79.87 | 4.13 | **7.68** |

Table 2

| Sub | Norm | Wind Size | Classif Acc [%] RBF-NN | Time [s] | Rate [bpm] |
|---|---|---|---|---|---|
| S1 | No | 310 | 73.54 | 3.46 | 6.56 |
| | Yes | 320 | **84.21** | 3.57 | 7.75 |
| S2 | No | 300 | 68.67 | **3.28** | 6.32 |
| | Yes | 340 | 81.28 | 3.98 | **8.12** |

## B. *Conclusions*

No artifact removal or noise reduction was carried out on the raw EEG data from subjects. This indicates the robustness of the proposed approach. However, the number of neurons in each auto-organizing fuzzy neural network increases when noise is increased. This approach shows good potential for online EEG feature extraction and can be further developed by implementing a multiple-step-ahead prediction technique. The system can perform online adaptation because it can autonomously add neurons to accommodate to the variations in the EEG data.

RBF-NN performs a better classification of the extracted features in comparison with LDA, due to the nonlinear function used for the hidden layer.

Further studies will investigate the success of the proposed algorithms on different motor imagery tasks and will look for other methods to improve the classification of the extracted features.

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