Pak. J. Biotechnol. Vol. 15 (Special Issue ICRAME 17) Pp. 32-35 (2018) V.V. Ramalingam et al.,
www.pjbt.org PISSN: 1812-1837, EISSN 2312-7791

ARTIFICIAL LIMB MOVEMENT SYSTEM USING K-STAR ALGORITHM - A DISCRETE WAVELET TRANSFORMATION APPROACH

V.V. Ramalingam[*1], S. Mohan[2], V. Sugumaran[3], B. Rebecca jeyavadhanam[4]

[1]Department of Computer Science and Engineering, S.R.M University, India. [2]Al Yamamah University, Riyadh, Kingdom of Saudi Arabia. [3]SMBS, VIT University, Chennai Campus, India. [4]Faculty of Science and Humanities, S.R.M University, Kattankulathur, India. E-mail: ramalingam.v@ktr.srmuniv.ac.in

ABSTRACT

Machine learning is one of the promising areas which contributes to human rehabilitation and this statement can be substantiated by the number of researches conducted in this field. In this study, we attempt to direct an artificial limb system with the help of Electroencephalogram (EEG) signals. EEG signals are created as a result of brain activities when humans intend to perform any action. Hence, capturing this signal and using them to control the artificial limb will be as close to how a human will control their normal hand. Four separate classes of EEG signals were recorded from 27 healthy subjects while they were instructed to perform various hand movements such as Finger open (Fopen), Finger close (Fclose), Wrist counterclockwise (WCCW) and Wrist clockwise (WCW). The recorded EEG signals were further classified with classification algorithm to identify the desired movement. Feature extraction, feature selection and feature classification are the three important phases of machine learning which needs to be focused on. The aim of this study is to mine Discrete Wavelet features from EEG signals, classify them with K-Star algorithm, and propose the best features that can be used to regulate the artificial limb.

Keywords: Classification, K-Star Algorithm, Discrete Wavelet Features, Electroencephalogram (EEG) signals.

1. INTRODUCTION

Whenever humans lose their limb due to any mishap, their daily routine activities are majorly impacted. Creating an artificial limb that can be controlled by human thought could be of greater potential. For this to happen, the brain activity of humans needs to be captured first. This is done using EEG electrodes and RMS kit. Then, the recorded brain activity which will be in the form of EEG signal needs to be classified into corresponding physical movement. Our study is aimed at classifying four distinct classes of hand movements such as finger open (Fopen), finger close (Fclose), wrist clockwise (WCW) and wrist counter clockwise (WCCW) rotation. We have considered only right-hand movement since majority of the world population is right handed. In addition, the movement classes chosen will attribute to majority of actions carried out using hand. EEG signals are composite in nature and therefore we equip machine-learning technique for its classification. Previous researches carried out in this area using EMG (Electromyogram) signals to control the artificial limb have revealed certain limitations. EMG signal capturing process is invasive when compared to non-invasive EEG signal capturing. Along with that, EMG signals can easily acquire cross talk from neighboring muscles and fatty tissue deposited over the muscle will impact the quality of captured signal. Hence, EEG signals are more efficient in controlling the limb since they are recorded because of brain activity. Feature extraction is carried out through Discrete Wavelet Transformation technique. Prior to Wavelets, researcher mainly trusted on Fourier transform for analyzing signals. Fourier transformation needs that the signal analyzed must be of stationary form. As we know that the Bio medical signals are non-stationary in nature, Fourier transformed will not be suitable to study the same. Hence, we have employed wavelet transformation to study the EEG signals. The author has proposed a technique for EEG signal-based pattern recognition in BCI based on dual-tree complex wavelet transform and particle swarm optimization. The features extracted were classified using linear discriminant analysis (LDA) and an accuracy of 90% was achieved (Aimin Wang, et al., 2016). The author has classified left and right-hand movements from EEG signals. Initially EEG signals were decomposed into several bands of real and imaginary coefficients with the help of Dual Tree Complex Wavelet Transform (DTCWT). Further, statistical features were computed from the same. Among the various classifier applied, KNN algorithm shows highest accuracy (Khairul Bashar, et al., 2015). Mehmet Kuntalp, et al., (2005) has exhibited a technique, which can assist in performing single limb exercise by applying force to individual joints using servomotor. Prima, et al., (2015) has proposed a method to EEG based emotion recognition. Wavelet energy is computed to serve as features and Back Propagation Neural Network (BPNN) is used as the classifier. The author has proposed a method to diagnose epilepsy through automatic evaluation of EEG signals. Discrete Wavelet transformation was used for feature extraction and Artificial Neural Network (ANN) was used for classification (Toprak, et al., 2007). Ramalingam, et al., (2016) has proposed a method to extort statistical features to control the non-natural limb. Four different classes of movements were accounted. Feature classification was performed using K-star algorithm. In this study the author has carried out a classification of left and right-hand movement using Naive Bayes, Multi layered Perceptron and Support Vector Machine. Wavelet based energy-entropy with three level of decomposition in combination with ten types of Daubechies wavelet was computed to serve as features. Results show that Daubechies wavelet with order 4 is best for high quality features (Rajdeep, et al., 2016). Upadhyay, et al., (2016) has performed classification of sleep under three different states such as awake, slow wave sleep (SWS), and Rapid Eye Movement (REM) using EEG signals. Wavelet coefficients were computed to serve as features and classification is performed using ANN. Results show that ANN in combination with wavelet features produces better accuracy and can be used to monitor patients.

2. MATERIALS AND METHODS

Electroencephalogram (EEG) signals were recorded from 27 distinctive and strong subjects. Two minutes of rest was provided among recording each movement sequence so that the patients do not experience any muscle fatigue or soreness. The subjects were requested to sit on flexible chair and the EEG electrodes (C3, C4, CZ, FZ and PZ) were positioned to subject's scalp. Suitable conductive gel must be applied to the scalp in advance. Fopen (Finger open), Fclose (Finger close), WCW (Clockwise wrist rotation) and WC-CW (Counterclockwise wrist rotation) movements were asked to carry out by the subjects. EEG signals were obtained from the electrodes placed on the scalp with the help of Electroencephalogram tool (RMS kit). The occurrence of the signal was ranging from 8 to 13 Hz. The signal length fixed as 1024 for all the five channels.

3. Feature Extraction: Prior to Wavelet feature extraction, Statistical features like Standard Deviation, Kurtosis Minimum, Skewness, Maximum, Sum, Mean, Mode, Standard Error, Variance, Count, Median and Range were computed from the EEG signals. This was carried out by writing an excel macro which will internally call the Descriptive Analysis Package from Data Analysis Tool list present in Microsoft Excel 2003 to carry out the task. The Statistical features were computed separately for each channel. On classifying these features using C4.5 Decision tree algorithm, we could infer that channel C4 exhibits higher accuracy (80.55%) in comparison to other channels. Hence, our further study will be focusing only on C4 channel shown in Fig. 1.

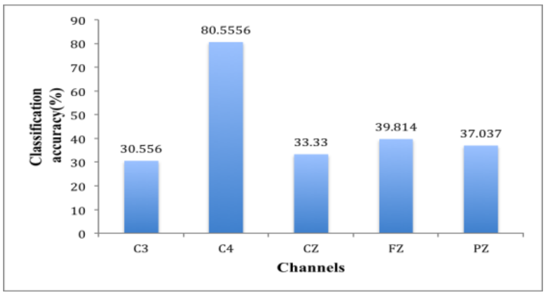

Figure1: Channels Vs Classification accuracy

3.1 Wavelet Feature Extraction: Wavelet Feature extraction is emphasized only on channel C4 as we have identified that it gives the highest classification accuracy when compared with other channels. The EEG signals are non-stationary signals and they are represented in the time-domain form. Therefore, this signal must be converted to time-frequency domain with the help of Discrete Wavelet Transform (DWT). Wavelet decomposition will provide us signal trend and details. Further decomposing this trend will result in the next level detail and trend. Length of the signal chosen as 1024 for each channels uniquely and therefore the total number of decomposition possible is 10. The feature vector V can be defined as V= (v1, v2, v3, v4, v5, v6, v7, v8, v9, v10).

The various discrete wavelet types considered is listed below.

- Bi-orthogonal Wavelet – bior1.1, bior 1.3, bior 1.5, bior 2.2, bior 2.4, bior 2.6, bior 2.8, bior 3.1, bior 3.3, bior 3.5, bior 3.7, bior 3.9, bior 4.4, bior 5.5, bior 6.8.
- Coiflet Wavelet – coif 1, coif 2, coif 3, coif 4, coif 5.
- Daubechies Wavelet – Db1, db2, db3, db4, db5, db6, db7, db8, db9, db10.
- Reversed Bi-orthogonal Wavelet - rbio1.1, rbio 1.3, rbio 1.5, rbio 2.2, rbio 2.4, rbio 2.6, rbio 2.8, rbio 3.1, rbio 3.3, rbio 3.5, rbio 3.7, rbio 3.9, rbio 4.4, rbio 5.5, rbio 6.8.
- Symlets Wavelet– sym 2, sym 3, sym 4, sym 5, sym 6, sym 7, sym 8.
- Discrete Meyer Wavelet –dmey.

3.2. Wavelet Selection: Feature vectors from the time domain signals were extracted through discrete wavelet transformation. To distinguish which wavelet form provides high classification accuracy, the feature vectors of each wavelet were classified with C4.5 algorithm. From the classification results, it concludes that dmey wavelet provide the highest classification accuracy of (87. 03%). Hence, we have considered only dmey wavelet for rest of the study.

4. Feature Selection: Only dmey wavelet has been considered for feature selection processes since it gave us highest classification accuracy. We have constructed a decision tree by considering all the feature vectors of dmey wavelet. From the constructed Decision tree, we can observe that only some of the features of dmey wavelet are contributing to the classification accuracy. They are v1, v2, v4, v5, v7 and v9. Classification carried out on the feature vectors v1, v2, v4, v5, v7 and V9 with C4.5 Decision tree algorithm after dimensionality reduction gave us an accuracy of 87.96%.

5. K-Star Algorithm: K-Star algorithm is an instance-based classification algorithm. Some of the variants of K-star algorithm are Locally Weighted Learning (LWL), IBK, and K-star. The way in which K-star algorithm differs from other instance-based learner is the use of entropy-based distance function. The basic assumption of this algorithm is, similar instances will have similar type of classification. The distance function is responsible for measuring the similarity between two instances and how similar they will be classified. K-star algorithm utilises entropic measure to transform a given instance into another instance based on a probability. The complexity of transformation relies on the distance between the instances. The function of K* is defined as:

$K\bullet(b/a) = \log_2 P\bullet(b/a)$

Where P is the probability function on a transformation T.

a and b are two different instances.

Note that K* algorithm is not exactly meant for measuring distance. K* is not a symmetric function. It is a non-zero function.

6. RESULTS AND DISCUSSION

In section 2, the statistical feature extraction and the channel selection based on statistical feature classification using C4.5 algorithm is explained. The classifier results show that channel C4 provides highest classification accuracy in classifying the right-hand movements. wavelet selection is explained in section 3. By looking at the classification accuracy of various wavelets, we can infer that the wavelet type dmey provides high classification accuracy. Section 4 caters about feature selection process carried on the extracted wavelet features and we were able to identify that the features v1, v2, v4, v5, v7 and v9 are the essential ones. Classification performed on the selected features using K-star algorithm provided an accuracy of 79.62%. Global blend is a crucial parameter that affects the classification accuracy of K-star algorithm is shown in Fig 2. Hence, this parameter was varied from 10 to 100 in steps of 10 and the corresponding accuracy was recorded. From the results, we can conclude that the classifier achieves a highest accuracy of 80.55% when the global blend is set to 10. Further increasing it results in reduction of classifier accuracy. The classifier performance has explained using confusion matrix and it has given in Table 1.

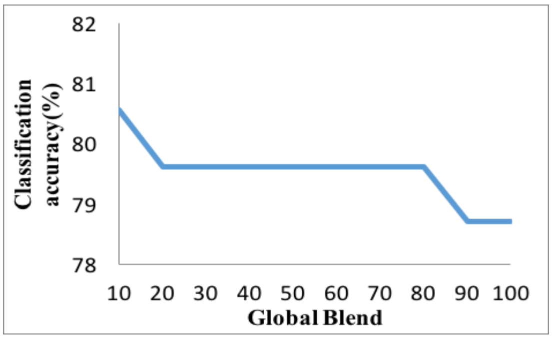

Figure 2: Global blend Vs Classification accuracy

The diagonal of the confusion matrix shows the correctly classified instances and the non-diagonal element presents the incorrectly classified instance. Column header shows the resultant class and row header shows the actual class of the movement.

Table 1: Confusion Matrix

	fopen	fclose	wcw	wccw
fopen	23	0	1	3
fclose	2	19	4	2
wcw	0	1	23	3
wccw	2	2	1	22

The classifier quality can be measured with parameters such as Precision, Recall, F-measure, True Positive rate (TP Rate), False Positive rate (FP Rate), ROC Area (Region of Curve).

True positive classifications are represented by True Positive rate. Their value is nearer to 1. False Positive rate links to false classification and its value is closer to 0 (0.04). Precision defines what part of instances which were retrieved are relevant. Recall is the fraction of relevant instances that were retrieved. F-measure is mentioned as the weighted average of recall and precision. ROC area is the area measure in the plot of True Positive rate and False Negative rate.

7. Conclusion

EEG signals are non-stationary signals. Hence, feature extraction was carried out through discrete wavelet transformation and classified using K-star algorithm and an accuracy of 79.62% was achieved. The global blend parameter that influences classification was varied and the accuracy was improved to 80.55%. Different techniques for feature extraction and feature classification may further contribute for improving the classification accuracy there by effectively controlling the artificial limb movement system.

8. REFERENCES

Aimin Wang et al., Brain EEG pattern recognition based on Dual-Tree Complex Wavelet Transform and Particle Swarm Optimization. Tenth International Conference on Sensing Technology. IEEE (2016).

Khairul Bashar et al., Identification of Arm Movements using Statistical Features from EEG Signals in Wavelet Packet Domain. International Conference on Electrical Engineering and Information & Communication Technology (lCEEICT). IEEE (2015)

Mehmet Kuntalp et al., Automatic Detection of Epilepti form Events in EEG by a Three-Stage Procedure Based on Artificial Neural Networks. IEEE Transactions on Biomedical Engineering 52(1): (2005).

Prima et al., Benyamin Kusumoputro. EEG Based Patient Emotion Monitoring using Relative Wavelet Energy Feature and Back Propagation Neural Network. IEEE (2015).

Rajdeep et al., Effects of Wavelets on Quality of Features in Motor-Imagery EEG Signal Classification. IEEE WiSPNET conference (2016)

Ramalingam, V.V. et al., Prosthetic Arm Control with Statistical Features of EEG Signals using K-star Algorithm. J. Applied Sci. 16 (4): 138-145 (2016).

Toprak et al. Automatic Recognition of Epilepsy from EEG using Artificial Neural Network and Discrete Wavelet Transform. Signal Processing and Communications Applications IEEE (2007).

Upadhyay et al., Wavelet-Neural Classification of Sleep EEG under Stressful Condition. IEEE Sixth International Conference on Developments in eSystems Engineering (2014).