EEG Based Patient Monitoring System for Mental Alertness Using Adaptive Neuro-Fuzzy Approach

Dilshad Begum
Dept of ISE, Ghousia College of Engineering, Ramanagar, Bangalore, India

K. M. Ravikumar,
Special Officer, VTU-Regional Office, Mysore, India

James. Mathew and Sanjeev Kubakaddi
ITIE Knowledge Solutions, Bangalore, India

Rajeev Yadav
Genia Photonics Inc, Laval, Canada
ryadav@alumni.concordia.ca

***Abstract*—Recent electrophysiological studies support command-specific changes in the electroencephalography (EEG) that have promoted their intensive application in the noninvasive brain computer interfaces (BCI). However, EEG is plagued by a variety of interferences and noises, thereby demanding better accuracy and stability for its application in the neuroprosthetic devices. Here we investigate wavelets and adaptive neuro-fuzzy classification algorithms to enhance the classification accuracy of cognitive tasks. Using a standard cognitive EEG dataset, we demonstrate improved performance in the classification accuracy with the proposed system.**

***Index Terms*— BCI, EEG, wavelets, adaptive neuro fuzzy interface system (ANFIS)**

I. Introduction

A patient recovering following a stroke, severe brain damage or spinal injury may suffer from unresponsive wakefulness syndrome (or vegetative state) [1]. Many of these patients remain unresponsive for prolonged period of times while some with limited cognitive capabilities. Rehabilitation of such patients is extremely challenging due to the difficulty in interpreting their cognitive abilities. The brain-computer interfaces (BCIs) which establishes a direct link between a human brain and a computer discovers the potential of computers to enhance physical and mental abilities; and often refers to the interaction of human brain with external devices [2]-[4].

The human brain is a signal generator, sending out millions of signals which can be measured and analyzed. Modern biomedical research has provided the method for extracting these brain signals in a convincing way to distinguish their characteristics from one another. It was soon discovered that these signals could be used to communicate with an external peripheral device, through proper machine learning techniques. Now, BCIs are often directed at assisting, augmenting, or repairing human cognitive or sensory-motor functions [5], [6].

Every time we think, move, feel or perform an activity, the neurons in our brain are at work. This work is carried out by small electric signals that transmit signals from neuron to neuron. BCI technology monitors this electrical activity, usually via the method of electroencephalography (EEG). EEG characteristics are then detected via special signal processing algorithms, and the user is able to classify and generate communication messages. BCI enables physically disabled persons to perform many activities, thus improving their quality of life and allowing them to be independent [2]-[4], [7]-[9]. A general BCI system uses a set of EEG samples for training and random samples for testing the trained classifier. However, the classification accuracy of the system performance is a great challenge. Identifying the best discriminating features in the EEG which is plagued by a variety of noise; in itself is a challenge then selecting a classification technique capable to distinguish a variety of time-varying patterns is another challenge. Widespread research and experiments have been conducted on algorithms to classify brain signals according to its characteristic features.

EEG patterns have been exploited widely in prosthetic control [10]; for example, they have been used to move the cursor on a computer display [11], to control hands-free or virtual wheelchairs [12], [13] and to move robotic limbs [13]-[17]. Different feature extraction techniques, such as autoregressive coefficients [18]-[22]; component analyses; spectral, spatial and correlation features[5], [6], [21], [23]-[26]; transform features (short-time (windowed)

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Fourier wavelet, and affine transform) [26]; and time-frequency-ambiguity features [19] have been experimented on using EEG signals with standard clustering and classification methods, including: support vector machines , K-nearest neighbor, linear discriminant analysis, Bayesian Classifier, Hidden Markov Model, neural networks , fuzzy classifiers, genetic algorithm, etc [27]-[36].

Adaptive Neuro-Fuzzy system is used in [18], [31], [37]-[40] to detect P-300 rhythm in EEG, which are obtained from visual stimuli followed by a motor response from the subject. The paper explored wavelet transform to extract features together with ICA algorithm. Nazmy *et al* [41] proposed an intelligent system for ECG classification based on ANFIS theory utilizing ICA feature extraction. ANFIS algorithm is utilized by Darvishi *et al* [37] to distinguish between imaginary left and right hand motion using wavelet features, in which the impact of cluster radius and number of fuzzy rules in determining classification accuracy is investigated. Barbosa *et al* [42] used five ANFIS classifiers to distinguish between five different mental tasks and compared the results with different neural network architecture like MLP and Hierarchical Hybrid Model. A study by Khare *et al* [43] compared the performance of different neural network algorithms in classifying EEG for five mental tasks with respect to wavelet transform features. Charles *et al* [44] explored auto regression features with neural networks for the discrimination of mental tasks. Ahamadi *et al* [45], [46] described a system for on-line controlling the hand movement in a virtual reality environment using Real-Time Recurrent Probabilistic Neural Network.

EEG is considered the best suited potential non-invasive interface, mainly due to its fine temporal resolution, ease of use, portability and low set-up cost. The project focuses on extracting characteristic features of EEG signals to control an external device, say alarm system. The research investigates EEG preprocessing, wavelet feature extraction and Neuro- Fuzzy classification to control an alarm system, alerting about one's mental state.

II. Method

A. Data Collection

In this research, a standard dataset from Purdue University has been used. EEG Recording was performed with a bank of Grass 7P511 amplifiers whose bandpass analogue filters were set at 0.1 to 100 Hz. Signals are taken using six electrodes in the central, parietal and occipital regions - C3 C4 P3 P4 O3 O4 with respect to 10-20 electrode system. EOG signal is recorded separately and the signals are claimed to be free from artifacts. Data is collected for two cognitive tasks – mental letter composing and geometric figure rotation. A single trial recorded consists of 2500 samples at a sampling frequency 250Hz. Ten trials of each task is considered for this study.

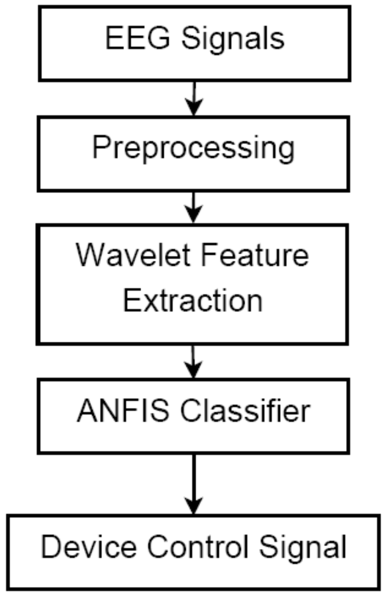


Figure 1. Algorithm flowchart for the proposed BCI system.

B. Preprocessing and Feature Extraction

Some pre-processing techniques are to be applied to the raw EEG signals to reduce error as well as computational complexity. While recording, EOG and line frequency artifacts are already removed in the dataset [47].

- *Normalization*: All the signals have to be normalized to the range of [-1 1] to make the calculation simpler.
- *Filtering*: The signals are then fed to an equiripple bandpass filter set to the range 0-40 Hz [6]. We are interested only in delta, theta, alpha, beta and lower gamma band signals, which have actionable information.
- *Wavelet feature extraction*: Wavelet features are widely accepted and utilized due to high discriminating properties in the active band (delta, theta, alpha, beta, and gamma) for a particular EEG condition. Wavelet decomposition gives coefficients in these band areas, which clearly signifies the brain signal. We considered wavelet decomposed band coefficients to represent each signal and to reduce the dimension of feature matrix statistical parameters that has been selected.

Wavelets divide the signal into different frequency components in a multi-resolution manner. As the EEG signals are non-stationary, Fourier Transform may not be a good choice. Since we couldn't fix a permanent window size for EEG patterns a time-frequency representation is adopted to distinguish the subsequent frequency components [48].

In wavelet transform, the signal is fed to filter bank structure, a series of low pass and high pass filters. To analyze the signal at different scales, different filter cutoff frequencies are chosen for the sub filters. The resolution of the signal, which is a measure of the amount of detail information in the signal, is changed by the filtering operations, and the scale is changed by up sampling and down sampling (subsampling) operations.

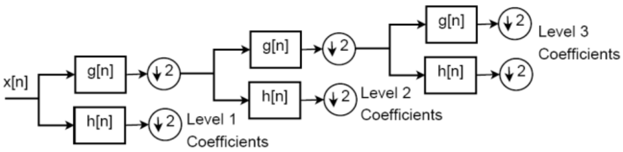


Figure 2. Three level decomposition tree of DWT [49].

The signal can be represented using a Mother wavelet - $\Phi(x)$ and its child wavelets, which are scaled and time shifted versions of the mother wavelet [48].

$$\Phi_{(s,l)}(x) = 2^{\frac{-s}{2}}\Phi\left(2^{-s}x - l\right) \tag{1}$$

The mother function $\Phi(x)$ is modified with respect to variables s and l to generate a series of wavelet family. The scale index s indicates the wavelet's width, and the location index l gives its position. The mother functions are rescaled, or dilated by powers of two, and translated by integers. Thus, the mother wavelet basis functions give a clear picture of the signal characteristics.

The wavelet transform is the convolution between the two functions x and ψ, which can be done in Fourier space using the Fast Fourier Transform (FFT) [48]. In the Fourier domain, the wavelet transform is simply,

$$W_n(s) = \sum_{k=0}^{N-1} \hat{x}(k)\hat{\psi}^*(\mathrm{s}\,\omega_\mathrm{k})\,\mathrm{e}^{\mathrm{i}\omega_\mathrm{k}\,\mathrm{n}\,\delta\,\mathrm{t}} \tag{2}$$

where the ^ indicates the Fourier transform (FT), and the Fourier transform of the time series is given by:

$$\hat{x}_k = \frac{1}{N}\sum_{n=0}^{N-1} x_n e^{-2\pi ikn/N} \tag{3}$$

To use this formula, the FT of the wavelet function should be known analytically. The wavelets are normalized as,

$$\hat{\psi}(s\omega_k) = \left(\frac{2\pi s}{\delta t}\right)^{\frac{1}{2}} \hat{\psi}_o(s\omega_k) \tag{4}$$

After preprocessing, the signals are subjected to wavelet decomposition and the coefficient features are extracted. The signal is decomposed to 6th level to extract the bands of interest using Daubechies wavelets (db14). Since the coefficient matrix is very large, we apply some statistical data reduction techniques. The final feature set will be a set of minimum of coefficients, maximum of coefficients, standard deviation, mean and power of the coefficient matrix (for each band-alpha, beta, gamma, delta , theta). Thus for a single electrode signal, a set of 25 features are extracted. Features are extracted for 8 trials each of two tasks- geometric figure rotation and letter composing.

C. *Classification*

The algorithm is trained for a set of data (EEG signals) which is been already taken from different subjects for two particular tasks. Since the task is clear identification and grouping of signal pattern, classification algorithms are preferred to regression methods. Out of the different classification algorithms like LDA, KNN, SVM, LVQ, NN, Neuro-Fuzzy etc, we select classifiers with higher adaptability and precision; i.e. ANFIS.

1) Neural fuzzy system

The term Neuro-Fuzzy refers to combinations of artificial neural network and fuzzy logic (Fig 3). Neural fuzzy systems provide a kind of automatic tuning method to fuzzy systems by the use of neural networks, but without altering their functionality. Neural networks can be used for the membership function elicitation and mapping between fuzzy sets that are utilized as fuzzy rules.

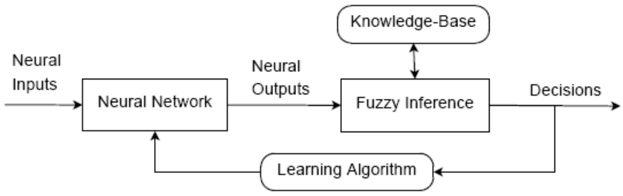


Figure 3. Neuro-fuzzy system [50].

During the training process, a neural network adjusts its weights in order to minimize the mean square error between the output of the network and the desired output. In Neuro-Fuzzy systems, the weights of the neural network represent the parameters of the fuzzification function, fuzzy word membership function, fuzzy rule confidences and defuzzification function respectively [50]. Thus the training of neural network results in automatically adjusting the parameters of a fuzzy system and finding their optimal values.

2) Adaptive neuro-fuzzy inference system (ANFIS)

Adaptive Neuro-Fuzzy Inference Systems are a class of adaptive networks that are functionally equivalent to fuzzy inference systems, incorporating the learning capabilities of neural networks and the robustness of fuzzy.

Fuzzy interface system maps input characteristics to input membership functions and again this to a set of rules. Rules could be set by the user's interpretation of the model characteristics. The rules are mapped to output membership functions and then to an output value. Neuro-adaptive learning techniques provide a method for the fuzzy modelling procedure to learn about a data set. It calculates the best membership function to map the given data using neural network structure. The membership function parameters changes throughout the learning process, according to a gradient vector, which describes the performance index of the fuzzy modelling [51].

Sugeno-Tsukamoto fuzzy model is a widely accepted neuro-fuzzy system. It is a universal approximator. The neuro-fuzzy system in this research follows a hybrid learning algorithm, Least Mean Square Algorithm for forward pass and Scaled Conjugate Gradient Method for backward pass. For a fuzzy inference system with two inputs x and y and one output z, a first-order Sugeno fuzzy model has rules as the following:

Input nodes (Layer 1): All nodes are adaptive nodes. The outputs are fuzzy membership grade of the inputs, given by

$$O_i^1 = \mu A_i(x), \qquad for\ i = 1,2 \tag{5}$$

$$O_i^1 = \mu B_{i-2}(y), \qquad for\ i = 3,4 \tag{6}$$

where x and y are the inputs to the node I, A is a linguistic label (small, large) and $\mu A_i(x)$ and $\mu B_{i-2}(\mathrm{y})$ can adopt any fuzzy membership function. For a Gaussian (bell)-shaped function,

$$\mu A_i(x) = \frac{1}{1 + \left\{(x - ci / ai)^2\right\} b} \tag{7}$$

where (ai, bi and ci) are the parameters of the membership function. Parameters are referred to as premise parameters.

Rule nodes (Layer 2): Rule layer is a fixed node labelled M whose output is the product of all the incoming signals. The outputs of this layer are the firing strengths of the rule, represented as:

$$O_i^2 = w_i = \mu A_i(x)\mu B_i(\mathrm{y}), \quad \mathrm{i} = 1,2 \tag{8}$$

Average nodes (Layer 3): In normalization layer also nodes are fixed nodes, labelled N, which gives normalized firing strengths

$$O_i^3 = \overline{w}_i = w_i / (\mathrm{w}_1 + \mathrm{w}_2), \quad \mathrm{i} = 1,2 \tag{9}$$

Consequent nodes (Layer 4): It is defuzzification layer in which all nodes are adaptive nodes. The output of each node is simply the product of the normalized firing strength and a first order polynomial.

$$O_i^4 = \overline{w}_i f_i = w_i(\mathrm{p_i x} + \mathrm{q_i x} + \mathrm{r_i}), \quad \mathrm{i} = 1,2 \tag{10}$$

Output nodes (Layer 5): This is summation neuron, a fixed node which computes the overall output as the summation of all incoming signals.

$$O_i^5 = \sum \overline{w}_i f_i = \sum\nolimits_{i=1} w_i f_i / (w_1 + w_2) \tag{11}$$

3) Scaled conjugate gradient method (SCG)

SCG is a supervised learning algorithm for feedforward neural networks, and is a member of the class of conjugate gradient methods.

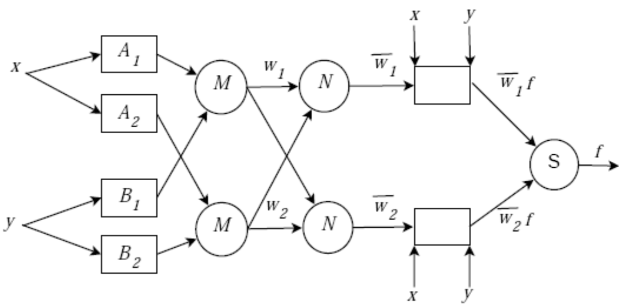


Figure 4. ANFIS structure [7].

Let $p = \exp\left(\frac{-\Delta E}{T}\right)$ be a vector from the space $T = T.\deg$, where N is the sum of the number of weights and of the number of biases of the network. Let be E be the error function we want to minimize [52]. Contrary to other conjugate gradient methods (CGMs), SCG differs in two points:

- Each iteration **k** of a CGM *computes* w_i , where R^N is a new conjugate direction, and $w_{k+1} = w_k + \alpha_k . p_k$ is the size of the step in this direction. Actually p_k is a function of α_k , the Hessian matrix of the error function, namely the matrix of the second derivatives. In contrast to other CGMs which avoid the complex computation of the Hessian and approximate α_k with a time-consuming line search procedure, SCG makes the following simple approximation of the term $E''(w_k)$, a key component of the computation of $\alpha_k : s_k$.
- As the Hessian is not always positive definite, which *prevents* the algorithm from achieving good performance, SCG uses a scalar α_k which is supposed to regulate the indefiniteness of the Hessian. This is a kind of Levenberg-Marquardt method, and is done by setting:

$$\begin{aligned} s_k &= E''(w_k).p_k + \lambda_k p_k \\ &\approx \frac{E'(w_k + \sigma_k . p_k) - E'(w_k)}{\sigma_k}, 0 < \sigma_k << 1 \end{aligned} \tag{12}$$

and adjusting λ_k at each iteration. This is the main contribution of SCG to both fields of neural learning and optimization theory.SCG has been shown to be considerably faster than standard back propagation and than other CGMs [52].

The research adopts Neuro-Fuzzy classifier for classifying the feature matrix into two groups. In this we use the k-means algorithm to initialize the fuzzy rules. For that reason, we should give the number of clusters for each class. Here all the input features are grouped to one cluster for each class. A Gaussian membership function is used for fuzzy set descriptions, because of its simple derivative expressions

The Scale gradient classifier based is on Jang's neuro-fuzzy classifier [51]. The differences are about the rule weights and parameter optimization. The rule weights are adapted by the number of rule samples. The scaled conjugate gradient (SCG) algorithm is used to determine the optimum values of nonlinear parameters. The SCG is faster than the steepest descent and some second order derivative based methods. Also, it is suitable for large scale problems [53], [54].

4) K-means clustering:

The *K*-means algorithm divides the data into *k* mutually exclusive clusters with actual observations. The clusters are defined by its member objects and centroid. The sum of distances from all objects in that cluster is minimized at the centroid. The objects are moved towards cluster centres using distance measurements like Euclidean, Mahalanobis, city block etc. and is iterated till the set of clusters become well- separable.

D. Testing Phase

Once the training is done, a fis structure is created with two classes EEG signals of random task are given to the system for testing The signals are pre-processed and wavelet features are extracted. This is tested with the fis structure and the neuro-fuzzy system returns the degree of closeness to either of the classes. This degree of closeness is rounded and is used to generate activation signals to control external device. If the test signal is grouped to any thought process, the alarm is set and alerts about the mental activeness of the subject.

E. External Device Control

The objective of the project is to control an alarm and led with respect to the classifier output. We use the Arduino UNO board to set up the external device.

The Arduino UNO board with ATmega328 microcontroller is used to facilitate external device control. In the board pin6 is connected to LED and pins 7, 9 and 11 are connected to 8ohm speakers. A simple program is loaded to the controller to activate the output pins when a digital 1 is coming through the serial port. Speaker ports are programmed with suitable delay to sound the output as an alarm. The system is tested successfully for random test signals.

TABLE I. ACTIVATION SIGNAL FOR OUTPUT CONTROL

Index	FIS Structure	Activation Signal	Device Control
1	Letter composing	0	No action
2	Figure Rotation	1	LED is ON Alarm is ON

III. RESULTS AND DISCUSSION

The project investigates the relation between EEG features and Fuzzy rules connecting them. Four different clustering techniques- K means, grid partitioning, subtractive clustering and Fuzzy C means are experimented with respect to two backpropogation network training algorithms, Levenberg-Marquardt and Scaled gradient conjugate.

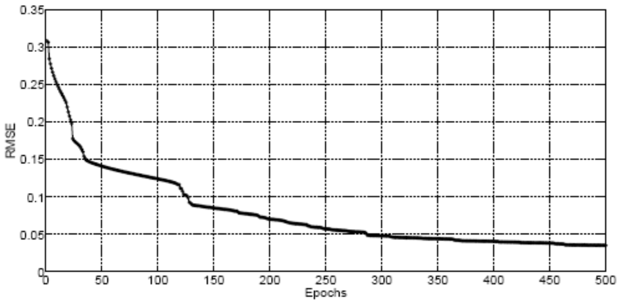


Figure 5. Training error for the SGC.

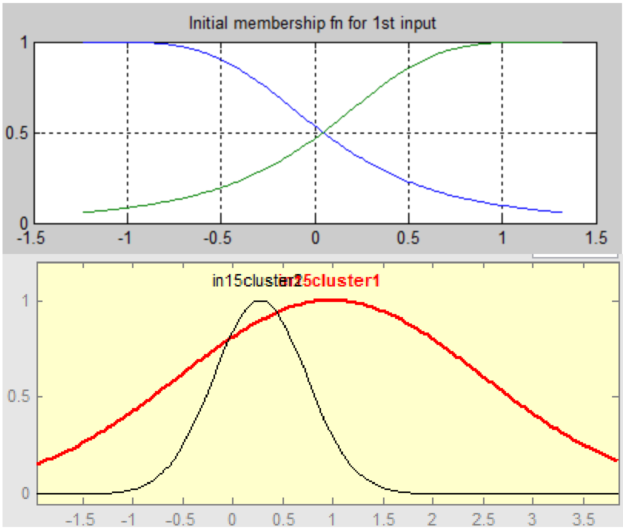


Figure 6. SGC membership function before and after training.

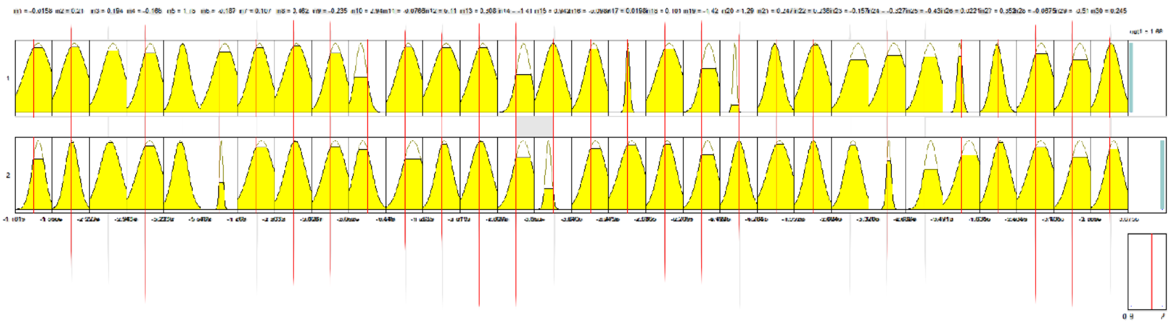
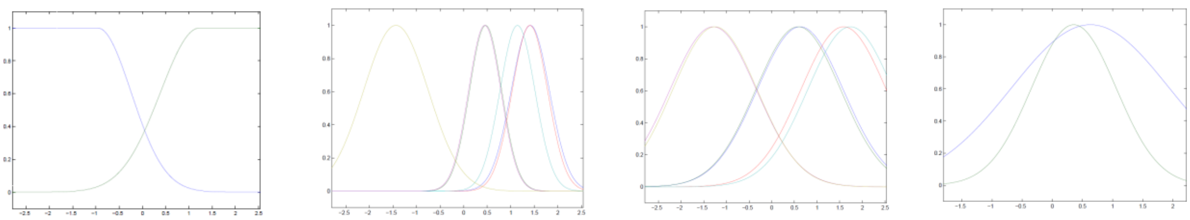
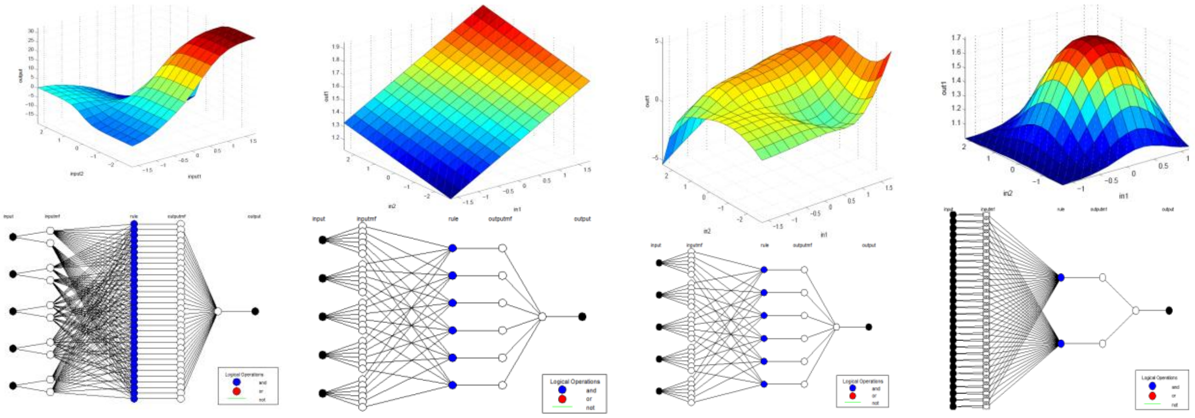


Figure 7. Fuzzy rules for the SGC network





(a): Grid Partitioning (b): FCM Clustering (c): Subtractive Clustering (d): Proposed SGC- k-means Clustering

Figure 8. Compares the membership Functions, Surface mesh and the network models of LM algorithm with (a) Grid Partitioning (b) Fuzzy C means (c) Subtractive Clustering(d) Proposed SGC algorithm with K means for EEG pattern classification.

The system is trained for 2 tasks over 500 iterations.

1) SCG-K means clustering:

For SGC algorithm, the training and testing recognition rate got converged to 100% and 92.5%, the mean square error got reduced to 0.0353 as shown in Fig. 5.

The membership functions that map the input to the rule base are user defined Gaussian functions and got reconfigured with the neural training epochs as shown in Fig 6. Initially the membership function is randomly defined, after setting the rules and fuzzification, the membership function got reshaped to accommodate range all range of feature values through the selected input nodes. For each input set the membership function defines two clusters for two classes, utilizing K-mean clustering technique.

Fuzzy sets AND rules for all the input clusters and classifies into two groups. These rules are put into the network as weights and after every training loop, the input functions got adjusted since the fuzzy weights are set to be strict and not subjected to any variations. The fuzzification process is detailed in Fig. 7.

2) Levenberg Marquardt- grid partitioning, fuzzy C means, subtractive clustering:

The Levenberg-Marquardt algorithm approaches the second-order training speed without calculating Hessian matrix. The Levenberg-Marquardt algorithm approximates Hessian matrix in the following Newton-like update:

$$X_{k+1} = X_k - [J^T J + \mu I]^{-1} J^T e \tag{13}$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. Using a standard backpropagation technique Jacobian matrix can be calculated, that is much simpler compared to computing the Hessian matrix. When μ=0, this is Newton's method, for large μ, this becomes a gradient descent with small step size. After each step μ is decreased to reach near error minimum and is increased only when a step would increase the performance function. Thus the performance function got reduced in each iteration step.

In subtractive clustering, each data point is assumed to be a potential cluster center and a measure of the likelihood that each data point is calculated based on the density of surrounding data points. The data point with the highest potential is selected to be the first cluster center. Then all data points in the vicinity of the first cluster center (as determined by radii) are removed so as to determine the next data cluster and its center location. This process is iterated until all of the data is within radii of a cluster center [24].

In FCM each data point is grouped to a cluster to some degree which is specified by a membership grade. The algorithm starts with an initial guess for the cluster centers, which is most likely incorrect. The cluster centers and the membership grades for each data point are updated iteratively till the cluster centers to the right location within a data set. This iteration is subjected to minimize an objective function which provides the distance from any given data point to a cluster center that is weighted by the membership grade of that data point.

TABLE II. COMPARISON OF TRAINING ERROR

	LM-Grid	LM-Subtractive	LM-FCM	SGC-K means
Error (500 iterations)	0.3383	0.4540	0.4525	0.0353

From Fig. 8, we can conclude that for FCM and subtractive clustering, the network model is less complex than grid partitioning. K means clusters follow straight forward approach in getting the classifier output to either of the two groups. The membership functions got adjusted to the fuzzy rules during training and FCM and subtractive methods form clusters for each set of input features. While in K means, all the input features got clustered into two classes, regardless the number of features provided and the user defined Gaussian membership functions got adjusted to accommodate the varying data points. The surface mesh energy output is more optimized in SGC method. The network gets overloaded when the input features are separately fed to the LM algorithm and it takes a long time to train the fuzzy network, but SGM is observed to avoid that time lag as it approaches the minimum error point through a faster and optimum path. The training error for 500 iterations got compared in Table II, and SGC approach gives a comparatively low error rate.

After the classification system is tested with random signals and the degree of closeness to specific classes are measured. This degree of closeness is used to group the signal into letter composing and figure rotation. For letter composing the system remain in the same state but for figure rotation an alarm signal is evoked.

IV. Conclusions

In this paper, wavelet based feature extraction is incorporated with Adaptive Neuro- Fuzzy Interface System classifier and various clustering and training algorithms got compared. The Neuro-Fuzzy classifier provides the information about the link between input features and the relationship with corresponding classes, adopting data clustering logic to form well-separable groups. The SGM and LM algorithms optimize the network to reduce the classification error, and it is seen that the SGM gives better classification results. The rule based classifier is proved capable enough to distinguish different mental activities which in turn activate the external device. The project proves the possibility of controlling external devices using mental thoughts in an optimized way via Neuro –Fuzzy EEG processing.

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Dilshad Begum is a PhD candidate in Electrical and Electronics Research Center Ghousia College of Engineering, Ramanagara Karnataka, under Visvesvaraya Technological University (VTU), India. She received BE Degree in Computer Science and Engineering from Gulbarga University Gulbarga in 2000 and MTech Degree from Visvesvaraya Technological University (VTU) in 2007 .Her current area of interest is in EEG data Processing, Brain Computer Interface and its Applications. (dil3339dan@gmail.com)

Ravi Kumar K. M Professor and Head of Information Science and Engineering Department, Ghousia collage of Engineering, Ramanagaram. He has completed his M.Tech in the field of Biomedical Instrumentation in the year 2002 and submitted his PhD thesis in 2009 (VTU, Belgaum). He is in the field of teaching from past 15 years and he has published ten papers in the International Conference and four in the International journal related to his research areas. He is member of various professional societies which include ISTE, MIE, SIS, and BMESI. His field of interest includes Digital Signal Processing, Human Computer Interface and Communication Systems. He is serving as Special Officer VTU, Belgaum (kmravikumar@rediffmail.com).

Sanjeev Kubakaddi is successful entrepreneur and proprietor of itie Knowledge Solutions Bangalore, company focusing on Biomedical, Embedded product development and technology training. He received his Bachelors in 1995, Master of Technology (M. Tech) in 2012. He is also working towards his PhD from Jain University. He is a renowned trainer in the areas of DSP, Image Processing and expert in Matlab®, Simulink® and Texas Instruments DSP. Mr. Sanjeev Kubakaddi (Sanjeev@itie.in) is successful entrepreneur and proprietor of itie Knowledge Solutions Bangalore, company focusing on Biomedical, Embedded product development and technology training. He received his Bachelors in 1995, Master of Technology (M. Tech) in 2012. He is also working towards his PhD from Jain University. He is a renowned trainer in the areas of DSP, Image Processing and expert in Matlab®, Simulink® and Texas Instruments DSP (Sanjeev@itie.in).

James Mathew completed his Bachelors in Electrical & Electronics Engineering from MG University, Kerala, India and Masters in Communication Engineering & Signal Processing from University of Plymouth, UK. His research interests are Cognitive Neuroscience, Neural Engineering, Brain Computer Interface, Image Processing, Machine Learning and Pattern Recognition.

Rajeev Yadav received the B.Sc. degree in physics and the M.Sc. degree in electronics both from the D.D.U. Gorakhpur University, Gorakhpur, India, in 1998 and 2000, respectively and Ph.D. in electrical engineering from the Concordia University, Montreal, Canada in 2012. He is currently a Research Scientist at the Genia Photonics Inc., Laval, Canada and a recipient of the prestigious NSERC Industrial R&D fellowship of Canada. Prior to this, he worked as a Research Scientist at the Leap Medical Inc. Montreal, Canada. He is member of the IEEE EMB, SP, CAS societies, CMBES, OSA and IBRO. He serves as committee member for the CMBES and OSA, editorial member and reviewer for over 30 international signal processing and biomedical engineering journals. His research interests include biophotonics, biomedical signal processing and pattern recognition with emphasis on their application to neural signals for critical care and neuroscience research, and neural prosthesis.