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Noor Kamal Al-Qazzaz
University of Baghdad, Iraq

Alaa A. Aldoori
University of Baghdad, Iraq

A. Buniya
University of Baghdad, Iraq

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EEG Neuro-markers to Enhance BCI-based Stroke Patient Rehabilitation

Noor Kamal Al-Qazzaz, Alaa A. Aldoori, A. Buniya

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Abstract

Stroke is the second largest cause of death worldwide and one of the most common causes of disability. However, several approaches have been proposed to deal with stroke patient rehabilitation like robotic devices and virtual reality systems, researchers have found that the brain-computer interfaces (BCI) approaches can provide better results. In this study, the electroencephalography (EEG) dataset from post-stroke patients were investigated to identify the effects of the motor imagery (MI)-based BCI therapy by investigating sensorimotor areas using frequency and time-domain features and to select particular methods that help in enhancing the MI-based BCI systems for stroke patients using EEG signal processing. Therefore, to detect the imagined movements that are typically required within conventional rehabilitation therapy with good identification accuracies, the conventional filters and wavelet transform (WT) denoising technique was used in the first stage. Next, attributes from frequency and entropy domains were computed. Finally, support vector machine (SVM) classification techniques were utilized to test the motor imagery (MI)-based BCI rehabilitation. The results demonstrate the capability of the WT denoising technique together with the used features and SVM classifier to discriminate the tested classes of the left hand, right hand and foot MI-based BCI rehabilitation. This study will help medical doctors, clinicians, physicians and technicians to introduce a good rehabilitation program for post-stroke patients.

Introduction

Stroke may cause severe impairment to a variety of functions, among which chronic motor disability is one of the greatest challenges. Rehabilitation can improve the motor function in chronic stroke patients. Mental practice of MI is effective when combined with conventional physical therapy for rehabilitation of both upper and lower extremities, which is important for the daily activities and skills. New techniques such as brain-computer interface (BCI) might offer promising recovery of motor function for stroke survivors (Mattout, Perrin, Bertrand, & Maby, 2015) . A BCI is a form of human-computer interface technology that enables control of a computer and outer devices by modulating neuro-physiological processes. One of the goals of BCI is to provide motor recovery for paralyzed extremities by utilizing neural signals from the brain.

The Electroencephalography (EEG) was used for BCI applications because EEG is a simple, low-cost, noninvasive tool that can provide information about the changes occurring in the cerebral cortex during the recovery process after stroke (N. K. Al-Qazzaz, Ali, Ahmad, Islam, & Mohamad, 2014; N. K. Al-Qazzaz, Ali, & Ahmad, 2018). Stroke is the second largest cause of death worldwide and remains as one of the leading causes of acquired disability in adults. While almost 85% of patients survive the initial injury, approximately 65% of stroke survivors will suffer residual disabilities that impairs daily function and quality of life (N. Al-Qazzaz, Hamid Bin Mohd Ali, Ahmad, Islam, & Escudero, 2017; N. K. Al-Qazzaz, Ali, Ahmad, Islam, & Escudero, 2017). It is necessary to find a good way to help these people enhance their lives to carry out daily functions like any normal human being who lives his life For this reason, new techniques have emerged to rehabilitate people suffering from stroke.

It has been suggested that MI may be beneficial in stroke rehabilitation by targeting the central motor system without the physical initiation of a motor task. Unlike active and passive movement therapies, the ability to perform MI is not dependent on the residual function of the paretic limb. More importantly, the primary motor cortex is directly engaged in MI as demonstrated by functional imaging studies on healthy subjects and even in clinical populations.

A number of experiments have investigated the ability of stroke patients to perform MI. These studies showed that most stroke patients are able to perform MI despite chronic or severe motor impairments. In recent years, advancements in the Spatio-temporal detection of event-related desynchronization /synchronization (ERD/ERS) of EEG waves (i.e. beta and alpha oscillatory rhythms) have provided a more direct and accurate measure of neurophysiological change during real and imagined movements. By analyzing the change in ERD/ERS patterns in EEG signals during MI, MI-BCI systems are able to translate the imagination of movements into motor commands, which allows for a patient to interact with their external environment (N. K. Al-Qazzaz, Alyasseri, et al., 2021).

The aims of this study are, to identify the effects of the MI-based BCI therapy by investigating sensorimotor areas using frequency and time-domain features to allow anatomically specific voluntary regulation for a stroke patient. To detect imagined movements that are typically required within conventional rehabilitation therapy with good identification accuracies. To select particular methods that help in enhancing the MI-based BCI systems for stroke patients using EEG signal processing.

To the author's best knowledge, this study has three contributions, firstly, it is the first use of a wavelet spectral power ratios (RP) features including (δ/θ), (θ/α), (α/β), (β/γ) and (θ/γ). Secondly, the first to employs the mentioned PR to characterize and classify the emotional EEG based on gender differences using support vector machine (SVM) and k-nearest neighbors (KNN) classifiers. Thirdly, the EEG elicitation protocol and EEG measurement procedure have never been used before for emotion data acquisition.

Method

Figure 1 shows the block diagram of the current study.

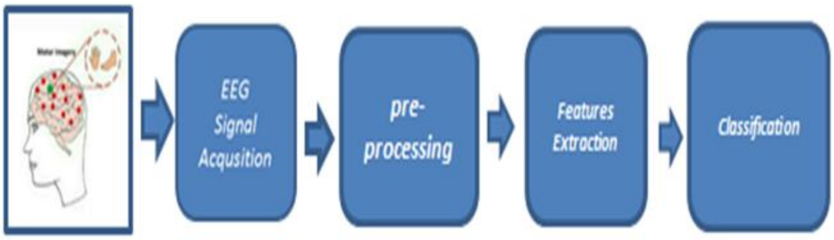

Figure 1. The Proposed Block Diagram of This Study.

EEG Acquisition and Recording

The proposed method was got from Berlin-BCI (BBCI) group. It is a EEG dataset (dataset1 motor imagery, uncued classifier application) among four different datasets used for BCI competition IV (Tangermann et al., 2012). A full description can be found at [http//ida.first.fhg.de/projects/bci/competition iv/desc1.html]. It consists of normal data (1a, 1b, 1f, and 1g) and artificial data (1c, 1d, and 1e). Our experiment uses the 100 Hz version of the data (Kang & Jun, 2009; Tangermann et al., 2012).

The recording was made using Brain Amp MR plus amplifiers (Brain Products GmbH, Munich, Germany) and a Ag/AgCl electrode cap (EASYCAP GmbH). Signals from 59 EEG positions were measured that were most densely distributed over sensorimotor areas. Signals were band-pass filtered between 0.05 and 200 Hz and then digitized at 1000 Hz with 16 bit (0.1 µV) accuracy. Also a version of the data was provided that was sub sampled at 100 Hz (He, Yu, Gu, & Li, 2009).

Data Recording Protocol

The session was divided into two parts recording of training data and recording of test data. Training data were provided with complete marker information such that it could be used by the competitors for adapting the parameters of the methods/models. In contrast, the test data which was provided to the competitor only consisted of the EEG signals. The corresponding markers have been kept secret until the submission deadline and have been used to evaluate the submissions (Tangermann et al., 2012).

For the training data (calibration data), in the first two runs, arrows pointing left, right, or down were presented as visual cues on a computer screen. Cues were displayed for a period of 4s during which the subject was instructed to perform the cued motor imagery task. These periods were interleaved with 2s of blank screen and 2s with a fixation cross shown in the center of the screen. The fixation cross was superimposed on the cues, i.e. it was shown for 6s,see Fig. 2. In each run 50 trials of each of the chosen two classes have been presented, resulting in a total of 200 trials. After every 15 trials a break of 15 s was given for relaxation. Between the runs there were longer breaks of 5–15 min (Tangermann et al., 2012).

For the test data (Evaluation data), the 4 runs followed which are used for evaluating the submissions to the competitions. Here, the motor imagery tasks were cued by soft acoustic stimuli (words left, right, and foot) for periods of varying length between 1.5 and 8 seconds. The end of the motor imagery period was indicated by the word stop. Intermitting periods had also a varying duration of 1.5 to 8s. Fig. 2, Note that in the evaluation data, there are not necessarily equally many trials from each condition (Tangermann et al., 2012).

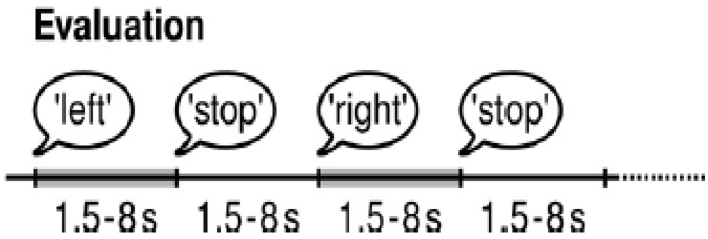

Figure 2. Data set 1 – Trial Structure.

Training data was collected in the calibration runs. Arrows pointing left, right, or down have been presented as cuesfor imagining left hand, right hand, or foot movements. After a fixation cross was presented for 2 s, the directional cue was overlaid for 4 s. Then the screen was blank for 2 s. In the test runs used for evaluation, spoken words have been presented as cues (Tangermann et al., 2012).

Preprocessing Stage

Conventional Filters: The sampling rate of the EEG signals of the used dataset is 100 Hz and the signals were filtered using a bandpass filter of frequency band within 8 and 30 Hz. In addition, a 50-Hz notch filter was utilized to remove the line noise. And then the Wavelet technique was used to remove the noise of the signal, and it is also considered a complementary stage to extract the features (N. K. Al-Qazzaz, Alyasseri, et al., 2021).

Wavelet Denoising Technique: The Symlet mother wavelet of order 9 'sym9' and four decomposition levels were selected to decompose the EEG signals because the sampling frequency of 128 Hz was used in this study (N. Al-Qazzaz, Hamid Bin Mohd Ali, Ahmad, Islam, & Escudero, 2015; N. Al-Qazzaz et al., 2017; N. K. Al-Qazzaz, S. H. B. M. Ali, S. A. Ahmad, M. S. Islam, et al., 2017). The decomposition coefficients of the six sub-signals through the DWT are cD1, cD2, cD3, cD4, cD5 and cA5, which represent the frequency content of the band-limited EEG signal (where cA is the decomposition approximation coefficient, and cD is the decomposition detail coefficients). The Stein's unbiased risk estimation (SURE) threshold has been used (N. K. Al-Qazzaz, Ali, Ahmad, Islam, & Ariff, 2014).

Features Extraction Stage

Frequency Domain Features: When the neurophysiological basis for motor imagery BCI, μ band or the Rolandic band (8 to 13 Hz) and β (13 to 30 Hz)] were extracted in EEG. Moreover, the power ratio of μ band to β band feature was computed from the recorded EEG dataset (N. K. Al-Qazzaz, Alyasseri, et al., 2021).

Time Domain Features: To investigate the time domain features, entropy has been used to measure the amount of uncertainty and to reveal the complexity of a dynamical system (N. K. Al-Qazzaz, Sabir, Al-Timemy, & Grammer, 2022). The most basic entropy measure used to analyze system complexity is Shannon entropy (ShEn) (Shannon, 1948), which is based on Boltzmann–Gibbs statistical mechanics and standard thermodynamics in which the effective microscopic interactions and the microscopic memory are of short range (Tsallis, 1999).

In spite of its great success in analysis of extensive systems, ShEn could not properly describe systems with long-range interactions, long-term memory effects,or abrupt changes (Borges & Roditi, 1998). A nonextensive statistics, known now as Tsallis entropy (TsEn), was proposed by Tsallis (Tsallis, 1988).

Although the generalization of nonextensivity was understood in the thermodynamical sense from earlier times, it now gets broader application beyond thermodynamics, and TsEn has been widely used in biomedical signal processing such as analysis of ECG (Torres & Gamero, 2000) and EEG (N. K. Al-Qazzaz, Sabir, Ali, Ahmad, & Grammer, 2020; N. K. Al-Qazzaz, Sabir, Ali, Ahmad, & Grammer, 2021; N. K. Al-Qazzaz, Sabir, Bin Mohd Ali, Ahmad, & Grammer, 2021; N. K. Al-Qazzaz, Sabir, & Grammer, 2019),recently. Studies showed that the Tsallis environment could provide more detailed information than the conventional Shannon counterpart, especially when used as burst or spike EEG analysis (N. K. Al-Qazzaz, S. Ali, S. A. Ahmad, & J. Escudero, 2017; N. K. Al-Qazzaz, S. H. B. M. Ali, S. A. Ahmad, & J. Escudero, 2017).

EEG Classification Stage

In the classification stage, the accuracy of classifiers strongly depends on the quality of the extracted features and classification model. Therefore, this study employed two popular classifiers, namely, support vector machine (SVM). SVM was proposed by Vapnik and developed based on computational learning theory, SVM has been extensively used in biomedical engineering, particularly in classification, regression, and density estimation (N. K. Al-Qazzaz, S. Ali, et al., 2017). The performance of the proposed system was evaluated using average classification accuracy and confusion matrix.

Results and Discussion

Results of Preprocessing Stage

In the preprocessing stage, the detrend function was used to remove the drift in the signals and to return the EEGs to the baseline. Moreover, the conventional Filters were used. Firstly, notch filter at 50 Hz was used to remove power line interface noise and a band pass filter with lower cutoff frequency corresponding to 8 Hz and the upper cutoff frequency of 30 Hz was used.

WT denoising technique using db8 mother WT was used to reduce the noise effect on the EEG signal. The artifactual components were sufficiently and successfully suppressed (blue color) compared with the original recorded EEG (red color). Fig. 3 illustrate Ch1 (which represents AF3 from the frontal region).

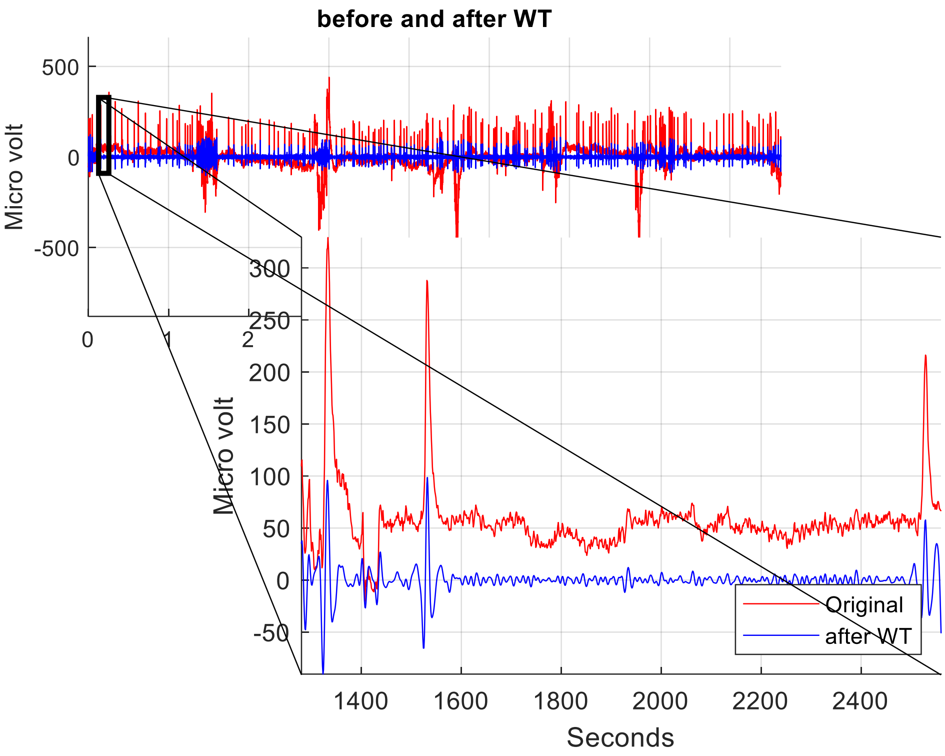

Figure 3. EEG Ch1 which Represents AF3 after Applying the WT Denoising Technique.

Results of Features Extraction Stage

In this step, μ band, β band and μ/ frequency domain features and TsEn time domain features were extracted from the EEG signals.

Fig. 4 to 7 show the scatter plot of μ, β and μ/β powers and TsEn entropy of EEG signals for subjects a and f. The plots clearly show 2 clusters that corresponding to the left hand and foot movements.

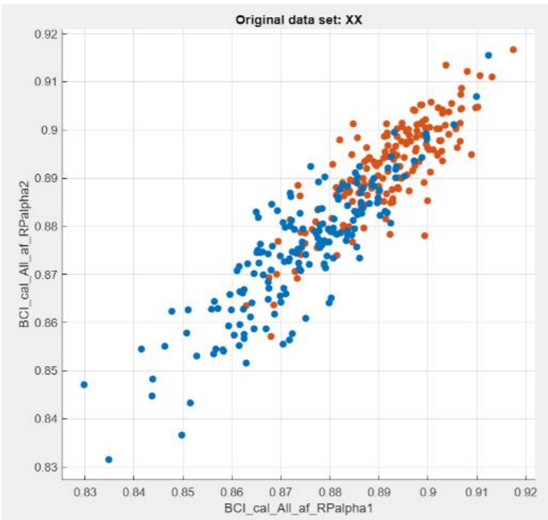

Figure 4. Scatter Plot of μ Bands Distribution to Ch1 and 2 for Subjects a and f.

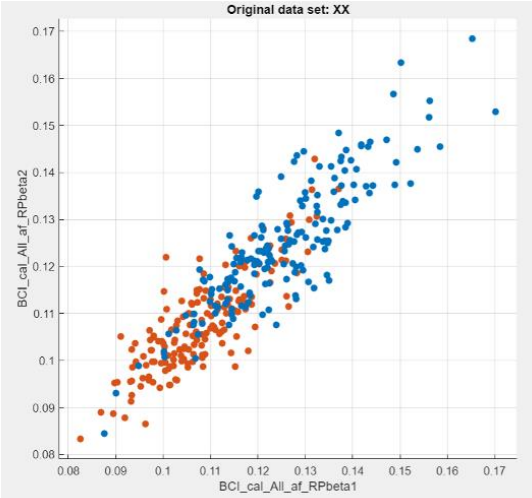

Figure 5. Scatter Plot of β Bands Distribution to Ch1 and 2 for Subjects a and f.

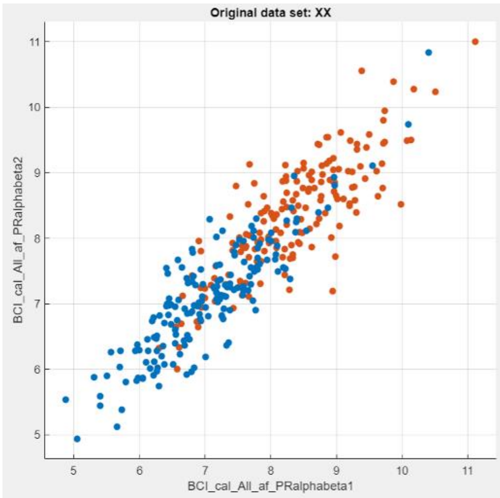

Figure 6. Scatter Plot of μ/β Bands Distribution to Ch1 and 2 for Subjects a and f.

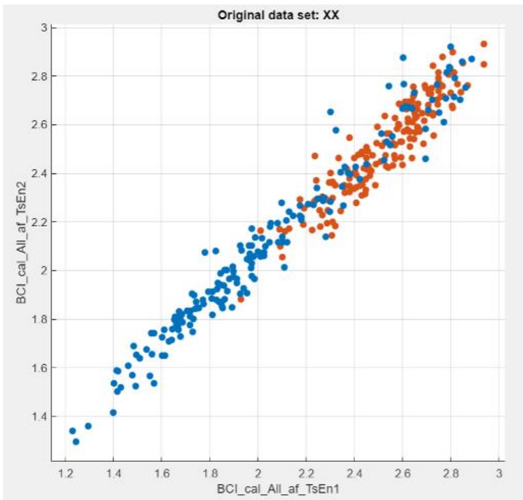

Figure 7. Scatter Plot of TsEn Distribution to Ch1 and 2 for Subjects a and f.

Fig. 8 to 11 show the scatter plot of μ, β and μ/β powers and TsEn entropy of EEG signals for subjects b and g. The plots clearly show 2 clusters that corresponding to the left hand and right hand movements.

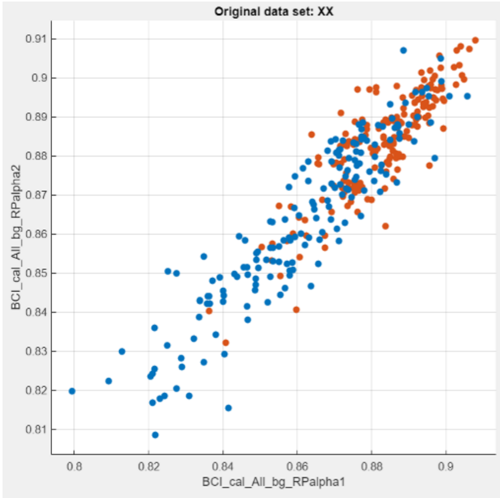

Figure 8. Scatter Plot of μ Bands Distribution to Ch1 and 2 for Subjects b and g.

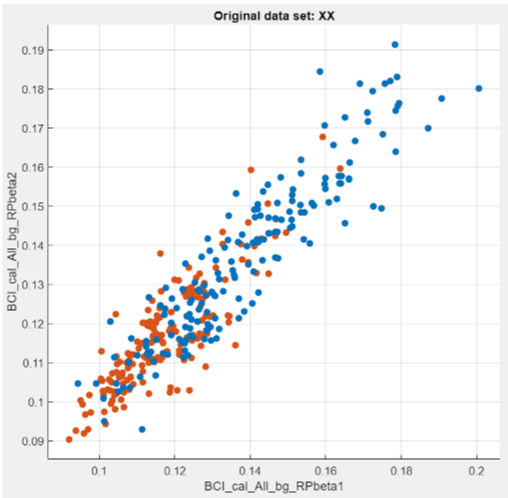

Figure 9. Scatter Plot of β Bands Distribution to Ch1 and 2 for Subjects b and g.

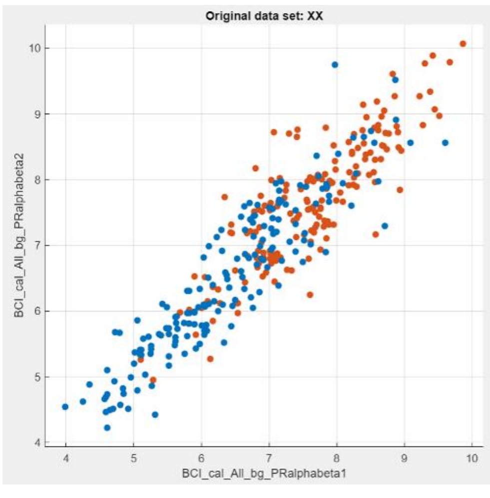

Figure 10. Scatter Plot of μ/β Bands Distribution to Ch1 and 2 for Subjects b and g.

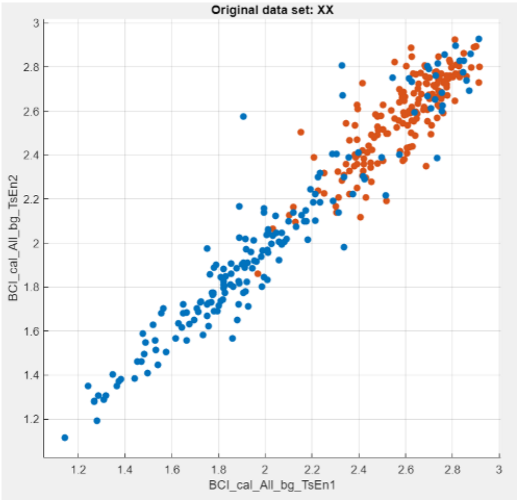

Figure 11. Scatter Plot of TsEn distribution to Ch1 and 2 for Subjects b and g.

Classification

SVM was used for classification the dataset. The confusion matrix, the performance of the classifier in terms of accuracy, sensitivity (recall), and precision were computed.

For subjects a and f , the classification of Left hand and foot movements were achieved with an accuracy of 93.35%, sensitivity of 94.15% and precision 92.66% for fusion set of features. Moreover, the confusion matrix is shown in Fig. 12.

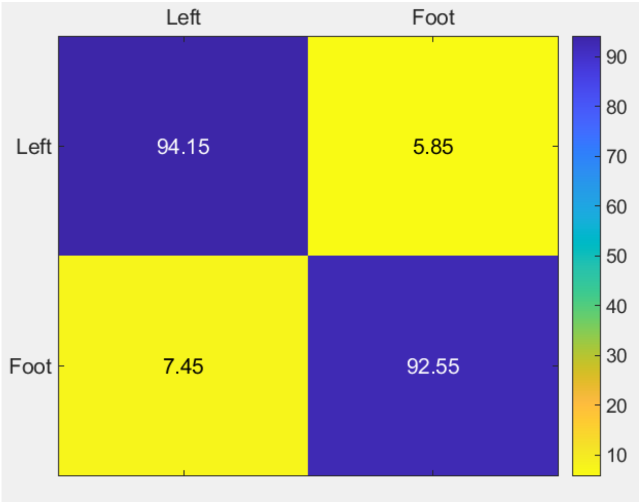

Figure 12. Confusion Matrix for Subjects a and f from the Classification of Left Hand and Foot Movements using SVM.

For subjects b and g , the classification of Left and Right hand movements were achieved with an accuracy of 91.85%, sensitivity of 92.42% and precision 91.37% for fusion set of features. Moreover, the confusion matrix is shown in Fig. 13.

Figure 13. Confusion Matrix for Subjects b and g from the Classification of Left and Right Hand Movements using SVM

Conclusion

In this chapter, the EEG signal is taken and inserted into Matlab to remove noise from it. Also, it has been proven that conventional filters such as notch and bandpass filters are a good choice for use in the preprocessing stage, Through them, we were able to remove noise from the signal and set a frequency for a specific range. It has also been proven that the wavelet filter is the best choice to address the problem of non-stationary signals, such as EEG. It has also been proven that the wavelet filter can remove ocular artifact noise, eye blinking noise and cardiac artefacts. It has also been proven that the Tsallis entropy can be analyze the complex signals. It is noteworthy to use that using SVM was a good choice for EEG classification. Through the use of all of the above, reliable markers were provided for people with stroke. This investigation was subjected to a number of limitations like small sample size resulting in a requirement to carry out further investigations with a larger database in the future.

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Author Information

Noor Kamal Al-Qazzaz
https://orcid.org/0000-0001-6566-3452
University of Baghdad
Iraq
Contact e-mail: *noorbme@kecbu.uobaghdad.edu.iq*

Alaa A. Aldoori
https://orcid.org/ 0000-0002-5461-6746
University of Baghdad
Iraq

A. Buniya
https://orcid.org/0000-0003-2905-1867
University of Baghdad
Iraq