European Journal of Molecular & Clinical Medicine
ISSN 2515-8260 Volume 07, Issue 08, 2020

Classification Of Mental Tasks By Using Statistical Process Control And Artificial Neural Networks

Mohd Rizwan Jafar[1], DS Nagesh[1]

[1]*Department of Mechanical Engineering, Delhi Technological University, Delhi 110042, India*

Abstract

EEG can be used to generate control signals for Brain Computer Interface (BCI) applications. In this paper Artificial Neural Networks (ANN) were used to classify mental tasks. Primary data was decomposed by the help of discrete wavelet transformation to extract features. Out of control events were identifiedusing statistical process control. These out of control events were removed from the original dataset. Two data sets were created, one containing all the events and other without the out of control events. Each dataset was divided into training dataset (80%) and testing dataset (20%). The classification efficiency of statistically controlled dataset was found to be 85.71%, as compared to 67.74% from the dataset without statistical process control.

Index Terms: brain machine interface, statistical process control, neural network

1. INTRODUCTION

Neurons in human brain communicates with each other by the help of electrical signals. The electric signal produced by a single neuron is known as action potential. This action potential is very small for a single neuron and is very difficult to be measured on the scalp. But our brain is composed of more then a 10^9 neurons. And the collective electrical potential generated by these neurons can be recorded on the scalp.These electrical signals carry sensory and motor information in central nervous system as well as in peripheral nervous system. Whenever a person sees something, imagines something, feels something an electoral activity is generated in the area of brain which are associated that particular stimuli. These electric signals can be recorded by placing electrodes on the strategically chosen locations on the body. Researchers have shown that there is a similar kind of pattern generated in the brain whenever same task is done or imagined. Understanding the way in which these signals work and using them to operate machines have opened tremendous opportunities. Researchers are using this technique to operate wheelchairs, upper limb prosthetic devices, lower limb prosthetic devices, exoskeletons and much more. It is also being used in rehabilitation of patients with stroke. Patients with diseases like tetraplegia or quadriplegia can be made capable ofmoving from one place to another on their own. There is a group of researcher who are using this technique to operate mobile and computer games and to make lifestyle devices like remotes for TV etc.

Brain machine interface is a method in which electrical potentials generated in the brain are used to operate a machine. In 1924 Berger et. al. first started recording these electrical potentials by the help of an electro-encephalography (EEG) machine. Since then there has been lots of researches in this domain, especially in past 20 years. As this technique is very revolutionary and has opened lots of opportunities of researchers, there are certain complexities associated with it too. The raw electrical signal obtained from the subject is very complex, hence it can not be used as it is. There are some complex pre processing techniques involved which help us to extract useful information. It is also very challenging task to classify these signals accurately. Researchers have been trying to understand the mechanism of generation of these potentials, nature of these potentials, the ways in which they can be manipulated artificially and last but not the least, the methods to identify and predict them. In this paper we have researched on a method which can be used to classify these electric potentials more efficiently. Based on this classification the state of cognition of the user can be predicted. The classification process for these electrical potentials involves many steps. To begin with, the electrical potentials are recorded by the help of an EEG machine. Electrodes are used to record these potentials. These electrodes can be placed surgically on the brain or externally on the scalp. As the surgical process involves lots of complexities, generally non-surgical method of recording is preferred. This process involves strategically placing electrodes on the predetermined locations on the scalp, are recording the potential difference. The placing of electrodes is as per international 10-20 system. The next step is to filter these signals. Researchers have been filtering these electric potential waves in a range of 0-80 Hz to predict the mental tasks. This process is called pre-processing. In this process artifacts from environment, eye blinks, electric power supply etc. are also removed from the recorded data. Researchers claim that removing these noises from the data can improve the classification accuracy. After pre-processing certain features are extracted from this data. It has been observed that the wave generated by the electric potentials of brain oscillates at multiple frequencies. Based on the frequency of oscillation, researchers have categorized these waves in four categories, namely alpha, beta, theta and delta. The frequency of these waves is in the range of 0-4 Hz, 4-8 Hz, 8-16 Hz and 16-32 Hz respectively. For different types of cognitive states, brain potentials oscillates differently. Hence these potentials are analyzed at different frequencies. Different methods have been used in past to extract features from this data, including but not limited to, power spectral density (PSD), Hilbert-Hwang Transformation (HHT), Band power features, Fast Fourier Transformation (FFT), Discrete Wavelet Transformation (DWT), Minimum Energy Combination method.

Lastly the extracted features can be used to classify these brain potentials. This process is called classification. The methods which are used by researchers most frequently for the classification purpose are Genetic Algorithm (GA), Artificial Neural Networks (ANN), Linear Discriminant Analysis (LDA), and Support Vector machine (SVM). In this article we have tried to claim these signals which are generated in the brain sometimes do not follow the same pattern even when same type of task is performed. These signals can be called ‘Out of control’ Signals. We have also tried to claim that removing these ‘out of control’ signals from the neural network training data can increase the overall classification accuracy. Till now researchers pre-process the signals by just filtering the data within a frequency range and remove environmental artifacts from them. Our approach adds an extra layer to pre-processing by removing out of control events too from the training data. A general process of brain machine interface is depicted in the Fig. 1.

The raw signals cannot predict the state of cognition properly. Certain Features need to be extracted from the raw signal to predict state of cognition. Different type of methods were used by researchers, Such as Discrete Wavelet Transformation[13], Fast Fourier Transformation[10][11], Logarithmic Band Power features[14][15],PSD and HHT[5-7],Band power features [8][9],Averaging method[16] to extract features.In order to classify mental tasks Artificial Neural Networks [1-11][13][17], Linear Discriminant Analysis [14][15][18],Genetic Algorithm [5-7], Support Vector Machine [16][19][20] were used. Table I gives the summery of these methods used by different researchers.

2. Methodology

Dataset:
It has been reported in the dataset, [1][2]that a 25 years old female subject volunteered for the recording of data .A screen was placed in front of the subject. As right and left ques appeared on screen subject was asked to imagine right or left hand. The sampling frequency of dataset was 128 Hz. Each trial was recorded according to international 10-20 system. Total recording duration of a single trial was 9s.For initial 2s subject was asked to stay quite. After two seconds a que was displayed on screen to indicate the beginning of trial. A total of 140 trials were recorded.

Pre-Processing:
As sampling frequency of dataset was 128 Hz, hence per trial 1152 events were obtained. As during initial 3 sec no mental task was imagined so these 3 sec were discarded. Now the remaining data of 6 sec gave 768 events per trial. This data was further processed in Matlab. The data was decomposed by using wavedec function at 4 levels. The output obtained was 1 approximation coefficient and 4 detail coefficients. Fig. 2 shows the decomposition tree of the transformation at 4 levels and Table II shows the frequency range of decomposed coefficients.
Approximation coefficient Ad and detail coefficient Db, Dcand Dd were used for further feature extraction process.

Feature Extraction:
Three detail coefficients and one approximation coefficient obtained in previous process were used for feature extraction. Mean of all the 4 coefficients was calculated separately. For a single trial and three channels i.e C4, CZ and C3, 4 features per channel were obtained. Hence for 3 channels total 12 feature per trial were obtained. Table III shows the extracted features from 3 channels and 4 sub-bands. Figure 3 to 6 shows the comparison of normal distribution of mean of extracted features of left and right motor imagery over alpha, beta, theta and delta sub-bands respectively.

Figure 3 4, 5 and 6 denotes the normal probability distribution curve of the mean of alpha beta, theta and delta sub bands over three channels C3, C4, Cz

Input and Output:
In order to generate input for the neural network the extracted features were normalized between 0.1 to 0.9. For output, right imagery was represented as 0.9 and left imagery as 0.1. The whole dataset was divided into training and testing data. 80% data was used to train network and remaining 20% for testing the network. Another dataset was obtained by removing out of control events.

SPC:
Mean and range control charts were used to identify out of control events. An upper control limit (UCL) and a lower control limit (LCL) was obtained by the helpof central line (CL) for mean and range chart respectively.

In order to construct$\overline{X}$ Chart
- CL is obtained by $\overline{\overline{X}} = \sum \overline{X}/g$
- UCL is obtained by $UCL_{\overline{X}} = \overline{\overline{X}} + A_2\overline{R}$
- LCL is obtained by$LCL_{\overline{X}} = \overline{\overline{X}} - A_2\overline{R}$

In order to construct R Chart
- CL is obtained by $\overline{R} = \sum R/g$
- UCL is obtained by $UCL_R = D_4\overline{R}$
- LCL is obtained by $LCL_R = D_3\overline{R}$

Where g, A_2 D_3 and D_4. are the number of subgroups and the factors for control limits respectively

The data between the upper control limit(UCL) and lower control limit(LCL) was taken as control data and the data which was above UCL or below LCL was considered as out of control data and was discarded form the dataset.

Neural Network for the classification of mental task:

The back propagation neural network was used in this work. The performance of neural network depends on the number of hidden layers and the number of neurons per layer. Hence different combinations of number of neurons and number of hidden layers were chosen to obtain high classification accuracy. The input layer of the neural network contained 12 neurons (for 12 extracted features obtained in 2.3) and the output layer consists of 1 neuron (for left or right imagery). A command was considered successfully predicted if the percentage of error lies within 10%. The best classification was achieved with a neural network having structure 12-36-36-36-36-1 for both the datasets(i.e with out of control data and without out of control data). A general block diagram of neural network having three hidden layers and sigmoid transfer function is shown in Fig. 8. The neural network was created using Matlab's neural network toolbox. Table 3 and 4 depicts the classification accuracy of different neural networks used in this research. Table 3 depicts networks using control data while Table 4 depicts networks without control data. Fig. 9 and 10 shows it graphically.

Table 3 and 4 – efficiency of classification of combinations of neurons per layer and hidden layers.

Figure 9 and 10 – efficiency of classification of combinations ofneurons per layer and hidden layers.

Result :

The best classification accuracy was achieved a neural network having a structure 12-36-36-36-1 for both the datasets. Out of 28 commands 19 were successfully identified before removing out of control events giving a classification accuracy of 67.74%. When out of control events were removed 17 commands were correctly identified out of 21 giving a classification accuracy of 85.71%. These results are summarized in Table 5 and 6.

Table 5 nd 6 – Best classification accuracy achieved using 4 hidden layers and having 36 neurons per layer in both the cases.

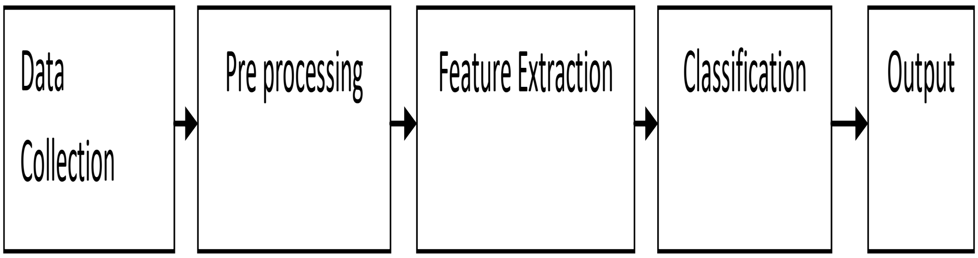


Figure 1 A – A general process of Brain Machine Interface

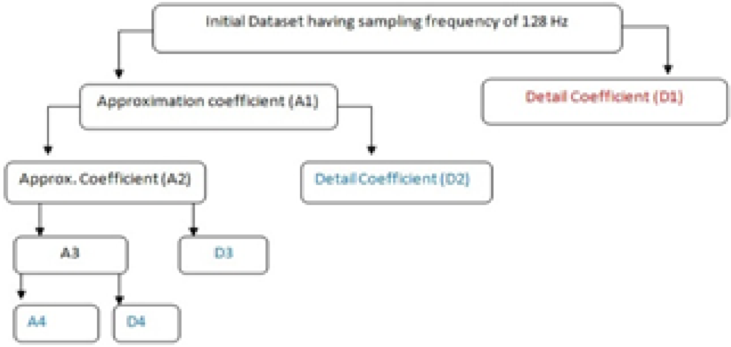


Figure 2. B- Decomposition tree of discrete wavelet transformation at 4 levels

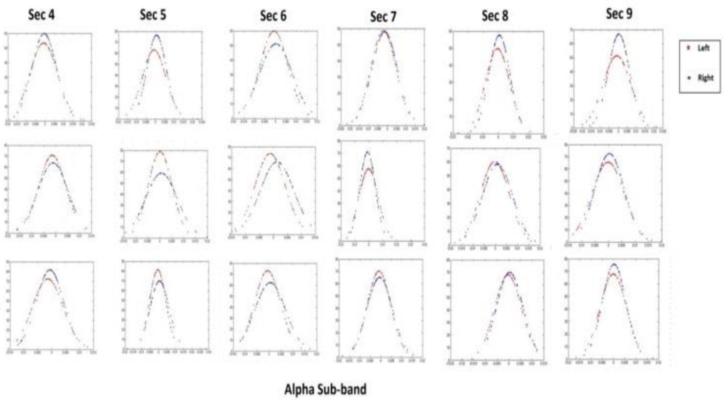
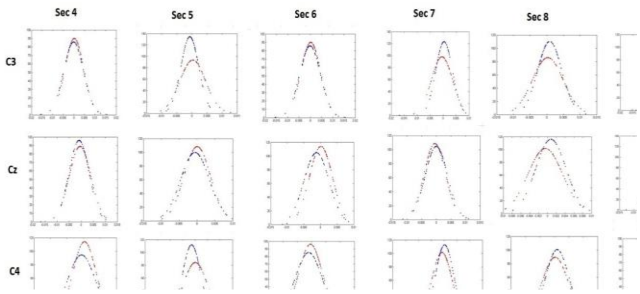


Figure 3.

Figure 4:



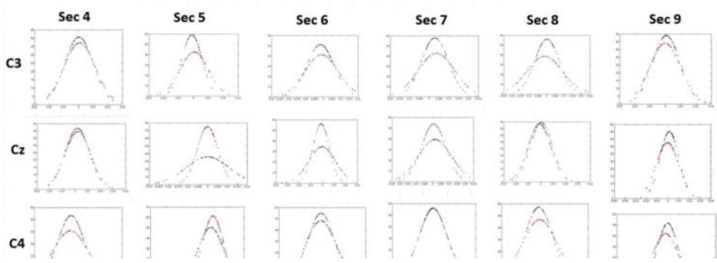


Figure 5:

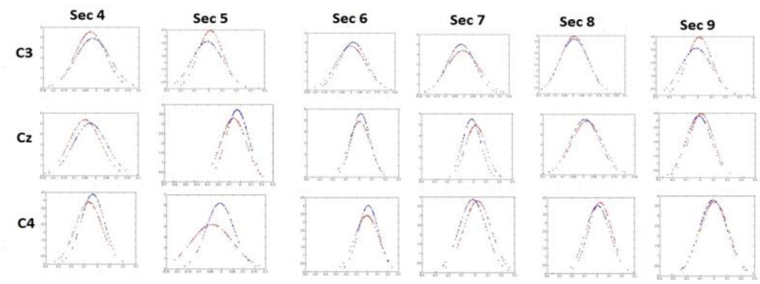


Fig 6:
Figure 6:

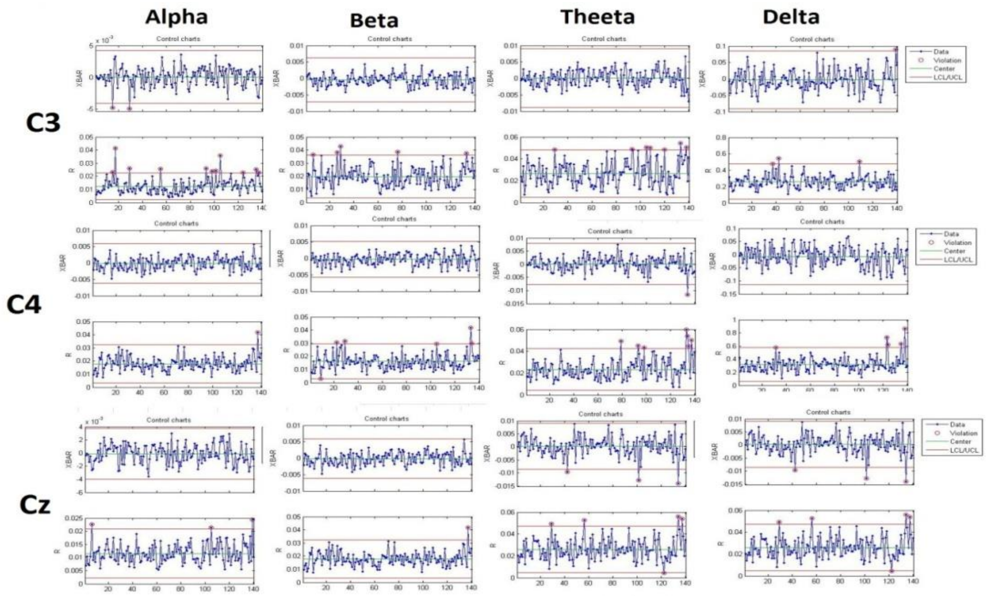


Fig 7: Mean and Range charts of alpha, beta, theta and delta sub-bands over c3, cz and c4 channels to identify out of control processes.

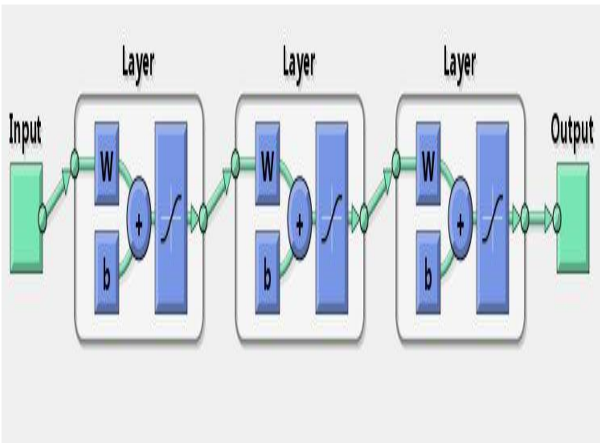


Figure 8: A general block diagram of a neural network with sigmoid transfer function

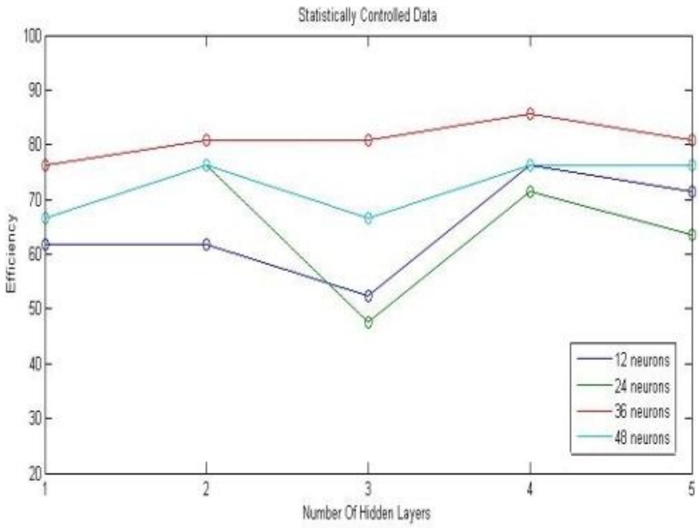


Figure 9:

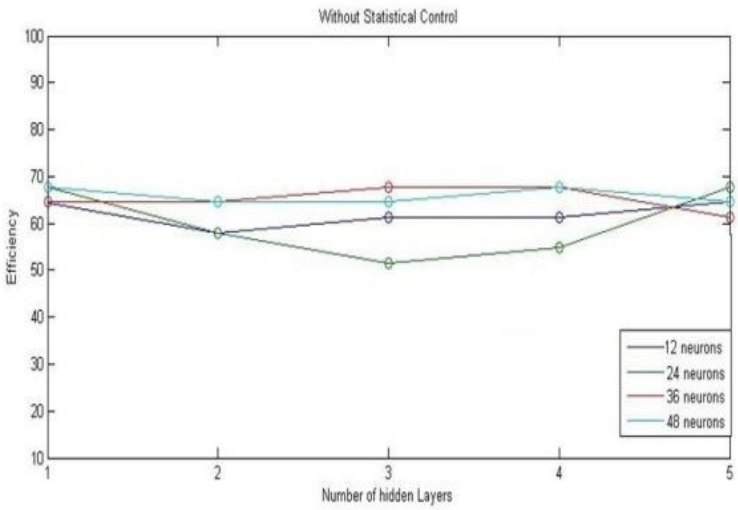


Figure 10:

Table I: Different approaches used in literature

Reference	Feature Extraction	Method of classification
[5][6][7]	PSD and HHT	GA and ANN
[8][9]	Band Power Features	ANN
[10]	Fast Fourier transformation	ANN
[11]	Fast Fourier transformation	ANN
[13]	Discrete Wavelet Transformation	ANN
[14][15]	logarithmic band power	Linear Discriminant Analysis
[16]	Averaging Method	Support vector machine
[17]	_	ANN
[18]	Band Power Method	Linear Discriminant Analysis
[19]	Minimum Energy Combination	Support Vector Machine
[20]	Wavelet Transformation	Support Vector Machine

Table II: Frequency range of Decomposed Signals

Signal	Frequency
Da	32 Hz to 64 Hz
Db	16 Hz to 32 Hz
Dc	8 Hz to 16 Hz
Dd	4 Hz to 8 Hz
Ad	0 to 4 Hz

Table III

Efficiency after removing out of control events					
Neurons per layer	Hidden layers				
	One	Two	Three	Four	Five
Twelve	61.901	61.901	52.3834	76.1906	71.4334
Twenty Four	66.6734	76.1907	47.6366	71.4251	63.6441
Thirty Six	76.1906	80.9567	80.9567	85.7124	80.9567
Fourty eight	66.6734	76.1956	66.6724	76.1956	76.1956

Table IV.

Efficiency without removing out of control events					
Neurons per layer	Hidden layers				
	One	Two	Three	Four	Five
Twelve	64.52	58.06	61.29	61.29	64.52
Twenty Four	67.74	58.06	51.61	54.84	67.74
Thirty Six	64.52	64.52	67.74	67.74	61.29
Fourty Eight	67.74	64.52	64.52	67.74	64.52

Table V Before removing out of control events

Task	Total	Correct	incorrect	%age error
Left	17	11	6	35.29
Right	11	8	3	27.27
All	28	19	9	32.26

Table VI. After removing out of control events

Task	Total	Correct	incorrect	%age error
Left	13	11	02	15.39
Right	08	06	02	12.5
all	21	17	04	14.29

3. CONCLUSION

Left or right imagery tasks were identified in this study by the help of discrete wavelet transformation. C3, C4 and CZ channels were used to record the data. After the feature extraction process out of control events were identified by statistical process control and were removed from the dataset. Later the data was classified by the help of neural networks. The classification accuracy increased when statistically controlled data was used.

REFERENCES

[1] G. P. Alois Schlögl, Christa Neuper, Gernot Müller, Bernhard Graimann, “BCI Competition II.” [Online]. Available: http://www.bbci.de/competition/ii/. [Accessed: 22-Jun-2019].

[2] B. Blankertz, K. Müller, G. Curio, T. M. Vaughan, G. Schalk, and R. Jonathan, “The BCI Competition 2003:,” vol. XX, pp. 100–106, 2004.

[3] S. Makeig, C. Kothe, T. Mullen, N. Bigdely-Shamlo, Z. Zhang and K. Kreutz-Delgado, "Evolving Signal Processing for Brain–Computer Interfaces," in Proceedings of the IEEE, vol. 100, no. Special Centennial Issue, pp. 1567-1584, 13 May 2012.
[4] Roman-Gonzalez A. (2012) EEG Signal Processing for BCI Applications. In: Hippe Z.S., Kulikowski J.L., Mroczek T. (eds) Human – Computer Systems Interaction: Backgrounds and Applications 2. Advances in Intelligent and Soft Computing, vol 98. Springer, Berlin, Heidelberg
[5] R. Chai, S. H. Ling, G. P. Hunter, Y. Tran and H. T. Nguyen, "Brain–Computer Interface Classifier for Wheelchair Commands Using Neural Network With Fuzzy Particle Swarm Optimization," in IEEE Journal of Biomedical and Health Informatics, vol. 18, no. 5, pp. 1614-1624, Sept. 2014.
[6] R. Chai, S. H. Ling, G. P. Hunter and H. T. Nguyen, "Mental non-motor imagery tasks classifications of brain computer interface for wheelchair commands using genetic algorithm-based neural network," The 2012 International Joint Conference on Neural Networks (IJCNN), Brisbane, QLD, 2012, pp. 1-7.
[7] R. Chai, S. H. Ling, G. P. Hunter and H. T. Nguyen, "Toward fewer EEG channels and better feature extractor of non-motor imagery mental tasks classification for a wheelchair thought controller," 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, San Diego, CA, 2012, pp. 5266-5269.
[8] R., H. , P., P. , Yaacob, S. , Adom, A. , Nagarajan, R. (2007), 'Motor Imagery Signal Classification for a Four State Brain Machine Interface', World Academy of Science, Engineering and Technology, Open Science Index 5, International Journal of Computer and Information Engineering, 1(5), 1375 - 1380.
[9] D. A. Craig, H. T. Nguyen and H. A. Burchey, "Two Channel EEG Thought Pattern Classifier," 2006 International Conference of the IEEE Engineering in Medicine and Biology Society, New York, NY, 2006, pp. 1291-1294.
[10] D. A. Craig and H. T. Nguyen, "Adaptive EEG Thought Pattern Classifier for Advanced Wheelchair Control," 2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Lyon, 2007, pp. 2544-2547.
[11] G. P. C. Neuper, A. Schlögl, “Enhancement of left-right sensorimotor EEG differences during feedback-regulated motor imagery,” Clin Neurophysiol. 16(4)373-82., 1999.
[12] A. O. G. Barbosa, D. R. Achanccaray and M. A. Meggiolaro, "Activation of a mobile robot through a brain computer interface," 2010 IEEE International Conference on Robotics and Automation, Anchorage, AK, 2010, pp. 4815-4821.
[13] Tsui, C.S.L., Gan, J.Q. & Roberts, S.J. A self-paced brain–computer interface for controlling a robot simulator: an online event labelling paradigm and an extended Kalman filter based algorithm for online training. Med Biol Eng Comput 47, 257–265 (2009). https://doi.org/10.1007/s11517-009-0459-7
[14] Tsui C.S.L., Gan J.Q. (2007) Asynchronous BCI Control of a Robot Simulator with Supervised Online Training. In: Yin H., Tino P., Corchado E., Byrne W., Yao X. (eds) Intelligent Data Engineering and Automated Learning - IDEAL 2007. IDEAL 2007. Lecture Notes in Computer Science, vol 4881. Springer, Berlin, Heidelberg
[15] B. Shin, T. Kim and S. Jo, "Non-invasive brain signal interface for a wheelchair navigation," ICCAS 2010, Gyeonggi-do, 2010, pp. 2257-2260.
[16] V. Gandhi, G. Prasad, D. Coyle, L. Behera, and M. M. Ginnity, “A Novel Paradigm for Multiple Target Selection Using a Two Class Brain Computer Interface,” 2009.
[17] M. Carra and A. Balbinot, "Evaluation of sensorimotor rhythms to control a wheelchair," 2013 ISSNIP Biosignals and Biorobotics Conference: Biosignals and Robotics for Better and Safer Living (BRC), Rio de Janerio, 2013, pp. 1-4.