A Survey of Analysis and Classification of EEG Signals for Brain-Computer Interfaces

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Abstract— *A Brain Computer-Interfaces (BCI) is a communication system that enables human brain to interact with machines or devices without involving physical contact by using EEG signals generated from brain activity. Selection of the processing technique of the EEG signals at each processing stage is very important to get the robust BCI system. The aim of this paper is to address the various techniques applied for BCI at each stage such as pre-processing, feature extraction and classification stage. This paper discussed the advantages, disadvantages and current trends of BCI at each stage. Finally, the initial experiment result at each BCI stage was discussed at the end of this paper which is different with previous survey paper.*

Keywords— Brain computer-interfaces; electroencephalography(EEG); pre-processing; feature extractiong; classification

I. Introduction

A Brain Computer-Interfaces (BCI) or Brain Machine-Interfaces (BMI) is a communication system that enables human brain to interact with machines or devices without involving physical contact by using electroencephalography (EEG) signals generated from brain activity [1] . The early BCI have been studied for the main motivation of providing assistive technologies for those with severe motor disabilities. However, due to the rapid improvement of computer and biosensor technologies other applications such as disease diagnostics, rehabilitation and prosthetics also have been studied among BCI researcher and some of them turn to a promising application [2].

A BCI methodology can be divided broadly into five phases. First phase is brain activity measurement, second phase is pre-processing, third phase is feature extraction, fourth phase is classification and final phase is control interface [1, 3]. The brain activity measurement or signal acquisition phase captures the brain signals using EEG sensor. After signal acquisition phase, signals need to be pre-processed. Pre-processing aims to simplify subsequent processing operations, improving signal quality without losing the significant information. In this step, the recorded signals are processed to clean and remove noisy data such as eye blinks artifacts, heart beat artifacts and muscular movements in order to get the relevant information embedded in the signals. The next phase is feature extraction. After getting the noise-free signals from the pre-processing phase, important features from the brain activities signals were extracted. The feature extraction phase identifies discriminative information in the recorded brain signals. It is very challenging stage to maintain the important information from loss and at the same time reduce the size of vector dimension to avoid the computational complexity. Representative features obtained from the previous stage were classified using classification approach and at this stage, a choice of good discriminative features is very important for getting effective classification result that reflect the user's intentions. Finally, the control interface phase converts the classified signals into meaningful information for devices such as a wheelchair, speech synthesizer and personal computer.

This paper address various techniques applied for BCI at pre-processing, feature extraction and classification stage. This paper also discussed the advantages, disadvantages and current trends of BCI at each stage and finally, the initial experiment result for all stages was discussed at the end of this paper which is different with other previous survey paper.

II. Brain Computer Interfaces

A. Pre-processing of EEG Signals

The EEG signals that are collected from acquisition equipment must be pre-processed to eliminate artifacts and noise such as eye blinks, heart beats, and other disturbing effects. There are various pre-processing approaches namely Common Spatial patterns (CSP), Principle Component Analysis (PCA)[3-5], Common Average Referencing (CAR)[4, 6], Surface Laplacian (SL)[3, 4, 7], adaptive filtering[4, 8], Independent Component Analysis (ICA) [3, 4] and digital filter[3].

Many use Common Spatial Patterns approach to process motor imagery based BCI. This method detects the pattern in EEG signal by constructing spatial filters that maximize the variance of one task and simultaneously minimize the variance of another task [9]. However, this method needs to be used with multiple electrodes and the performance of the

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classification can be affected by changing the electrode position [4].

On the other hand, Principle Component Analysis make use of mathematical procedure that utilize an orthogonal transformation to change a set of observations of correlated vectors into a set of linearly uncorrelated vectors called principal components[10]. The advantage of PCA is that it can reduce the dimension of the feature vectors [4].

Common Average Referencing is a spatial filter that remove the typical activity of EEG and leave the idle activity of each individual EEG signal in a specific electrode [10]. The referencing approach is used to improve the Signal to Noise Ratio (SNR) cause by artifacts in EEG signals. In this approach, eliminating of the mean of all electrodes will produce a clean signal. CAR outperforms all referencing methods and indicates good classification accuracy results. However, finite sample density and insufficient head coverage of EEG electrode cause complication in calculating the average of electrode in common referencing methods[4, 6].

Surface Laplacian generally is the effective spatial filter based approach used in BCI studies. This approach is used to improve the SNR of the signal and as an aid identification of the sources [11]. SL solves the electrode reference problem and it is robust against artifacts generated at uncovered regions by the electrode cap, it is also a method of viewing the EEG signal with high spatial resolution. However, the problem is that it is too sensitive to the choice of spline parameters during spline interpolation [4].

In addition, Adaptive filtering is a technique that attempts to model the relationship between two signals in an iterative manner. An adaptive filter consists of four parts: the signals being processed, the structure that describe the input or output relation, the parameter, which can be iteratively varied to alter the filter's input or output relationship. The adaptive algorithm such as LMS, NLMS and RLS, describes how the parameters are adjusted [8, 12]. Jun Lu et.al [13] introduced a new adaptive filter design call adaptive Laplacian (ALAP) filter. This filter was reported enable to provide better performance for sensorimotor rhythms (SMR)-based BCIs. An ALAP filter employs a Gaussian kernel to construct a smooth spatial gradient of channel weights and then simultaneously seeks the optimal kernel radius of this spatial filter and regularization parameter of linear ridge regression. This optimization is based on minimizing the leave-one-out cross-validation error through a gradient descent method and is computationally feasible. By using data from 22 individuals, the result of shows that proposed technique may help to improve the accuracy and robustness of SMR-based BCIs[13]. The advantage of adaptive filters is that it is able to modify signal features according to signal being analyzed and works well for the signals with overlapping spectra [4].

Independent Component Analysis split the artifacts from the EEG signals into independent components based on the characteristics of the data without depending on the reference channels. The ICA algorithm decomposes the multi-channel EEG data into temporal independent and spatial-fixed components [4]. It is computationally efficient and algorithms have proven their ability for artifacts removal and source extraction for a specific class of signals [14]. ICA shows high performance when the size of the data to decompose is large and it perform better than PCA [4].

Frequency selective digital filters such as low-pass, high-pass, band-pass and band-stop filter have been widely used in artifact processing especially for muscle artifact removal. However, this approach requires EEG signal and artifact occupy distinct frequency bands which almost never found in reality[15]. The most common digital filters utilized in EEG signal are band-pass and notch filter [16]. The notch filter is able to remove electrical line noise cause by EEG electrode grounding easily [17].

Pre-processing of artifacts noise in EEG signals plays important role for getting meaningful information for the next stage which is feature extraction stage. Most of the existing methods concentrate on either spatial filter (CSP, CAR, PCA, SL, ICA) or temporal filter (Fourier Analysis, Autoregressive) or both of the filters. The big difference between spatial filter and temporal filter is that the response time during online analysis where temporal filter not as useful as spatial filter[7]. Table I. shows the comparison of the pre-processing approach.

TABLE I. COMPARISON OF PRE-PROCESSING APPROACH

No	*Approach*	*Advantages*	*Disadvantages*
1	**CSP**	▪ Works well for Motor Imagery data	▪ Needs multiple electrode
2	**PCA**	▪ Reduction of feature dimension	▪ Not as good as ICA
3	**CAR**	▪ Outperforms all the reference methods	▪ Needs sufficient head coverage
4	**SL**	▪ Robust against the artifacts at uncovered electrode	▪ Sensitive to artifacts ▪ Sensitive to spline pattern
5	**Adaptive Filter**	▪ Works well for the signals with overlapping spectra	▪ Needs two signals (including reference signal)
6	**ICA**	▪ Computationally efficient ▪ High performance for large data sized	▪ Require more computational for decomposition
7	**Digital Filter**	▪ Easily remove electrical grounding noise	▪ Requires EEG signal and artifact occupy distinct frequency bands

B. Feature Extraction

Significant set of features from pre-processed EEG signals are extracted using Principal Component Analysis (PCA), Independent Component Analysis (ICA), Wavelet Transformations (WT), Wavelet Packet Decomposition (WPD), Auto Regressive (AR), and Fast Fourier Transform (FFT) [4].

Principal Component Analysis (PCA) is used in the pre-processing approach and it is also utilized in feature extraction stage. It is a strong technique for analyzing and for dimension reduction of data without losing information. It extracts the information present at time series multichannel into a principle component. PCA reduce the dimension of signals by removing the artifacts and by producing the principle components[4]. Using PCA feature extraction, performance of classification can be improve compared to others feature extraction approach [10]. However, the weakness of this approach is it assumes data is linear and continuous, and for complicated set of features it is unable to process the data [4].

Independent Component Analysis can be utilized to pre-process EEG signals and it can also be used as a feature extraction approach. ICA forms the components that are independent to each other. From the components essential features are extracted using ICA. An important application of ICA is Blind Source Separation (BSS). This helps in identifying the independent signals and also noise separation from brain signals. The advantages of ICA are computationally efficient, and it indicates high performance for large sized data such as EEG signals [4].

Wavelet Transform (WT) is mathematical technique extensively used for extracting information from various types of continuous data such as image and speech data. This approach is suitable for non-stationary signals due to flexible method of representing the time-frequency domain of signal[1]. The advantages of WT are It is able to analyze the signal with discontinuities through variable window size, able to analyze signals both in time and frequency domain, and able to extract energy, distance or cluster. However, the disadvantage is lack of specific methodology for apply to the pervasive noise [4].

Wavelet Packet Decomposition (WPD) is extended version of wavelet decomposition (WD). However, it is different from the WD, where only approximation at each resolution level is decomposed to yield approximation and detail information at higher level. WPD can provide a more precise frequency resolution compared to WD [18]. WPD can extract features in both time and frequency domain with the coefficients mean of WT. WPD shows better performance. It shows good performance in the extraction process of non-stationary. However, it increased in terms of computation time [4].

Auto Regressive (AR) approach have been used in a number of studies to model EEG signal by representing the signal at each channel as a linear combination of the signal at previous points [19]. It is used for feature extraction in time domain analysis. With shorter duration of data records, this approach yields better frequency resolution and reduces the spectral loss issue. It is the most frequently used approach for non-stationary signals such as EEG where AR parameters are supplied to the model. The disadvantage lies in establishing the AR parameter model property [4].

Fast Fourier Transform (FFT) approach employs mathematical technique to EEG data analysis. Characteristics of the acquired EEG signal to be analyzed are computed by power spectral density (PSD) estimation in order to selectively represent the EEG samples signal [5, 20]. FFT extracts the signal features by transforming the signals from time domain to frequency domain. It works well for stationary signals and in linear random process. However, It not applicable for non-stationary signals and cannot measure both the time and frequency [4].

It is a challenging task to design suitable features for BCI system since useful information of brain signals is hidden in a highly noisy environment and information of interest could be overlapped in time and space due to simultaneous activity of brain. Therefore, it is insufficient to use simple method such as band pass filter to extract the desired band power[1]. High dimension of feature vectors are not recommended for the next classification stage to avoid computational complexity. Dimensional reduction method such as PCA and ICA are efficient for minimizing the number of features while maximizing the classification performance. The comparison of the feature extraction approach is shown in Table II.

TABLE II. COMPARISON OF FEATURE EXTRACTION APPROACH

No	*Approach*	*Advantages*	*Disadvantages*
1	**PCA**	▪ Dimension reduction without losing data	▪ Unable to process complicated set of data
2	**ICA**	▪ Computationally efficient ▪ High performance for large data sized	▪ Require more computational for decomposition
3	**WT**	▪ Suitable for non-stationary signals ▪ Able to analyze signal in time and frequency domain	▪ Lacking of specific methodology to apply to pervasive noise
4	**WPD**	▪ Able to analyze the non-stationary signals	▪ Increase computational time
5	**AR**	▪ Require short duration of data ▪ Reduce spectra loss problems and give better frequency resolution	▪ Not applicable to stationary signals
6	**FFT**	▪ Works well for stationary signals	▪ Not applicable for non-stationary signals ▪ Unable to measure both time and frequency

C. Classification

After features have been extracted, the extracted vectors are classified into various classifiers. The most famous classifier in BCI are Artificial Neural Network (ANN), k-Nearest Neighbour (k-NN), Linear Discriminant Analysis (LDA) and SVM [1, 4].

Artificial Neural Network (ANN) is a non-linear classifiers construct from a huge number of interconnected elements called neurons. Each neuron in ANN imitates the biological neuron and is capable of performing computational tasks. Multi-Layer Perceptron Neural Network (MLPNN) is the most widely used neural network structure consist of three layers namely input layer, hidden layer and output layer [1, 4]. The MLPNN is able to provide a useful general procedure for motor imagery classification. The advantage of MLPNN is that its fast operation, ease of implementation and requiring small training sets. However, it difficult to build and the performance is highly depends on the number of neuron in hidden layer [4]. Hema et.al [21] proposed a methods to design a four state brain machine interface (BMI) using EEG signal recorded from the C3 and C4 locations. Two classification algorithms are used: Elman recurrent neural network and functional link neural network. The result shown that back propagation algorithm has higher average classification of 93.5%, while the PSO algorithm has better training time and maximum classification.

Nearest neighbour classifier assign a feature vector to a class based on its nearest neighbours. It is called as k-Nearest Neighbour (k-NN) classifiers if the feature vector is from the training set. k-NN is a non-parametric approach where it predicts objects values or class memberships based on the k-closest training examples in the feature space. It allocates the label of a test sample with the majority label of its k-nearest neighbours from the training set. As reported in [22], the researcher used adaptive weighted distance nearest neighbor algorithm for classification of EEG signals. This classification algorithm assigns a weight to each training sample to control its influence in classifying test samples. The weights of training samples are used to find the nearest neighbour of an input query pattern. The classification result shown that combination of Weighted Distance Nearest Neighbour (WDNN) and selected features can significantly outperform the basic nearest-neighbour and the other methods proposed in the past. k-NN is simple to understand, transparent, easy to implement, and debug [4]. However, this classifier is rarely used in BCI research due to its sensitivity to the dimensionality of the features vector [1, 4].

Linear Discriminant Analysis (LDA) makes models of the probability density function respectively. LDA is simple to use and has low computational complexity. It provides an excellent result. For non-Gaussian distributions LDA may not maintain the complex structure in the data. LDA fails if the discriminatory function is not in mean but in the variance of the data [1, 4]. LDA is usually applied to classify pattern into two classes although it is possible to extend the approach to multiple classes [1].

Support Vector Machine (SVM) is a linear classifier that is widely used by most of the BCI applications. SVM was developed by Vapnik [23] and was motivated by statistical learning theory following the principle of structural risk minimization. SVM finds a hyper plane to differentiate the data sets. It separates data sets with clear gap to classify them into their appropriate category. The hyper plane maximizes the margin that is the distance between the hyper plane and the nearest points from each class that are called as support vectors. The objective of this method is to provide good generalization by maximizing the performance of machine while minimizing the complexity of learned model [4]. Siuly [24] proposed three algorithms for classification of motor imagery (MI) task EEG signals: cross-correlation based logistic regression (CC-LR), modified CC-LR with diverse feature sets and cross-correlation based least square support vector machine (CC-LS-SVM). The proposed algorithms are tested on two benchmarks datasets. This study concluded that CC based LS-SVM algorithm is a promising technique for the MI signal recognition and it offers great potential for the development of MI-based BCI analyses which assist clinical diagnose and rehabilitation tasks. SVM has widely used in BCI due to its simple classifier and robust against high dimensionality [1].

However, there is no method to estimate the general superiority of classifier over another one. The performance of classifier is better than another, only due to a specific dataset. Therefore, selection of the best classifier highly depends to the characteristics of the dataset [5, 25]. At the same time, two main factors should be considered when selecting the classifier are curse of dimensionality and bias-variance tradeoff. Curse of dimensionality is that the number of training data needed to offer good results rises exponentially with the dimension of the feature vectors, while bias-variance tradeoff is characteristics of classifier towards high bias with low variance [1]. In addition, the current trend of BCI research is trying to ensemble the classification technique [25]. Classification fusion is one of the methods that can be used to improve the performance of BCI. Table III shows the comparison of classification approach.

TABLE III. COMPARISON OF CLASSIFICATION APPROACH

No	*Approach*	*Advantages*	*Disadvantages*
1	**ANN**	▪ Fast Operation ▪ Ease of impementation	▪ Performance depends on the number of neuron in hidden layer
2	**k-NN**	▪ Simple to understand ▪ Easy to implement	▪ Sensitive to irrelevant and redundant features
3	**LDA**	▪ Simple to use ▪ Low computational complexity	▪ Usually applied for two classes
4	**SVM**	▪ Performance is better compare to other linear classifier	▪ High computational complexity

III. ANALYSIS AND CLASSIFICATION OF EEG SIGNALS USING BCILAB

BCILAB is a MATLAB toolbox and also available with EEGLAB plugin for the design, prototyping, testing and experimenting of Brain Computer Interface. The toolbox has been developed by C. Kothe at the Swartz Center for Computational Neuroscience (SCCN), University of California San Diego (UCSD). It was inspired by the preceding PhyPA BCI toolbox created by C. Kothe and T. Zander at Human-Machine Systems, Berlin Institute of Technology[26]. .

The EEG dataset used in this analysis is a flanker task data provided in the BCILAB toolbox version1.01. The dataset consists of two classes of markers, class A and class B. The standard Windowed Mean paradigm was used as a sequence of signal pre-processing, feature extraction and machine learning stages. The defining property of the paradigm is the feature extraction, in which windowed averages of signal data per channel are computed and used as features for the subsequent machine learning stage. Finally, Support Vector Machine (SVM) and Linear Discriminant

Analysis (LDA) were used as a classification algorithm. The performance of the BCI was evaluated using the Mis-classification Rate (MCR) [27, 28] consist of True Positive Rate (TPR), False Positive Rate (FPR), True Negative Rate (TNR), False Negative Rate and Error Rate (ER).

The Mis- Classification Rate summary results are shown in Table IV. The Error Rate (ER) of 9% was achieved using SVM classification approach. For True and False Positive Rate (TPR,FPR), 27% and 73% were achieved using this technique. For True and False Negative Rate (TNR, FNR), 100% and 0% were achieved. On the other hand, The Error Rate (ER) of 5% was achieved using LDA classification approach and it outperformed the SVM approach. For True and False Positive Rate (TPR,FPR), 87% and 13% were achieved using this technique and it also outperformed the SVM approach. However, for True and False Negative Rate (TNR, FNR), 96% and 4% results were achieved and it slightly worst compared to SVM.

As stated in [28], for the typical uses of the toolbox, SVMs are not as frequently used as LDA, primarily due to the need for proper regularization, which is often prohibitively costly. For quick tests, the method can be used without regularization, however. When extremely many feature or trials are used, SVMs are likely more useful than in standard settings.

TABLE IV. MIS- CLASSIFICATION RATE RESULT (%)

Approach	*TPR*	*FPR*	*TNR*	*FNR*	*ER*
SVM	**27**	**73**	**100**	**0**	**9**
LDA	**87**	**13**	**96**	**4**	**5**

IV. CONCLUSION

This paper has addressed the various techniques applied for BCI at pre-processing, feature extraction and classification stage. This paper also discussed the advantages, disadvantages and current trends of BCI at every stage. Finally, an experiment using BCILAB was conducted to investigate the initial performance of BCI. Based on data provided in the BCILAB, LDA approach outperformed the SVM approach in terms of lower Error Rate (ER) performance.

REFERENCES

[1] L. F. Nicolas-Alonso and J. Gomez-Gil, "Brain computer interfaces, a review," *Sensors,* vol. 12, pp. 1211-1279, 2012.

[2] M. Moore Jackson and R. Mappus, "Applications for Brain-Computer Interfaces," in *Brain-Computer Interfaces*, D. S. Tan and A. Nijholt, Eds., ed: Springer London, 2010, pp. 89-103.

[3] G. Pfurtscheller, C. Brunner, R. Leeb, R. Scherer, G. Müller-Putz, and C. Neuper, "The Graz Brain-Computer Interface," in *Brain-Computer Interfaces SE - 5*, B. Graimann, G. Pfurtscheller, and B. Allison, Eds., ed: Springer Berlin Heidelberg, 2010, pp. 79-96.

[4] M. R. Lakshmi, D. T. V. Prasad, and D. V. C. Prakash, "Survey on EEG Signal Processing Methods," *International Journal of Advanced Research in Computer Science and Software Engineering,* vol. 4, pp. 84-91, 2014.

[5] A. Viet Hoang, V. Manh Ngo, H. Bang Ban, and Q. Thang Huynh, "A real-time model based Support Vector Machine for emotion recognition through EEG," in *Control, Automation and Information Sciences (ICCAIS), 2012 International Conference on*, 2012, pp. 191-196.

[6] Mohammed J. Alhaddad, "Common Average Reference (CAR) Improves P300 Speller," *International Journal of Engineering and Technology,* vol. 2, pp. 451-489, 2012.

[7] B. He, S. Gao, H. Yuan, and J. Wolpaw, "Brain–Computer Interfaces," in *Neural Engineering*, B. He, Ed., ed: Springer US, 2013, pp. 87-151.

[8] M. K. Ahirwal, A. Kumar, and G. K. Singh, "Adaptive filtering of EEG/ERP through Bounded Range Artificial Bee Colony (BR-ABC) algorithm," *Digital Signal Processing,* vol. 25, pp. 164-172, 2// 2014.

[9] L. Velásquez-Martínez, A. M. Álvarez-Meza, and C. G. Castellanos-Domínguez, "Motor Imagery Classification for BCI Using Common Spatial Patterns and Feature Relevance Analysis," in *Natural and Artificial Computation in Engineering and Medical Applications*. vol. 7931, J. Ferrández Vicente, J. Álvarez Sánchez, F. de la Paz López, and F. J. Toledo Moreo, Eds., ed: Springer Berlin Heidelberg, 2013, pp. 365-374.

[10] X. Yu, P. Chum, and K.-B. Sim, "Analysis the effect of PCA for feature reduction in non-stationary EEG based motor imagery of BCI system," *Optik - International Journal for Light and Electron Optics,* vol. 125, pp. 1498-1502, 2// 2014.

[11] D. J. McFarland, "The advantages of the surface Laplacian in brain–computer interface research," *International Journal of Psychophysiology,* 2014.

[12] M. K. Ahirwal, A. Kumar, and G. K. Singh, "Adaptive filtering of EEG/ERP through noise cancellers using an improved PSO algorithm," *Swarm and Evolutionary Computation,* vol. 14, pp. 76-91, 2// 2014.

[13] J. Lu, D. J. McFarland, and J. R. Wolpaw, "Adaptive Laplacian filtering for sensorimotor rhythm-based brain–computer interfaces," *Journal of neural engineering,* vol. 10, p. 016002, 2013.

[14] G. Korats, S. Le Cam, R. Ranta, and M. Hamid, "Applying ICA in EEG: Choice of the Window Length and of the Decorrelation Method," in *Biomedical Engineering Systems and Technologies*. vol. 357, J. Gabriel, J. Schier, S. Van Huffel, E. Conchon, C. Correia, A. Fred, *et al.*, Eds., ed: Springer Berlin Heidelberg, 2013, pp. 269-286.

[15] S. Motamedi-Fakhr, M. Moshrefi-Torbati, M. Hill, C. M. Hill, and P. R. White, "Signal processing techniques applied to human sleep EEG signals—A review," *Biomedical Signal Processing and Control,* vol. 10, pp. 21-33, 3// 2014.

[16] S. Amiri, A. Rabbi, L. Azinfar, and R. Fazel-Rezai, *A Review of P300, SSVEP, and Hybrid P300/SSVEP Brain- Computer Interface Systems*, 2013.

[17] N. Mammone, F. La Foresta, and F. C. Morabito, "Automatic Artifact Rejection From Multichannel Scalp EEG by Wavelet ICA," *Sensors Journal, IEEE,* vol. 12, pp. 533-542, 2012.

[18] Q. Wei, B. Wan, and Z. Lu, "Optimal Frequency Band Selection Based on Filter Banks and Wavelet Packet Decomposition in Multi-class Brain–Computer Interfaces," in *Unifying Electrical Engineering and Electronics Engineering*. vol. 238, S. Xing, S. Chen, Z. Wei, and J. Xia, Eds., ed: Springer New York, 2014, pp. 1329-1336.

[19] V. Lawhern, W. D. Hairston, K. McDowell, M. Westerfield, and K. Robbins, "Detection and classification of subject-generated artifacts in EEG signals using autoregressive models," *Journal of Neuroscience Methods,* vol. 208, pp. 181-189, 7/15/ 2012.

[20] A. S. Al-Fahoum and A. A. Al-Fraihat, "Methods of EEG Signal Features Extraction Using Linear Analysis in Frequency and Time-Frequency Domains," *ISRN Neuroscience,* vol. 2014, p. 7, 2014.

[21] C. Hema, M. Paulraj, S. Yaacob, A. Adom, and R. Nagarajan, "Motor imagery signal classification for a four state brain machine interface," *International Journal of Biomedical Sciences,* vol. 3, pp. 76-81, 2008.

[22] E. Parvinnia, M. Sabeti, M. Zolghadri Jahromi, and R. Boostani, "Classification of EEG Signals using adaptive weighted distance

nearest neighbor algorithm," *Journal of King Saud University-Computer and Information Sciences,* vol. 26, pp. 1-6, 2014.

[23] C. Cortes and V. Vapnik, "Support-vector networks," *Machine learning,* vol. 20, pp. 273-297, 1995.

[24] Siuly, "Analysis and classification of EEG signals," Ph.D, University of Southern Queensland, 2012.

[25] A. Soria-Frisch, "A Critical Review on the Usage of Ensembles for BCI," in *Towards Practical Brain-Computer Interfaces*, B. Z. Allison, S. Dunne, R. Leeb, J. Del R. Millán, and A. Nijholt, Eds., ed: Springer Berlin Heidelberg, 2013, pp. 41-65.

[26] A. Delorme, T. Mullen, C. Kothe, Z. Akalin Acar, N. Bigdely-Shamlo, A. Vankov*, et al.*, "EEGLAB, SIFT, NFT, BCILAB, and ERICA: New Tools for Advanced EEG Processing," *Computational Intelligence and Neuroscience,* vol. 2011, p. 12, 2011.

[27] M. Billinger, I. Daly, V. Kaiser, J. Jin, B. Allison, G. Müller-Putz*, et al.*, "Is It Significant? Guidelines for Reporting BCI Performance," in *Towards Practical Brain-Computer Interfaces*, B. Z. Allison, S. Dunne, R. Leeb, J. Del R. Millán, and A. Nijholt, Eds., ed: Springer Berlin Heidelberg, 2013, pp. 333-354.

[28] SCCN. (2010, 10-10-2014). *BCILAB*. Available: http://sccn.ucsd.edu/wiki/BCILAB