Brain-actuated Control of Wheelchair Using Fuzzy Neural Networks

Rahib H.Abiyev, Nurullah Akkaya, Ersin Aytac, Irfan Günsel, Ahmet Çağman, Sanan Abizade
Near East University, Applied Artificial Intelligence Research Centre, Lefkosa, Mersin-10, North Cyprus
Emails:rahib.abiyev@neu.edu.tr;nurullah@nakkaya.com;

Abstract - *In this paper, a brain-actuated control of the wheelchair for physically disabled people is presented. The design of the system is focused on receiving, processing and classification of the brain signals and then performing control of the wheelchair. The number of experimental measurements of brain activity has been done using human control commands of the wheelchair. Using obtained data including brain signals and control commands the design of classification system based on fuzzy neural networks (FNN) is performed. The structure and learning algorithm of FNN used for brain-actuated control are presented. The training data is used to design the system and then test data is applied to measure the performance of the control under real conditions. The approach used in the paper allows reducing the probability of misclassification and improving the control accuracy of the wheelchair.*

Keywords: Brain-computer interface, wheelchair, fuzzy neural networks, electroencephalogram signal.

1 Introduction

The measuring human brain signal and converting it into control signals needs the development of the interface between the brain and computer and then implementing the control of devices. A brain computer interface (BCI) provides communication between computer and mind of pupils. This interface can be based on brain activity during muscular movements or the changes of the rhythms of brain signals. These brain activities can be detected using electroencephalographic (EEG) signals. BCI transforms the EEG signals produced by brain activity into control signals which can then lasted be used for controlling the wheelchair without using muscles. Since the brain signals are very weak we need to apply some spatial and spectral filters and amplifiers to the EEG signals in order to extract characteristic features of these signals. Several EEG signals can be detected, resulting in different types of BCI. These signals are based on the change of frequencies, change of amplitudes. For example during voluntary thoughts the frequencies of signals are modified, during movement a synchronisation/ desynchronisation of brain activity which involves μ rhythm amplitude change. This relevant characteristic makes rhythm based BCI suitable to be used.

Recently some research works have been done to develop many applications of BCI for wheelchairs. BCI is a control interface that translates human intentions into appropriate motion commands for the wheelchairs, robots, devices, etc. [1] considers the application of BCI and control of wheelchair in an experimental situation. The research considers the driving of a simulated wheelchair in a virtual environment (VE) before using BCI in a real situation. [2] describe a BCI system which control the wheelchair that moves in only one direction- move forward. In [3] a simulated robot is designed that performs two actions- 'turn left then move forward', or 'turn right then move forward'. [4,5] uses three possible commands turn left, turn right and move forward. In [6] BCI is designed using EEG signal captured by eight electrodes. Wavelet transform was used for feature extraction and the radial basis networks were used to classify the predefined movements. In [7] controller based on the brain-emotional-learning algorithm is used to control the omnidirectional robot. [8] presents the design of an asynchronous BCI based control system for humanoid robot navigation using an EEG. [10] considers a non-invasive EEG-based Brain Computer Interface (BCI) system to achieve stable control of a low speed unmanned aerial vehicle for indoor target searching. [10-15] consider the design of brain controlled wheelchair. The constraction of viable brain–actuated wheelchair that combines brain computer interface with a commercial wheelchair, via a control layer, is considered. BCI allows improving the quality of life of disabled patients and letting them interact with their environment. The processes of feature extraction and classification is very important in BCI design and has a great affect to the performance of the BCI system. Set of research have been done for improvement of the feature extraction and classification algorithms [16-19]. [16,17] considers feature extraction algorithms for Brain-Computer Interfaces.

Recently different clustering algorithms based on support vector machine, linear discriminant analysis, neural networks are applied for classification of brain signals [18]. [19] used features, optimised in the sense of statistically significant and potentially discriminative coherences at a specific frequency and applied linear discriminant for classification purpose. SVM based classification [20] and linear discriminant analysis (LDA) [21] are used for classification purpose of brain signals. [22] uses fuzzy logic and [23] uses neural networks with fuzzy particle swarm optimisation for BGI design. In [24] continuous wavelet transform is used to extract highly representative features and an Adaptive Neuron-Fuzzy Inference System (ANFIS) is used for classification. Fuzzy logic provides a simple way for determining a conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. Fuzzy Logic's approach to control problems mimics how a person would make faster decisions.

As shown feature extraction and classification plays an important role in designing brain based control for obtaining of high classification accuracy. In BCI design, a classification error (a wrong command) can cause dangerous situations, so it is crucial to guarantee a minimum error rate to keep the users safe. Different clustering algorithms based on support vector machine, linear discriminant analysis, neural networks are applied for classification of brain signals [18]. Fuzzy classification represents knowledge more naturally to the way of human thinking and is more robust in tolerating imprecision, conflict, and missing information. In this paper, fuzzy neural network is used for the design of BCI in order to achieve efficient brain based control of wheelchair. Signal processing, feature extraction and classification algorithms are designed for brain-actuated control of wheelchair.

2 BCI system architecture

Fig.1 depicts BCI based control of the wheelchair. BCI system consists of an Emotiv headset connected to a computer where classification algorithms are run which is connected to a micro-controller that controls the movement of motors. A BCI based control system is usually composed of six main units: signal acquisition unit, signal preprocessing unit, feature extraction unit, classification unit, control action unit and wheelchair motors unit. The brain signals are captured using an emotive headset utilizing 14 channels. These input signals are sent to the signal processing unit. The signals in preprocessing block after filtering and scaling are entered to the feature extraction block. The basic features are extracted and send to the classification system. The output signals of the classification block are motor signals (clusters) that are sent to the wheelchair.

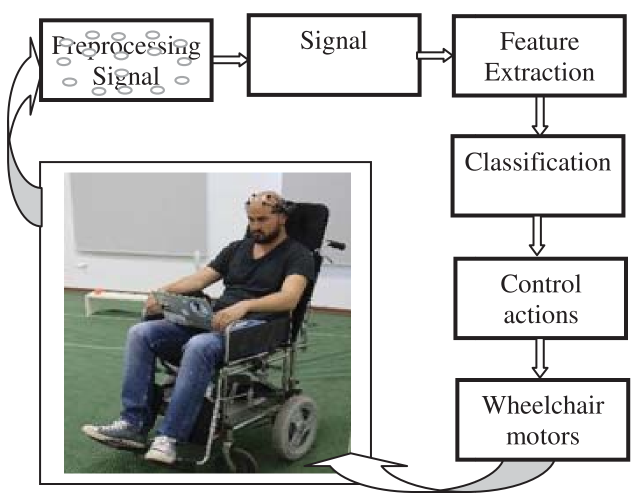

Fig. 1. The BCI based control of the wheelchair

In signal acquisition block the EEG signals are captured using the Emotiv headset. Emotiv EPOC is an EEG Headset which supplies 14 channel EEG data (Fig.2) and 2 gyros for 2- dimensional controls. Its features are adequate for a useful BCI in case of resolution and bandwidth. Our system uses upper face gestures for actuation commands since most Emotiv sensors are located in the frontal cortex they are the most reliable signals to detect.

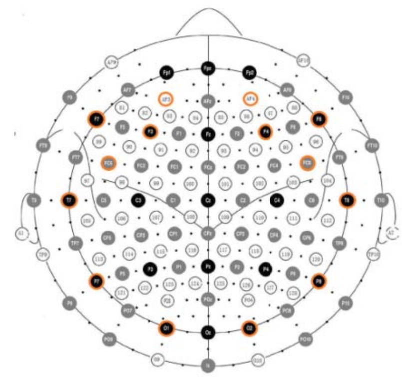

Fig.2. Emotiv's sensor Layout compared to standart 72 sensors layout. The distribution of EEG electrodes. Fourteen channels are marked for data acquisition.

The measured signals are sent to the system input. The signals are very long for processing. Therefore, the feature extraction technique is applied in order to decrease the signal size and extract more important features for classification. In the paper, two different approaches are used for processing of the input sensor signals: With Fast Fourier Transform (FFT) and without FFT. The input signal received from the headset is divided into windows having 2 sec time interval with 50% overlap (Fig.3). The use of overlapping windows allows us to increase the accuracy of the classification. Each two second window corresponds to 256 samples of data. Each second headset returns 128 data samples. The obtained signals from the channels, stored as windows, are then sent to normalisation block. Each channel is normalised in order to center each channel on zero by calculating the mean value of each channel for the window, then subtracting it from each of the data points in the channel. After normalisation, Hamming window is applied to each channel in the window. EEG signals do not generally repeat exactly, over any given time interval, but the math of the Fourier transform assumes that the signal is periodic over the time interval. This mismatch leads to errors in the transform called spectral leakage. Hamming window is used to mitigate this problem. Then fast Fourier transform (FFT) is applied to each channel in the window to find out the frequency components of the signal. Each frequency component is used as a feature, which results in 64x14 features. In order to increase the performance of the classification, the features are ranked by evaluating the worth of a frequency by measuring the information gain with respect to the class. The expected information gain is the change in information entropy (H) from a prior state to a state that takes some information as given:

$$\text{InfoGain(Class,Frequency)} = H(\text{Class}) - H(\text{Class} \mid \text{Frequency})$$

Information Gain, selects a subset of the original representation attributes according to Information Theory quality metric, Information Gain. This method computes the value of the metric for each attribute, and rank the attributes. Then simply decide a threshold in the metric and keep the attributes with a value over it.

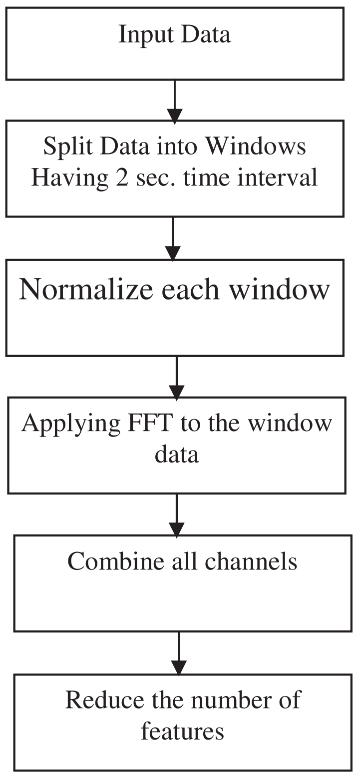

Fig.3. Signal Preprocessing unit.

After frequency representation, all channels in the window are combined in to a single unit so as to apply classification on all channels at once. The filtering operation is applied in order to select important features of the brain signals. These features are used for classification purpose. The whole signal preprocessing stages are shown in Fig. 3. In the second approach the acquired brain signal after windowing, normalisation and combining operations are used for classification purpose.

These signals are input for the classification. After the classification the signals the output of classification system is used to activate the wheelchair. Even though during training system reports 100% success rate in real world conditions it does misclassify, a state machine is used to further increase safety and reduce misclassification. As an example, the system won't transition from forward motion to backward motion without stopping in neutral. The output of the state machine drives the microcontroller which controls the motors on the wheelchair. The number of classes is equal to the number of control actions.

3 FNN Based Classification

The features extracted from the EEG signals are used for classification and determining control action. In this paper, we propose a novel approach for the classification of brain signals using FNN based classifier. The extracted features are input signals of the FNN based classifier. The classifier based on the above features classifies the signals into the six classes: move forward, move backward, switch on, stop, turn left and turn right. The fuzzy neural system combines the learning capabilities of neural networks with the linguistic rule interpretation of fuzzy inference systems. The design of FNN includes the generation of IF-THEN rules [25-28]. Here, the problem consists in the optimal definition of the premise and consequent part of fuzzy IF-THEN rules for the classification system through the training capability of neural networks, evaluating the error response of the system. There are two basic types of IF-THEN rules used in fuzzy systems. These are Mamdani and Takagi-Sugeno-Kang (TSK) type fuzzy rules. The first one consists of rules, whose antecedents and consequents parts utilize fuzzy values. The second type fuzzy system uses the rule base that has fuzzy antecedent and crisp consequent parts. The second type of fuzzy system approximates nonlinear system with linear systems and has the following form.

If x_1 is A_{1j} and x_2 is A_{2j} and … and x_m is A_{mj} Then

$$y_j = b_j + \sum_{i=1}^{m} a_{ij} x_i \qquad (1)$$

Here x_i and y_j are input and output signals of the system, respectively, $i=1,...,m$ is the number of input signals, $j=1…r$ is the number of rules. A_{ij} are input fuzzy sets, b_j and a_{ij} are coefficients.

The structure of fuzzy neural networks used for the classification of EEG signals is based on TSK type fuzzy rules and is given in Fig. 4. The FNN includes six layers. In the first layer, the x_i $(i=1,…,m)$ input signals are distributed. The second layer includes membership functions. Here each node corresponds to one linguistic term. Here for each input signal entering the system, the membership degree to which input value belongs to a fuzzy set is calculated. To describe linguistic terms, the Gaussian membership function is used.

$$\mu 1_j(x_i) = e^{-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}}, \quad i = 1,...,m, \;\; j = 1,...,r \qquad (2)$$

where m is a number of input signals, r is a number of fuzzy rules (hidden neurons in the third layer). c_{ij} and σ_{ij} are centre and width of the Gaussian membership functions, respectively. $\mu 1_j(x_i)$ is membership function of i-th input variable for j-th term.

The third layer is a rule layer. Here number of nodes is equal to the number of rules. Here R_1, R_2,…,R_r represents the rules. The output signals of this layer are calculated using t-norm min (AND) operation.

$$\mu(x) = \prod_i \mu 1_j(x_i), \;\; i=1,..,m, \; j=1,...,r \qquad (3)$$

where Π is the min operation.

These $\mu_j(x)$ signals are input signals for the fifth layer. Fourth layer is a consequent layer. It includes n linear systems. Here the values of rules output are determined.

$$y1_j = b_j + \sum_{i=1}^{m} a_{ij} x_i \tag{4}$$

In the fifth layer, the output signals of the third layer are multiplied by the output signals of the fourth layer. The output of j-th node is calculated as

$$y_j = \mu_j(x) \cdot \mathrm{y}1_j$$

In the sixth layer, the output signals of FNN are determined as

$$u_k = \frac{\sum_{j=1}^{r} w_{jk} y_j}{\sum_{j=1}^{r} \mu_j(x)} \tag{5}$$

Here u_k are the output signals of FNN, ($k=1,..,n$). After calculating the output signal, the training of the network starts.

and the gradient algorithm is applied to design the consequent parts of the fuzzy rules. Fuzzy c-means clustering is applied in order to partition input space and construct antecedent part of fuzzy if-then rules. In the results of partitioning the determined cluster centers will correspond to centers of the membership functions used in input layer of FNN. The width of the membership function is determined using distance between cluster centers. After the design of the antecedents parts by fuzzy clustering, the gradient descent algorithm is applied to design the consequent parts of the fuzzy rules. At the beginning, the parameters of the FNN are generated randomly. To generate a proper FNN model, the training of the parameters has been carried out. For generality we have given the learning procedure of all parameters of FNN using gradient descent algorithm. The parameters are the membership function of linguistic values in the second layer of the network and the parameters of the fourth and fifth layers. Training includes the adjusting of the parameter values. In this paper, we applied gradient learning with adaptive learning rate. The adaptive learning rate guarantees the convergence and speeds up the learning of the network. In addition, the momentum is used to speed-up the learning processes.

At first, on the output of the network, the value of cost function is calculated.

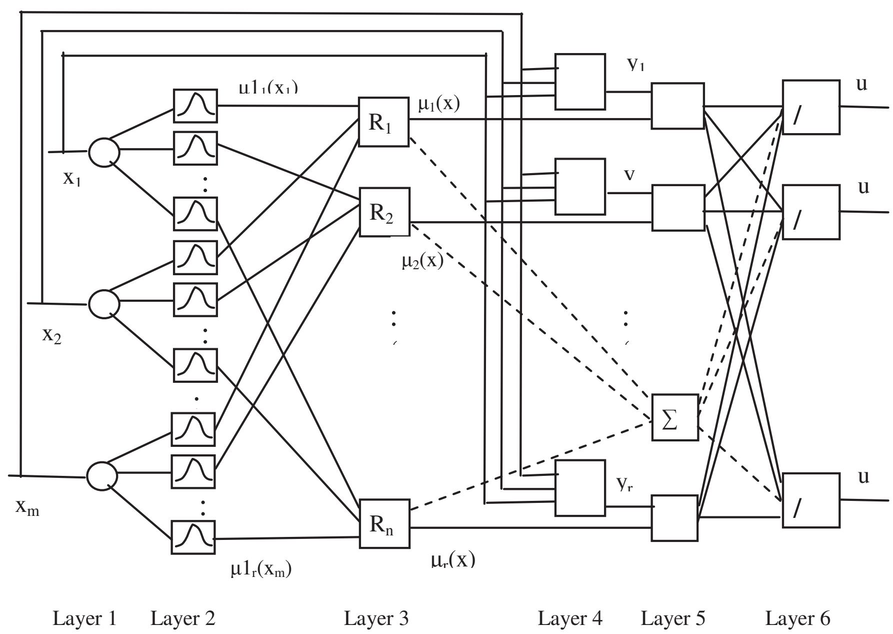

Fig. 4. FNN based identifier

4 Parameter Learning

The design of FNN (Fig. 4) includes determination of the unknown parameters that are the parameters of the antecedent and the consequent parts of the fuzzy if-then rules (1). In the antecedent parts, the input space is divided into a set of fuzzy regions, and in the consequent parts the system behaviour in those regions is described [25-28]. In this paper, the fuzzy clustering is applied to design the antecedent (premise) parts,

$$E = \frac{1}{2} \sum_{k=1}^{n} (\mathrm{u}_k^d - u_k)^2 \tag{6}$$

Here n is the number of output signals of the network, u_k^d and u_k are desired and current output values of the network ($k=1,..,n$), respectively. The parameters w_{jk}, a_{ij}, b_j, (i=1,..,m, j=1,..,r, $k=1,..,n$) in consequent part of network and the parameters of membership functions c_{ij} and σ_{ij} (i=1,..,m, j=1,..,r) of in the premise part of FNN structure are adjusted using the following formulas.

$$w_{jk}(t+1)=w_{jk}(t)-\gamma\frac{\partial E}{\partial w_{jk}}+\lambda(w_{jk}(t)-w_{jk}(t-1));$$

$$a_{ij}(t+1)=a_{ij}(t)-\gamma\frac{\partial E}{\partial a_{ij}}+\lambda(\mathrm{a}_{ij}(t)-a_{ij}(t-1)); \qquad (7)$$

$$b_{j}(t+1)=b_{j}(t)-\gamma\frac{\partial E}{\partial b_{j}}+\lambda(\mathrm{b}_{j}(t)-b_{j}(t-1));$$

$$c_{ij}(t+1)=c_{ij}(t)-\gamma\frac{\partial E}{\partial c_{ij}}+\lambda(c_{ij}(t)-c_{ij}(t-1));$$

$$\sigma_{ij}(t+1)=\sigma_{ij}(t)-\gamma\frac{\partial E}{\partial \sigma_{ij}}+\lambda(\sigma_{ij}(t)-\sigma_{ij}(t-1)); \qquad (8)$$

$$i=1,...,m;\quad j=1,...,r;\quad k=1,...,n.$$

Here γ is the learning rate, λ is the momentum, m is the number of input signals of the network (input neurons) and r is the number of fuzzy rules (hidden neurons).

Using equations (7) and (8) the correction of the parameters of FNN is carried out.

Convergence is very important problem in learning of FNN model. The convergence of the learning algorithm using gradient descent depends on the selection of the initial values of the learning rate. The derivation of the convergence is given in [33, 34].

5 Experiments and Results

The BCI system is simulated and used in real life application. The EEG signals are measured with Signal acquisition unit- the Emotiv EPOC headset. In the experiments, we have utilized 14 channels for measuring EEG signals. The measured EEG signals have different rhythms within the frequency band. The experiments show that measuring brain signals is difficult so we have tested our system using brain muscle signals. The signals obtained from 5 sample channels are shown in Fig.5. Fig.5(a) depicts a neutral pose, patient relax not doing anything. Fig.5(b) depicts a positive gesture. As shown in figures, the EEG signals with positive gesture pose are changing more frequently than a neutral pose. In the paper, the FFT is applied to extract important features of the signal. After preprocessing stage, given in section 2, the important features of these signals are extracted and used for classification purpose. The number of extracted features was determined as 100. These signal are inputs for FNN system. Outputs of FNN model are clusters. Six clusters are used in the experiment: Move Backward, Move Forward, Switch on, Stop, Turn Left, and Turn Right. For each cluster, the system recorded 10 seconds of data.

The classification of the EEG signals is performed using FNN model. To synthesis classification model the FNN structure with hundred input- and six output neurons is generated first.

.

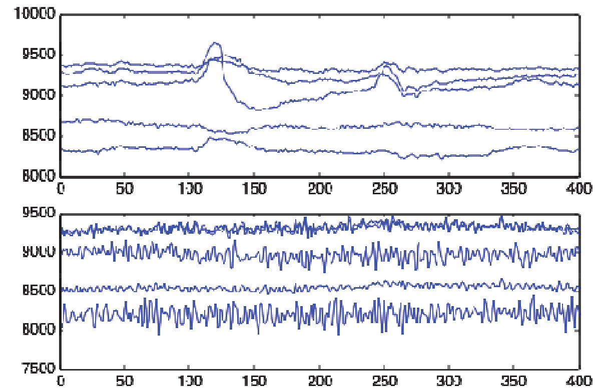

Fig.5. EEG signals for five channels: a) neutral pose, b) positive gesture pose

Fuzzy classification is applied in order to partition input space and select the parameters of the premise parts, that is the parameters of Gaussian membership functions used in the second layer of FNN. Fuzzy c-means clustering is used for the input space with 5 clusters for each input. 5 fuzzy rules are constructed using different combination of these clusters for 100 inputs. After clustering input space gradient decent algorithm is used for learning of consequent parts of the fuzzy rules, that is parameters of the 4-th layer of FNN. In learning of FNN 10 fold cross validation is used for separation the data into training and testing set.

The initial values of the parameters FNN are randomly generated in the interval [-1, 1] and, using the gradient algorithm derived above, they are updated for the given input-output training pairs. As a performance criterion, RMSE is used.

The training is carried out for 1000 epochs. The values of the parameters of the FNN system were determined at the conclusion of training. Once the FNN has been successfully trained, it is then used for the classification of the EEG signals. During learning, the value of RMSE was obtained as 0.223264 for training data, and 0.241625 for evaluation. After learning, for the test data the value of RMSE was obtained as 0.257986 with 100% accuracy of classification. Fig. 6 depicts RMSE values obtained during training. The design of FNN model is performed using a different number of rules. Table 1 includes results of simulations wit 5, 6, 9 and 16 rules respectively. As shown accuracy of FNN classification model are 100%.

For comparison purpose, we test the system using different classification techniques. In the result of classification, the following results are obtained (Table 2). As shown the simulation results demonstrate the efficiency of application FNN model in the classification of EEG signals. These clusters activate the corresponding control signal which is then used to actuate the motors of the wheelchair..

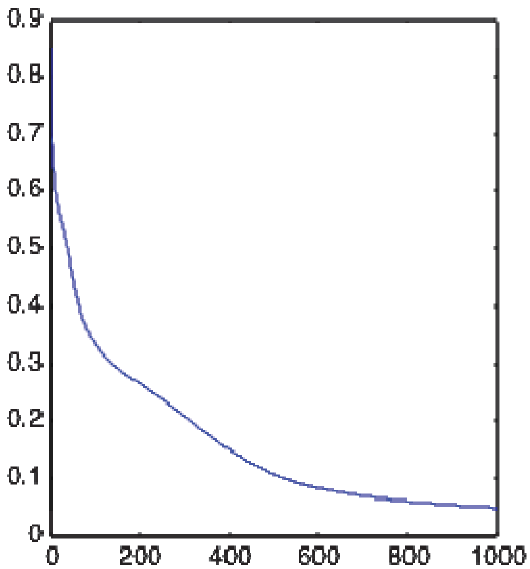

Fig. 6. Training of FNN

Table 1. Classification results.

Number of Rules	Correctly Classified Instances	Incorrectly Classified Instances	Training RMSE	Evaluation RMSE	Test RMSE
5	92%	3	0.465492	0.464918	0.476516
6	100%	0	0.223264	0.241625	0.257986
9	100%	0	0.152714	0.153688	0.153874
16	100%	0	0.047268	0.048324	0.048262

Table 2. Classification results

Method	Correctly Classified Instances	Incorrectly Classified Instances	Mean absolute error	Root mean squared error
SVM	96%	4%	0.2424	0.32
MLP (NN) (6 hidden neurons)	100%	0	0.048	0.0958
Bayesian	94%	6%	0.024	0.1549
Random tree	74%	26%	0.104	0.3225
FNN	100%	0	1.824	0.258022

6 Conclusions

The paper presents BCI based on FNN for the wheelchair. The emotional and muscular states of the user are evaluated for control purpose. The design of BCI has been done to actuate a brain controlled wheelchair using six mental activities of the user: Move Backward, Move Forward, Switch on, Stop, Turn Left and Turn Right. For classification of EEG signals FNN with 10 fold cross validation data set is used. The design of the FNN system is implemented using fuzzy c means classification and gradient descent algorithm. The obtained 100% classification results prove that the used techniques are a potential candidate for the classification of the EEG signals in the design of brain based control system. In the future, we are going to improve the number of commands for control of wheelchair and decrease detection time of the EEG signal used for measuring brain activities and design efficient brain controlled wheelchair.

7 References

[1] Galán, F., Nuttin, M., Vanhooydonck, D., Lew, E., Ferrez, P.W., Philips, J., de Millán,J.R.: Continuous brain-actuated control of an intelligent wheelchair by human EEG. In: Proceedings of the 4th International Brain-Computer Interface Workshop and Training Course, TU Graz/Büroservice, Graz, pp. 315–320 (2008)

[2] Leeb, R., Friedman, D., Müller-Putz, G.R., Scherer, R., Slater, M., Pfurtscheller, G.: Self-Paced (Asynchronous) BCI Control of a Wheelchair in Virtual Environments: A Case Study with a Tetraplegic. Computational Intelligence and Neuroscience. Article ID 79642 (2007)

[3] Tsui, C.S.L., Gan, J.Q.: Asynchronous BCI Control of a Robot Simulator with Supervised Online Training. In: Yin, H., Tino, P., Corchado, E., Byrne, W., Yao, X. (eds.) IDEAL 2007. LNCS, vol. 4881, pp. 125–134. Springer, Heidelberg (2007)

[4] Scherer, R., Lee, F., Schlögl, A., Leeb, R., Bischof, H., Pfurtscheller, G.: Towards elfpaced Brain-Computer Communication: Navigation through virtual worlds. IEEE Transactions on Biomedical Engineering 55(2), 675–682 (2008)

[5] Anas Fattouh, Odile Horn, Guy Bourhis. Emotional BCI Control of a Smart Wheelchair. IJCSI International Journal of Computer Science Issues, Vol. 10, Issue 3, No 1, May 2013

[6] Vijay Khare, Jayashree Santhosh, Sneh Anand, Manvir Bhatia. Brain Computer Interface Based Real Time Control of Wheelchair Using Electroencephalogram. International Journal of Soft Computing and Engineering (IJSCE) SSN: 2231-2307, Volume-1, Issue-5, November 2011.

[7] Maziar A. Sharbafi, Caro Lucas, and Roozbeh Daneshvar. Motion Control of Omni-Directional Three-Wheel Robots by

Brain-Emotional-Learning-Based Intelligent Controller. IEEE Trans. on Systems, Man, and Cybernetics—Part C: Applications and Reviews, Vol. 40, No. 6, 2010

[8] Yongwook Chae, Jaeseung Jeong, and Sungho Jo. Toward Brain-Actuated Humanoid Robots: Asynchronous Direct Control Using an EEG-Based BCI. IEEE Trans. On Robotics, Vol. 28, No. 5, 2012

[9] Tianwei Shi, Hong Wang, Chi Zhang. Brain Computer Interface system based on indoor semi-autonomous navigation and motor imagery for Unmanned Aerial Vehicle control. Expert Systems with Applications 42 (2015) 4196–4206

[10] Tom Carlson, Robert Leeb, Ricardo Chavarriaga and Jos´e del R. Mill´an. The Birth of the Brain–Controlled Wheelchair. IEEE/RSJ International Conference on Intelligent Robots and Systems October 7-12, 2012. Vilamoura, Algarve, Portugal, pp. 5444-5445

[11] B. Rebsamen, C. Guan, H. Zhang, C. Wang, C. Teo, M. H. Ang, Jr., and E. Burdet, "A brain controlled wheelchair to navigate in familiar environments," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 6, pp. 590–598, Dec. 2010

[12] Iturrate, J. M. Antelis, A. Kubler, and J. Minguez, "A noninvasive brain-actuated wheelchair based on a p300 neurophysiological protocol and automated navigation," IEEE Trans. Robot., vol. 25, no. 3, pp. 614–627, Jun. 2009.

[13] G. Vanacker, J. del R. Mill´an, E. Lew, P. W. Ferrez, F. G. Moles, J. Philips, H. V. Brussel, and M. Nuttin, "Context-based filtering for brain-actuated wheelchair driving," Comput. Intell. Neurosci., vol. 2007, pp. 1–12, May 2007

[14] Rahib H.Abiyev, Nurullah Akkaya, Ersin Aytac, Irfan Günsel, Ahmet Çağman. Development of Brain Computer Interface for Wheelchair. The International Biomedical Engineering Congress 2015 (IBMEC-2015), 12-14 March 2015, Girne, North Cyprus

[15] Lei Cao, Jie Li, Hongfei Ji, Changjun Jiang. A hybrid brain computer interface system based on the neurophysiological protocol and brain-actuated switch for wheelchair control. Journal of Neuroscience Methods. Volume 229, 30 May 2014, Pages 33–43

[16] F. Lotte, C.T. Guan, "*Regularizing Common Spatial Patterns to Improve BCI Designs: Unified Theory and New Algorithms*", IEEE Transactions on Biomedical Engineering, vol. 58, no. 2, pp. 355-362, 2011

[17] Xiaomu Song, Suk-Chung Yoon. Improving brain–computer interface classification using adaptive common spatial patterns. Computers in Biology and Medicine 61 (2015) 150–160

[18] Lusheng Bi, Xin-an Fan, Yili Liu. EEG-based brain controlled mobile robots: a survey. IEEE Tran. on Human-Machine Systems, V:43,No2,2013.

[19] Rocio Salazar-Varas, David Gutiérrez. An optimized feature selection and classification method for using electroencephalographic coherence in brain–computer interfaces. Biomedical Signal Processing and Control. 18 (2015) 11–18

[20] E. Hortal·, D. Planelles, A. Costa, E. Iáñez, A. Úbeda, J.M. Azorín, E. Fernández. SVM-based Brain–Machine Interface for controlling a robot arm through four mental tasks. Neurocomputing, Volume 151, Part 1, 3 March 2015, Pages 116–121

[21] Yonghui Fang, Minyou Chen, Xufei Zheng. Extracting features from phase space of EEG signals in brain–computer interfaces. Neurocomputing 151 (2015) 1477–1485

[22] Mandeep Kaur & Poonam Tanwar. Developing brain computer interface using fuzzy logic. International Journal of Information Technology and Knowledge Management July-December 2010, Volume 2, No. 2, pp. 429-434

[23] Chai R, Ling SH, Hunter GP, Tran Y, Nguyen HT.Brain-computer interface classifier for wheelchair commands using neural network with fuzzy particle swarm optimization. IEEE J Biomed Health Inform. 2014 Sep;18(5):1614-24. doi: 10.1109/JBHI.2013.2295006.

[24] Darvishi S, Al-Ani A. Brain-computer interface analysis using continuous wavelet transform and adaptive neuro-fuzzy classifier. Conf Proc IEEE Eng Med Biol Soc. 2007; 2007:3220-3.

[25] Rahib H.Abiyev. Fuzzy Wavelet Neural Network Based on Fuzzy Clustering and Gradient Techniques for Time Series Prediction. Neural Computing & Applications, Vol. 20, No. 2, pp. 249-259, 2011

[26] Rahib Hidayat Abiyev, Controller based on Fuzzy Wavelet Neural Network for Control of Technological Processes. In proceeding of IEEE International Conference on Computational Intelligence for Measurement Systems and Applications, IEEE CIMSA 2005, pp.215-219, Giardini Naxos - Taormina, Sicily, ITALY , 20-22 July 2005.

[27] Rahib H. Abiyev, Time Series Prediction Using Fuzzy Wavelet Neural Network Model. ICANN-2006. Lecture Notes in Computer Sciences, Springer-Verlag, Berlin Heidelberg, 2006. pp.191-200.

[28] Abiyev R.H, Abiyev V, Ardil C. Electricity Consumption Prediction Model using Neuro-Fuzzy System. Proceedings of the World Academy of Science Engineering and Technology, Vol.8,pp.128-131, Oct 26-28, 2005, Budapest, Hungary.