Prosthetic Arm Control using Clonal Selection Classification Algorithm (CSCA) - A Statistical Learning Approach

V. V. Ramalingam[1]*, S. Mohan[2] and V. Sugumaran[3]

[1]Research and Development Centre, Bharathiar University, Coimbatore - 641 046, Tamil Nadu, India;
ramabi1976@gmail.com
[1]Department of Computer Science, Faculty of Engineering and Technology, S.R.M University,
Kattankulathur - 603203, Tamil Nadu, India
[2]AL Yamamah University, Riyadh, Kingdom of Saudi Arabia; s.mohan77@gmail.com
[3]VIT University, Chennai Campus, Chennai - 600048, Tamil Nadu, India; v_sugu@yahoo.com

Abstract

Objectives: In monitoring brain activities, Electroencephalogram (EEG) signals play a significant role. As brain activities are many and highly dynamic in nature, processing of EEG signals is a challenging task. Since classification is more accurate when the pattern is simplified through representation by well performing features, feature extraction and selection play an important role in classification systems such as Clonal Selection Classification Algorithm (CSCA) algorithm. **Methods/ Analysis:** This study is one such attempt to perform the prosthetic limb movements using EEG signals. In this research, the performance of CSCA for prosthetic limb movements of EEG signals has been reported. **Findings:** In this paper, the EEG signals are acquired for four different limb movements like finger open (fopen), finger close (fclose), wrist clockwise (wcw) and wrist counterclock wise (wccw). These EEG signals can be used to build a model to control the prosthetic limb movements using CSCA algorithm. The statistical parameters were extracted from the EEG signals. The best feature set was identified using J48 decision tree classifier. The well performing features were then classified using CSCA algorithm. The classification performance of CSCA has been reported. **Novelty/Improvement:** Our work is useful for controlling artificial limb with movements using EEG signals. The signal processing of EEG signals is a complex task and requires sophisticated techniques to yield a better classification accuracy.

Keywords: CSCA, Classification, Electroencephalogram (EEG) Signals, Statistical Features

1. Introduction

The loss of human limb is a major issue that intensely limits the everyday capabilities and interaction of the persons. Hence, an attempt is made to find the solution for artificial limb with movements. There can be two types of signals that are of direct use for the above purpose: EMG and EEG. EMG signals are available in the muscles and they contain a large amount of information for the purpose of limb movements. However, there are many instances where the subject loses most part of the limb. In such cases the EMG signals that are available near the affected area (shoulder, upper arm) may not be of great use. Moreover, EMG signals are secondary signals, whereas EEG signals are primary signals. Since the EEG signal originates from brain activities. The characteristics remain almost same irrespective of the extent of amputation. This gives a feeling that EEG signals are the best candidate for controlling movements of artificial limbs. It is not fully true because of the fact that the EEG signals are a product of some thought process; this complicates the decoding process of EEG signals. Now, the challenges to decode effectively the information buried inside the EEG signals. This study is a humble attempt to do the

---

Author for correspondence

same for the purpose of controlling the prosthetic arm. In[1] the author conducted an experiment and reported that the PSD (Power Spectral Density) was the well suited method to distinguish right and left hand writing movements using EEG signals. In[2] conducted experiments on two types of EEG signals set-A and set-E. Set-A and Set-E contains the EEG signals which were recorded from healthy volunteers in the state of eyes open and from epilepsy patients during epileptic seizures respectively. For feature extraction, spectral analysis of the EEG signal was carried out with three model-based methods, namely Burg autoregressive-AR, moving average –MA, Yule- walker autoregressive moving average-ARMA methods. The features were trained by LS-Support Vector Machine classifier and produced better classification accuracy. In[3-5] reported the field of medical sciences there is a great requirement for the development of automated systems. Such automated system can detect the neurological disorders and help prevent the misinterpretation of EEG signals by the Analyst. In[6] investigated a novel approach on the implementation of multiclass Support Vector Machine (SVM) with the Error Correcting Output Codes (ECOC) trained on the extracted eigenvector features for classification of EEG signals. In[7] was presented to classify the EEG signals. Features were extracted using fourth-level Wavelet Packet Decomposition (WPD). Genetic Algorithm (GA) was used for feature selection and identified the best features to form the optimal feature subset. The approximate entropy values were derived as the feature vector and a Learning Vector Quantization (LVQ) was used as the classifier to attain the best classification accuracy for the normal and epileptic subject. In[8] Multilayer Perceptron Neural Network (MLPNN) architecture was used for detecting the electroencephalographic changes. Three sets set-A, set-D and set-E of EEG signals was used and classified by the MLPNN classifier. Lyapunov exponents were extracted from the EEG signals, and given as the inputs to the MLPNNs. Finally, the features were trained with Levenberg-Marquadt algorithm. The results have proven that the MLPNN has potential for the classification of EEG signals. In[9] the author conducted an experiment from the EEG signals. Decision making was taken on the two stages of feature extraction and classification process. The diverse and composite input features of EEG signals were obtained by the eigenvectors. The classification was performed on diverse features (modified mixture of expert-MME) and composite feature (mixture of experts-ME) with five

data set (set-A, set-B, set-C, set-D, and set-E). The result demonstrated that the MME trained on diverse features have achieved a higher evel of classification performance than ME. In[10] the author reported the wavelet was an effective time–frequency analysis tool for analyzing EEG signals and most capable technique to extract features from EEG signals. In[11] presented the controlling process of prosthetic limb movements based on surface EMG signals extracted from remnant muscles are the promising ones in the analysis of EMG signals. There were three feature extraction techniques, namely autoregressive coefficients, mean frequency and EMG histogram used in the study. The combined features of mean frequency and EMG histogram were given as the input to the neural network classifier. Hence, the EMG histogram feature vector performed well for the classification of prosthetic limb movements. In[12] the author developed an EEG based Brain controlled Wheelchair using BCI with the help of Neuro sky technology. In[13] a novel hybrid approach was proposed to control the arm of flexible robots by using neural networks with fuzzy and particle swarm optimization algorithm. Most of the research works mainly focused on the interpretation of EEG signals that are very difficult and thus demand a lot of skill. Automated systems have been proposed to solve these problems. Thus, it is clear that there are only a few literatures available for identification of limb movements using EEG signals. Hence, there is more scope for designing a suitable automated system for recognizing limb movements using EEG signals. In the present study, four different limb movements, namely finger open (fopen), finger close (fclose), wrist clockwise (wcw) and wrist counterclock wise (wccw) are considered. The machine learning approach has been used to control the human limb movements. The majority of the people are right handlers around the world, thus EEG signals of only right hand limb movements are considered for this study. The decision tree clearly shows the structural information contained in the data (features) and explains the feature information in the form of decision making 'if then' rules. The 'if then' rules can be easily implemented in embedded systems to control the four different limb movements. Otherwise, one has to implement the classifier itself in embedded systems. Hence, Clonal Selection Classification Algorithm classifier has been chosen for the present study to build a predictive model for right-hand limb movements. The classifier performance largely depends on the information present in the features extracted from the EEG signals. Here statistical features

were extracted from the EEG signals of four different limb movements and fed into the classifier. The features will be useful for classification only if the signals are acquired properly. Hence, in section 3, system architecture and data acquisition processes are explained in detail. The Clonal Selection, Classification Algorithm (CSCA) classifier with the statistical features has been proposed as a suitable classifier for the EEG signals.

2. Materials and Methods

Most of the researchers used the datasets (http://www. meb.uni-bonn.de/epileptologie/science/ physik/eegdata. html) available in public domains. No unique work has been found in the data collection process. In the present study, an effort is taken for data collection process. EEG signals are recorded from 27 healthy volunteers while performing the four different limb movements viz., finger open, finger close, wrist clockwise and wrist counter clockwise at the relaxed state. These four limb movements are the predominant physiological measures of the human being. Thus, the four limb moments viz., finger open, finger close, wrist clockwise and wrist counter clockwise are considered for the study. The complete architecture of the present study is shown in Figure 1.

EEG signals are recorded for each limb movement respectively. The complete dataset consist of four different classes (fopen, fclose, wcw and wccw) each signal containing 27 single-channel EEG signals of 60 seconds duration is used for the present analysis. Each signal has been selected subsequently for visual inspection toremove the artifacts.

EEG signals were recorded for the four classes using the standardized electrode placement method. The experimental setup containing the RMS kit (Ranges of Transmission: 100feet from the sight). Signals from electrodes C3, C4, CZ, FZ and PZ contains the information related to right hand movements[14,15] and thus are selected

in this study to identify the different limb movements. Conductive gel, Cotton ball, wipes, computer unit connected with RMS kit and software tools (Microsoft Excel & MATLAB 2010a). The required features were extracted through the MATLAB and processed by excel application. These lab instruments are used with the following procedure to conduct the experiments successfully. Initially, the primary experimental setup was confirmed to retrieve the EEG signals. The volunteers with short and oil free hair was employed to record the EEG signals. In order to stick the electrodes on the scalp region, conductive gel medium was used and the electrodes were cleaned properly with alcohol wipes. The electrodes such as C3, C4, CZ, FZ and PZ were placed on the scalp region, according to the order is shown in Figure 2. The electrodes were fixed from the starting position at O1. The first two electrodes were placed in the frontal region, the other two electrodes were placedin the occipital region and the last one was placed in the middle of the scalp. The safety measures were taken properly before recording the EEG signals[16].

Further, the instructions were given to the volunteers to commence the activity of finger open and monitored the changes in the EEG signals. The 10 seconds of EEG data were saved under the file name "open". To avoid the muscle fatigue, five minutes of rest were allowed to volunteer between each sequence of activity. Instructed to the volunteers to perform the activity finger close and monitored the changes in the EEG signals through the five channels and the data were saved under the file name "fclose". The same set of procedure has been followed for the rest of the activities via, wrist clockwise and wrist counter clockwise. The data points were written continuously into the disk space of a computer unit which was connected with RMS
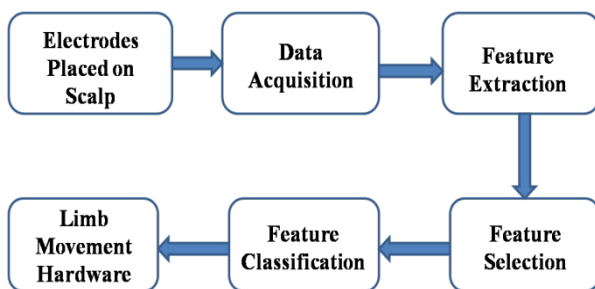

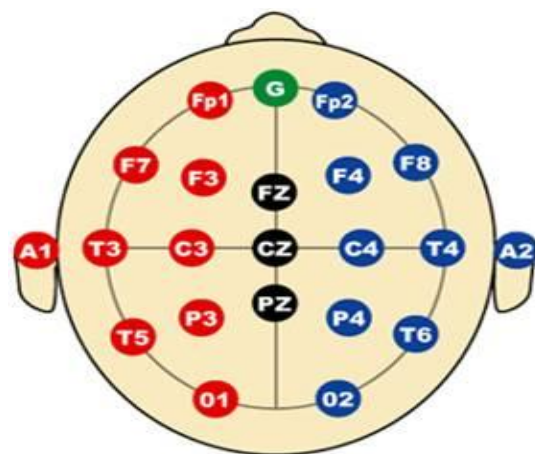**Figure 1.** System architecture of prosthetic arm.

Figure 2. EEG electrode placement 10 – 20 system.

kit at a sampling rate of 8 Hz to 13 Hz. The length of EEG signal was fixed at 1024 (samples).

2.1 Channel Selection

The dataset described in section three was taken and the statistical parameters were computed for each channel. Then C4.5 algorithm was used to perform the dimensionality reduction and classification with the default confidence factor value is 0.25 and the minimum number of objects is 2. From the conducted experiments, amongst the channels C3, C4, CZ, FZ and PZ, the best classification accuracy was achieved by C4 channel. Hence, only the C4 channel has been considered for the rest of the study. This is evident from Figure 3.

2.2 Feature Extraction

Feature extraction is the process of determining the characteristic of the signal using some mathematical measure. In this study, the EEG signals of various conditions are considered as the input to the classifier. Classification algorithm is employed to map the attributes from the input space to the output space. The output space contains four regions representing the four limb movements. A set of 1024 data points of digitized EEG signals was taken as the input data to the classifier. Generally, classifiers findit difficult to manage the huge number of input variables. To minimize the number of input variables, researchers follow a few measures of the data points instead of the data themselves. These measures are called as 'features'. The definition of features is application dependent. The way of computing, such a measure is referred to as 'feature extraction'.

2.2.1 Statistical Features

Feature extraction is the process of deriving various parameters for EEG signals. Basically, the statistical
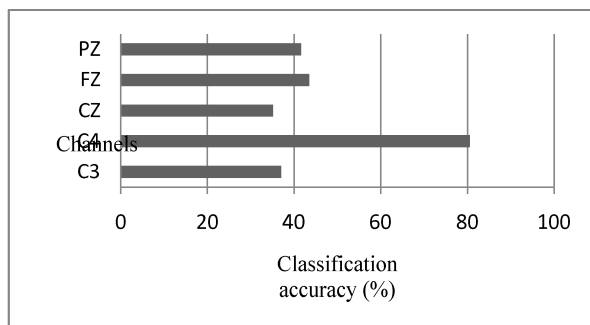

Figure 3. Channels Vs Classification accuracy.

features were derived from the EEG signals. The statistical measures are mean, median, standard deviation, mode, standard error, sample variance, skewness, kurtosis, range, maximum, minimum, sum and count. They were computed and used as the input to the classifier. Table 1 gives a descriptionof the essential features.

2.3 Feature Selection

Feature selection is an important process in machine learning. The feature selection process can be used for either to improve classifier accuracy scores or to boost their performance. With sufficient data and time, it is fine to use all the input features, including those irrelevant features, to approximate the primary function between theinput and the output. There are two problems with the irrelevant features. (i) It will induce greater computational

Table 1. Description of important statistical features

Name of the features	Description
Mean	It is used to describe the sum of the entire data sample divided by the number of data samples.
Median	It is used to describe that separates the higher values of the lower values in a data sample.
Standard deviation	How much variation exists in the data sample from the average value.
Mode	It is that value that appears the maximum number of times in a data point.
Standard error	It shows that the error encountered when a statistic of sampling distribution varies from its value.
Sample variance	It is a measure of spread for a set of sample variance.
Skewness	It describes the asymmetry from the normal distribution in a set of data sample.
Kurtosis	It shows that the distribution of giving data around the mean.
Range	In a set of data, the difference in the highest and lowest value is set to be a range.
Maximum value	It refers to the maximum value in a given data sample.
Minimum value	It refers to the minimum value in a given data sample.
Sum	It refers to the sum of all data point values of a given sample.
Count	Count is the total number of data sample.

cost. (ii) The irrelevant input features may mislead the training process. Hence those input features with little effect on the output, may be ignored in order to keep the size of the approximator model small. Hence the feature selection process plays a vital role in predicting the classification accuracy. To find the best subset, J48 decision tree classifier was used to evaluate all possible combinations of the input features exhaustively. Obviously, the computational cost of exhaustive search is prohibitively high, with considerable danger of over fitting. This can be avoided through greedy methods, such as forward selection. In this paper, one such greedy selection algorithm called J48 decision tree has been used to enhance the classification accuracy of the classifier. However, all the features extracted from the EEG signals may not contribute well in classification. Upon the feature selection process, the significant and appropriate features will be identified. The classification accuracy was computed and noted down for the selected features. Finally, the good features in descending order of their contribution to classification accuracy are "C4 mean", "C4 median" and "c4 maximum".

2.4 Clonal Selection Classification Algorithm

In recent years, artificial immune system has been used to solve complex problem domains using the benefits of natural immune systems. In a biological process the immune system protects an

organism from the potentially harmful materials (antigens) such asbacteria, viruses, etc. These antigens (pathogenic materials) are neutralized by an antibody. This immune function is performed by the B-cells (B lymphocyte cells) and T-cells (T lymphocyte cells) which are acting as a recognition cell. These cells are suited to specific antigens. Affinity is the degree of similarity between are cognition cell and a pathogenic. During an immune response, many clones are generated through hyper mutation to gain a better match with the antigen. During the hyper mutation, the mutated clones maintain the highest match (affinity) with the antigen. This process is termed as Clonal selection theory[17].

The Clonal Selection Classification Algorithm (CSCA) has been designed using this Clonal selection theory which is used to defend the organism from incursion. The goal of the algorithm is to develop a memory pool of antibodies that represents a solution to the fault diagnosis problem. This final pool of memory antibodies

is provided through local and global search. In the local search more clones are produced through affinity maturation (process of an adaptive ability of an immune system). In global search, randomly generated antibodies are inserted into the population to increase the diversity. The main objective of the clonal selection classifier algorithm is to maximize the classification accuracy. In order to maximize the classification accuracy, the diverse population with high fitness antibodies is essential instead of a single antibody solution. This is obtained by revealing the antibody to a set of antigens. However, a single exposure to all antigens is a practical problem with the large data sets. Hence a batch training methodology was adapted to break the training set into partitions as batches. The partition sets acts as a system which is permitted to the pathogen sets for multiple exposures after which the system acclimatizes the fitness of an antibody. This batch training process is adopted in the Clonal Selection Classification Algorithm. Each data set in a class act as antigens. An antibody with highest fitness score is used to train the partition set. The affinity (distance measure) is used to classify the data set belongs to unknown class. Overview of the Clonal selection Classification algorithm[18] is shown in Figure 4. The following parameters are used in CSCA algorithm:Initial population size (S): Defines the number of antigens with which to seed the antibody population; Total generations (G): The number of generations used to train the system. Clonal selection factor (a): Used to either increase or decrease the number of clones produced each generation. Minimum fitness threshold (ε): Used to prune the antibody population size.
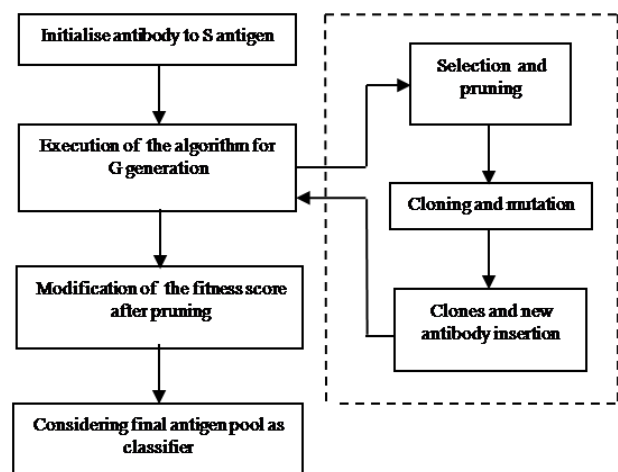

Figure 4. Functional diagram of CSCA algorithm.

Algorithmic procedure of a CSCA:

Step 1: Antibody (G) is exposed to randomly selected antigens(S).

Step 2: Entire populations are selected and exposed to antigen set and fitness score is calculated for each antibody.

Step 3: The clones are generated and mutated for the selected set.

Step 4: The generated clones and the selected antigens are inserted into the population.

Step 5: The antibodies with less fitness score ($<\varepsilon$) are removed (pruned) from the selected set.

Step 6: Modified fitness score is calculated after pruning.

Step 7: Raw data are exposed to antibody population. With the highest affinity, the antigens are applied to classify the data.

3. Results and Discussions

The four limb movements of EEG signal namely, fopen, fclose, wcw, and wccw are taken for this study. The machine learning approach has been used with the statistical features. The classification performance of CSCA algorithm is reported.

The C4.5 algorithm is used to perform the dimensionality reduction. A decision tree has been developed. There from well contributing features are selected for classification following footsteps of Sugumaran[19]. For EEG signals, out of 12 features, the selected statistical features are "C4 median", "C4 maximum" and "C4 mean". The selected features were classified by using CSCA algorithm. Table 2 shows the parameter used for the classification using CSCA. Table 3 shows the classification accuracy of the selected number of features. Referring Table 3, the classifier gives the maximum classification accuracy. The best classification accuracy is 79.62% using EEG signals. Here the objective is to find the best parameter out of statistical parameters with which the highest classification accuracy can be achieved.

The classification and misclassification details are presented in the form of confusion matrix. Confusion matrix for EEG signals is shown in Table 4. All the diagonal elements of the confusion matrix represent the number of correctly classified data points and the non diagonal elements represent the incorrectly classified data points. In this fashion, the classification accuracies were found and compared. First row in the confusion matrix represents, the number of data sets correspond-

Table 2. Parameters for CSCA

Generations completed	5
Antibodies pruned per generation	182.4 (75.235)
Antibodies without error per generation	14.8 (1.166)
Population size per generation	238.6 (1.855)
Antibody fitness per generation	0.67 (0.514)
Antibody class switches per generation	8.2 (4.665)
Selection set size per generation	4 (0)
Training accuracy per generation	82.778 (1.717)
Inserted antibodies per generation	4 (0)
Cloned antibodies per generation	215.8 (0.748)
Data reduction percentage	83.333%
Total antibodies	18
Total training instances	108

Table 3. Effect of number of features on the classification accuracy.

Number of features	Classification accuracy of CSCA (%)
1	74.07
2	78.55
3	76.85
4	78.70
5	71.29
6	70.37
7	69.44
8	72.22
9	69.44
10	73.14
11	77.77
12	**79.62**

Table 4. Confusion matrix for CSCA with statistical features.

	fopen	fclose	wccw	wcw
fopen	22	4	1	0
fclose	1	24	1	1
wccw	5	3	18	1
wcw	0	3	2	22

ing "fopen" condition. In the first element in the first column represents, how many data sets are classified as "fopen"condition. In the first row, 22 data sets are correctly classified as "fopen" condition and 5 data sets are misclassified as "fclose", "wccw" and "wcw". Similarly, second row,the second elements in the confusion matrix represent "close" condition. The second element in the second column indicates, 24 data sets belong to "fclose" condition is correctly classified as "fclose "condition. The non diagonal elements represent, how many data sets belongs to "close" condition is misclassified as other conditions. The third and fourth row gives the information about the "wrist counter clockwise" condition and "wrist clockwise" condition respectively.

3.1 Classification Error Analysis

The sensitivity, specificity and total classification accuracy were computed to test the performance of the classifier. The sensitivity, specificity and total classification accuracy are defined as

Sensitivity = number of true positive(TP) / (number of true positive(TP) + number of false negative(FN))

Specificity = number of true negative(TN) / (number of true negative(TN) + number of false positive (FP))

Total classification accuracy = number of correct instances / total number of instances.

In order to determine the performance of CSCA classifier used for classification of the EEG signals, the classification accuracies (specificity, sensitivity and total classification accuracy) on the test datasets are presented in Table 5.

Table 5. The values of the statistical parameters of the classifier

Classifier	Classes	Statistical parameters (%)		
		Sensitivity	Specificity	Total classification accuracy
CSCA	fclose	88.88	92.59	
	fopen	81.48	87.65	79.62
	wccw	66.66	95.06	

In this case, the sensitivity shows the less percentage than the specificity measure. However, the specificity is 95.06% and 97.53% for classes 'wccw' and 'wcw' respectively.One can confidently say that the noun 'wccw' and non 'wcw' classes were identified correctly by the classifier. However, the sensitivity for these classes is 66.66% and 81.48% respectively. This indicates that the classifier is not able to identify these classes ('wccw' and 'wcw') correctly. Similarly, the sensitivity and specificity measures are high for the classes 'fclose' and 'fopen'. This indicates the ability of the classifier to classify these classes from others easily.

From Table 6 shows the realistic picture of the classifier's performance. The achieved classification accuracy is 79.62%. The kappa statistics is a measure of the agreement between predicted and observed categories of data set. In this case, the kappa statistics happens to be 0.72.

The following could be considered for judging the quality of the model. TP rate and FP rate are the two important statistical measures for the same. The TP rate represents a rate of true positive that has a value nearer to 1 (0.8). Likewise, the FP rate or false positive has a value close to 0 (0.03) is shown in Table 7. The slight variation is due to some misclassification of four different class like fclose, fopen, wccw and wcw.

Table 6. Summary of Classifier's Result

Correctly Classified Instances	79.62
Incorrectly Classified Instances	20.37
Kappa statistic	0.72
Mean absolute error	0.10
Root mean squared error	0.31
Relative absolute error	27.13
Root relative squared error	73.62
Total Number of Instances	108

Table 7. Detailed accuracy by class – CSCA algorithm

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
0.815	0.062	0.815	0.815	0.815	0.877	fclose
0.889	0.086	0.774	0.889	0.828	0.901	fopen
0.667	0.025	0.900	0.667	0.766	0.821	wccw
0.852	0.086	0.767	0.852	0.807	0. 883	wcw

4. Conclusion

The proposed work considered four classes of right hand limb movements includes finger open (fopen), finger close (fclose), wrist clockwise (wcw) and wrist counterclock wise (wccw). The statistical features were extracted from the EEG signals. The set of well contributed statistical features were classified using CSCA algorithm and achieved the best classification accuracy of 79.62%. Thus, EEG signals can be used for prosthetic limb movements with CSCA classifier. The signal processing of EEG signals is a complex task and requires sophisticated techniques to yield a better classification accuracy. A better feature extraction technique may be used in order to improve the classification accuracy.

5. References

1. Fadzal CWNF, Mansor W, Khuan LY. Analysis of EEG Signal from Right and Left Hand Writing Movements. IEEE Control and System Graduate Research Colloquium. 2012; 354–58.

2. Elif DU. Least squares support vector machine employing model-based methods coefficients for analysis of EEG signals. Expert Systems with Applications. 2010; 233–39.

3. Adeli H, Zhou Z, Dadmehr N. Analysis of EEG records in an epileptic patient using wavelet transformation. Journal of Neuro Science Methods. 2003; 123(1):69–87.

4. Agarwal R, Gotman J, Flanagan D, Rosenblatt B. Automatic EEG analysis during long-term monitoring in ICU. Electroencephalography and Clinical Neurophysiology. 1998; 107(1):44–58.

5. Hazarika N, Chen JZ, Tsoi AC, Sergejew A. Classification of EEG signals using wavelet transform. Signal Processing. 1997; 59(1):61–72.

6. Elif DU. Analysis of EEG signals by combining eigenvector methods and multiclasssupport vector machines. Computers in Biology and Medicine. 2008; 38(1):14–22.

7. Ocak H. Optimal Classification of epileptic seizures in EEG using wavelet analysis and genetic algorithm. Signal Processing. 2008; 88(1):1858–67.

8. Ubeyli ED. Statistics over features: EEG signals analysis. Computers in Biology and Medicine. 2009; 39(1):733–41.

9. Ubeyli ED, Guler I. Features extracted by eigenvector methods for detecting variabilityof EEG signals. Pattern Recognition Letters. 2007; 28(1):592–603.

10. Adeli H, Zhou Z, Dadmehr N. Analysis of EEG records in an epileptic patient using wavelet transform. J Neurosci Methods. 2003; 123(1):69–87.

11. Aishwarya R, Prabhu M, Sumithra G, Anusiya M. Feature Extraction for EMG based Prosthesis control. ICTACT Journal on Soft Computing. 2013Jan; 3(2):472–77.

12. Rani JAB, Umamakeswari A. Electroencephalogram-based Brain Controlled Robotic Wheel chair. Indian Journal of Science and Technology. 2015 May; 8(S9):188–97. Doi: 10.17485/ijst/2015/v8iS9/65580.

13. Khoobjo E. New Hybrid Approach to Control the Arm of Flexible Robots by using Neural Networks, Fuzzy Algorithms and Particle Swarm Optimization Algorithm. Indian Journal of Science and Technology. 2015 Dec; 8(35):1–5. Doi:10.17485/ijst/2015/v8i35/87127.

14. Dornhege G, Millan JR, Hinterberger T, McFarland DJ, Muller KR. Toward Brain - Computer Interfacing, 1st ed., MIT Press, Massachusetts. 2007.

15. Bhattacharyya S, Konar A, Tibarewala DN. A differential evolution based energy trajectory planner for artificial limb control using motor imagery EEG signal. Biomedical Signal Processing and Control. 2014; 11(1):107–13.

16. Electroencephalography (EEG) and Electromyography (EMG) Measurement of Action Potentials in the Brain and Muscle by Sara Johannesmeyer and Kaleigh Lindeman Main Source: CleveLabs, from CleveMed. 2012.

17. Brownlee J. Artificial immune recognition system (AIRS), a review andanalysis, Technical report, 2005.

18. Brownlee J. Clonal selection theory and CLONALG the clonal selectionclassification algorithm (CSCA), Technical report, 2005.

19. Sugumaran V, Muralidharan V, Ramachandran KI. Feature selection using Decision Treeand classification through Proximal Support Vector Machine for fault diagnostics of roller bearing. Mechanical Systems and Signal Processing. 2007 Feb; 21(2):930–42.