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Average Partial Power Spectrum Density Approach to Feature Extraction for EEG-based Motor Imagery Classification

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Abstract Brain Computer Interface (BCI) has attracted many researchers in recent years, in which one of non-invasive techniques for the BCI issue is Electroencephalography (EEG). This EEG technique can allow to investigate human brain related to muscle for diagnosis and rehabilitation. In this paper, we proposed an Average Partial Power Spectrum Density (APPSD) approach and a bandpass filter to classify mental tasks using an EGG system with 24 channels, in which the relevant mental tasks are: left hand movement, right hand movement and rest. The proposed approach is the combination of the 2 Hz bandpass filter and the APPSD algorithm in the specific frequency ranges to find out features of imagery for classification. For the accuracy of the feature extraction, outliers which sparsely appear in the range of the PSD are removed. From the obtained features of movements, an Artificial Neuron Network (ANN) model was used to classify imagery status. Experiments were performed on 2 subjects with 200 runs per one subject to illustrate the effectiveness of the proposed method.

Keywords EEG Technique, Bandpass Filter, Average Partial Power Spectrum Density Method, Neuron Network Model

1. Introduction

EEG signal was firstly recorded by Hans Berger in 1924. The human brain's electrical charge is maintained by billions of neurons which are constantly exchanging ions with the extracellular. This process generates a voltage. When the wave of ions reaches the electrodes on the scalp, they can push or pull electrons on the metal on the electrodes. Since metal conducts the push and pull of electrons easily, the difference in push or pull voltages between any two electrodes can be measured. These voltages over time are the EEG signals[1].

Non-invasive and invasive techniques have been used in BCI applications in recent years[2, 3], in which the non-invasive techniques such as Electroencephalography (EEG)[4], functional Magnetic Resonance Imaging (fMRI)[5] and Near Infrared Spectroscopy (NIRS)[6] are often used for diagnosis and rehabilitation. The main advantage of these techniques is that the sensors are designed to directly contact the scalp surface with electrodes for recordings of brain activity.

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There were many applications based on recorded EEG signal for last years. The problem of rehabilitation and diagnosis based on EEG features has attracted a lot of researchers in recent years. A mean threshold algorithm was proposed to detect eye blinks using EEG[7]. The activity of eye blinking related to the delta area of human brain was investigated using EEG technology. In particular, a BCI system can allow people communicate and control external devices without using traditional motor output pathways[8]. One can translate brain activities into messages or commands to control devices[10].

For classification of EEG signals, a recursive training algorithm to generate recognition patterns from EEG signals was proposed to control an electric wheelchair[11]. Mental task was classified using prefrontal EEG[12]. The relevant mental tasks used are mental arithmetic, ringtone, finger tapping and words composition with additional tasks which are baseline and eyes closed. Another application is that the feature extraction is based on the Hilbert Huang Transform (HHT) energy method and the classification algorithm is based on an Artificial Neural Network (ANN) with the Genetic Algorithm (GA) optimization[13].

Base on different ranges of frequency, EEG signal obtained from human brain is often divided into five kinds: Delta (δ: 1-4 Hz), Theta (θ: 4-7 Hz), Alpha (α: 8-12 Hz), Mu (μ: 8-13 Hz), Beta (β: 13-30 Hz), Gamma (γ: over 30

Hz)[14]. Moreover, μ and β are recorded on primary motor cortex related to human activity. During motor imagery, EEG signals accompany power changes in movement related m (8–12 Hz) and b (18–26 Hz) rhythms, representing a power increase or decrease named event-related desynchronization and synchronization (ERD=ERS) in specific motor cortex areas[15].

In this paper, we proposed the recognition algorithm for developing a brain computer interface using EEG technique. First of all, EEG data obtained from human brain are centered with zero mean. For feature extraction of motor imagery, data are calculated using an Average Partial Power Spectrum Density (APPSD) approach and a bandpass filter. In this approach, the sparse outliers are removed for more accurately feature extraction. From the obtained features, an Artificial Neural Network model is employed to classify motor imagery[16] as shown in Figure 1.

The remaining sections corresponding to blocks in the above diagram are held for more details. Data acquisition, pre-processing and feature extraction are presented in Section 2. Structures of the artificial neural network are also shown in this section. Section 3 is the results and discussion of our work. Conclusion is briefly represented in Section 4.

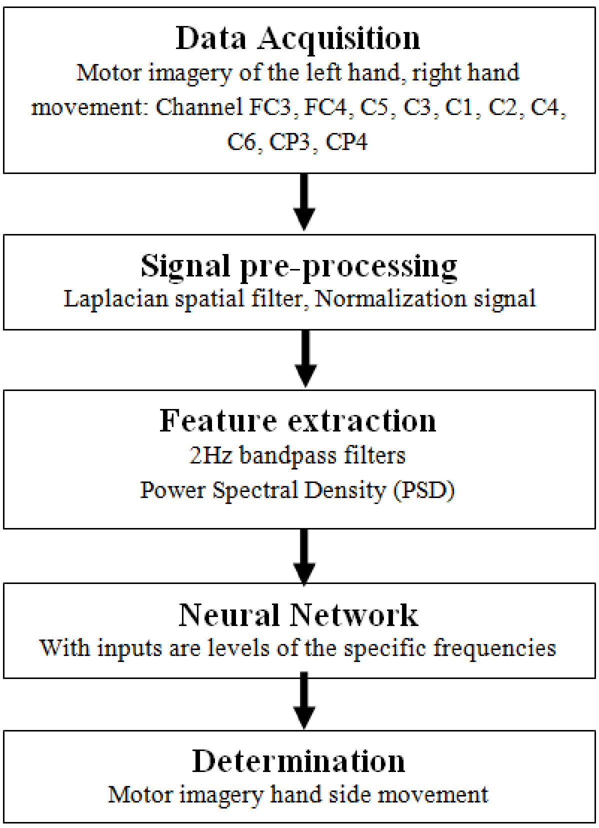


Figure 1. Block diagram of Recognition algorithm

2. Materials and Methods

2.1. Data Acquisition

Figure 2. The Biosemi system connected to a desktop

EEG signals were obtained from BioSemi ActiveTwo as shown in Figure 2. This BioSemi system was located at Room 104 of Biomedical Engineering Department, International University, Vietnam. The system has 64 channels are based on the international 10/20 system[17] as shown in Figure 3.

Two right handed participants (1 male: 32 years old, 62 kg weights, 1 female: 21 years old, weigh 47 kg) were invited to participate into this study. The subject informed consents agreement after reading and understanding the experiment protocol and the EEG technique. Offline data were obtained from the Biosemi system during the subject performing motor imagery of the left hand movement and right hand movement.

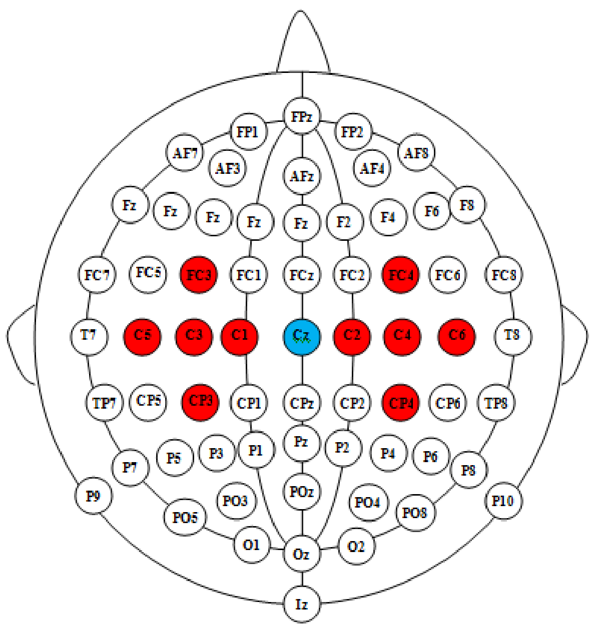


Figure 3. Ten red electrodes for signal collection: C1 to C6, CP3, CP4, FC3, FC4 and one blue Cz reference

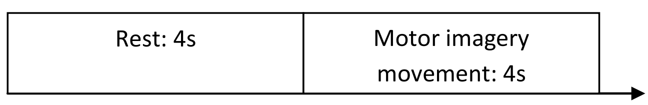


Figure 4. Time protocol for motor imagery

The subjects were instructed to perform the mental task, the motor imagery of the left hand and right hand. In this motor imagery, a protocol includes 4 s (Rest) – 4 s (motor imagery) is shown in Figure 4. It means that the mental tasks include:

– Rest: The participants relaxed in 4 s.

– Motor imagery movement: The participants imagine he left/right hand movement continuously in 4 s.

– He/she did with this protocol 10 times for left hand imagery and that for right hand imagery per a run of experiment.

EEG signals were sampled at 512 Hz, and were recorded using electrodes FC3, FC4, C5, C3, C1, C2, C4, C6, CP3, CP4 with the reference electrode placed on Cz. These electrodes installed at the motor cortex area and sensorimotor activity[18] with the standard electrode positions of the international 10-10 system. The recorded data will be applied for training and testing.

2.2. Signal Pre-processing

All recorded samples from the 6th to 7th seconds were used for analyzing motor imagery. Signal from 2nd to 3rd seconds were for detecting rest time. After that, a discrete surface Laplacian spatial filter was implemented on channel *C3*, *C4*[19]. We got the new processed signals, $C3_n$ and $C4_n$, using the following equations

$$C3_n = 4C3 - FC3 - C5 - C1 - CP3 \quad (1)$$

$$C4_n = 4C4 - FC4 - C6 - C2 - CP4 \quad (2)$$

To use these channel signals for feature extraction, one normalized by shifting the signals to be the mean signals as described in the following formula:

$$C3_{na}(i) = C3_n(i) - \overline{\mu}_{\mathbf{C3_n}} \quad (3)$$

$$C4_{na}(i) = C4_n(i) - \overline{\mu}_{\mathbf{C4_n}} \quad (4)$$

in which, $\overline{\mu}_{\mathbf{C3_n}}$, $\overline{\mu}_{\mathbf{C4_n}}$ is the average value of $C3_n$ and $C4_n$, respectively.

In particular, an original signal of $C3_n$ was processed to produce the mean signal and then its spectrum was calculated as shown in Figure 5a, b, c.

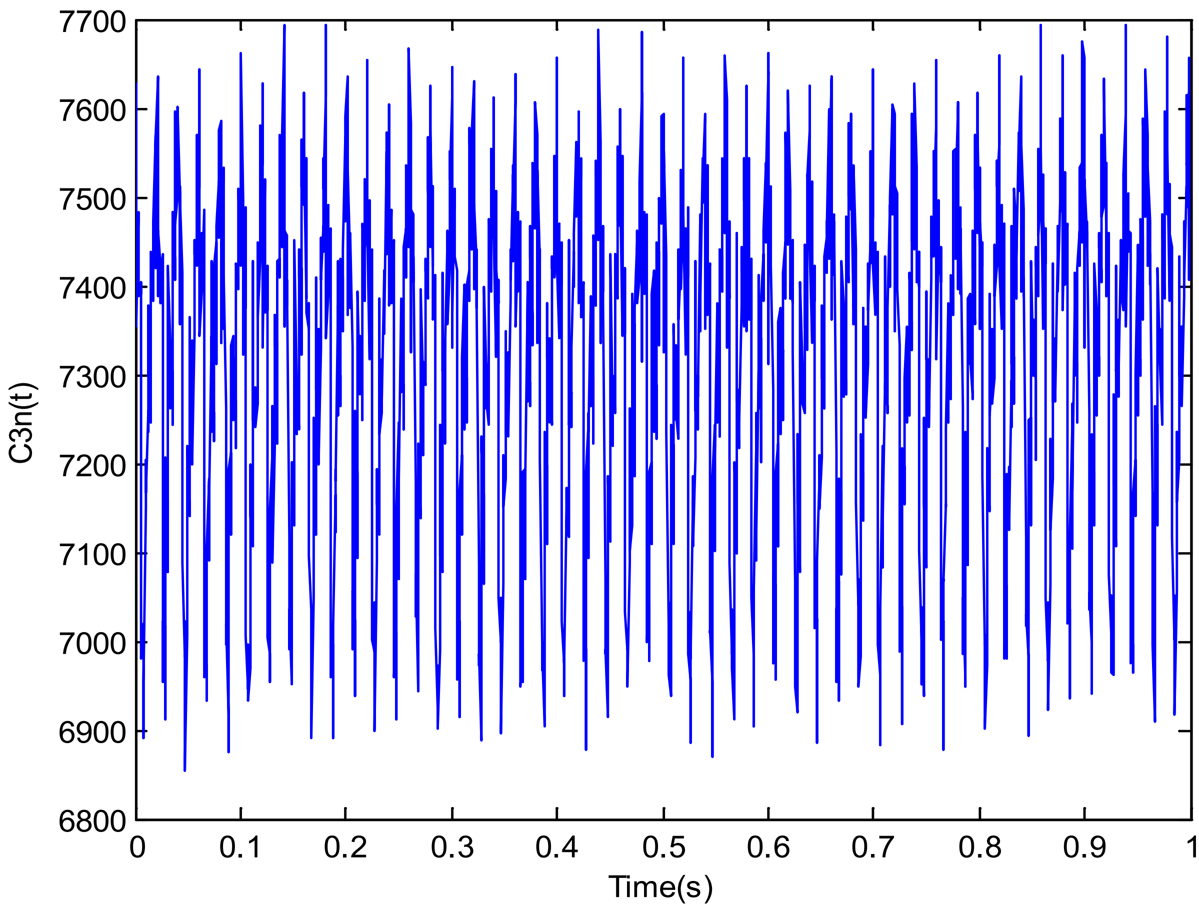


Figure 5a. Original signal of $C3_n$

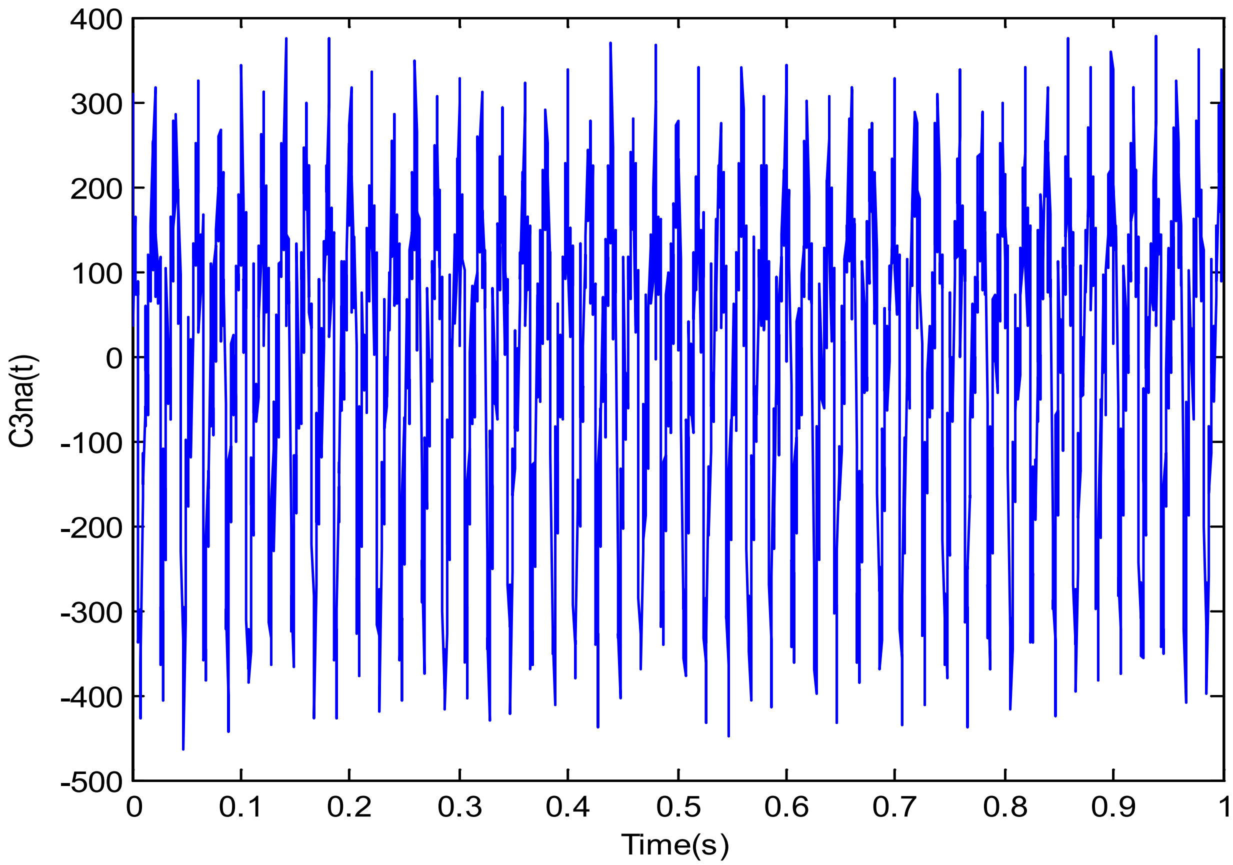


Figure 5b. Signal of $C3_n$ normalized

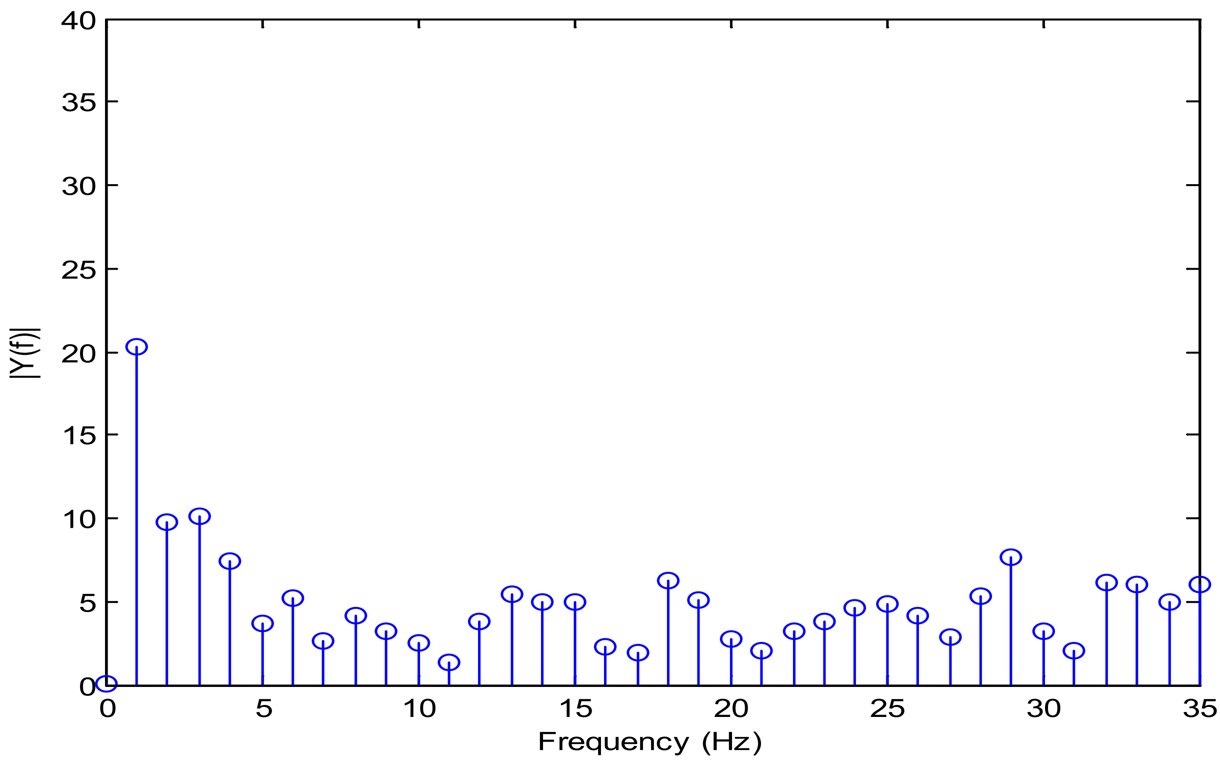


Figure 5c. Spectrum of normalized $C3_n$ signal

2.3. Feature Extraction

After the signal was shifted to the average point, the obtained mean signals $x[n]$ of channels, $C3_{na}$ and $C4_{na}$, were passed through a 4-order Butterworth band pass filter with the impulse response $h(n)$, n, k = 1,2,….

In this paper, for extraction of features, the APPDS algorithm is employed. In particular, the filters have pass-band frequency of 2 Hz with order of 4 were applied. More details, there are 11 bandpass filters. The first one has the pass-band of 8 – 10Hz and the second is the pass-band of 10 – 12Hz. In similarity, the 11th filter has the pass band of 28 – 30Hz. Figure 6 shows the amplitude response of the 2 Hz bandpass filter. The FFT algorithm was applied for the output signal of the Butterworth band pass filter to determine the frequency spectrum. Based on this spectrum, one can know the frequency bandwidth of signal.

Assume that the outputs of $C3_{na}$ after passing through the 1st to 11th filter are $C3_1$, $C3_2$, …, $C3_{11}$, respectively. One of the output of the filters is shown in Figure 7a. Similarly to those of $C4_{na}$, we have $C4_1$, $C4_2$, …, $C4_{11}$, respectively. Therefore, the PSD of the outputs were determined for calculating the average values of separated parts which were considered as features for training and testing. Each part corresponds to 11 parts of the bandpass filters. The average values of the PSD of $C3_{na}$ on each part 8–10 Hz, 10–12 Hz, …, 28–30 Hz were named F1, F2,…, F11 as shown in Figure 7b for one case. In the case of $C4_{na}$, The average values are F12, F13, …, F22.

Before analysis of characteristics of the signals, one needs to remove the outliers which are outside of the interval[x1-1.5 * A, * A +1.5 x3] as shown in Figure 8.

The statistical analysis of right hand movement imagery is shown in Figure 9. Each characteristic is represented using box plot[20]. From the above implementation, currently there are 22 values of doing imagery of movement left/right side. These values are used as the inputs of the network for training and testing.

2.4. Classification

There are many classification techniques, such as Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), Artificial Neural Networks (ANN), etc. In this paper, we used ANN for training and classification and the multilayer feed forward network is chosen here. The net has 3 layers: input, hidden and output layer. Input samples are 22 values got above. For good performance of the network, its input must be chosen carefully. Outlier was discarded. In Figure 9, the sample 9 of F14 is removed before used for training. The number of node of hidden layer is chosen of 10. Figure 10 shows the used network.

With the hidden layer, the double sigmoid function was utilized while the sigmoid function was for the output layer. Standard back propagation is applied for training this 3-layer neural network. It is a gradient descent algorithm, in which the network weights are moved along the gradient negative of the performance function.

With this argument, the training is based on the minimization of the following error function:

$$E = \sum_{n=0}^{N-1} (O_n - d_n)^2 \qquad (5)$$

where N is number of samples, O is network output and d is desired output.

In this paper, the output layer is designed to produce 3 nodes to represent three tasks such as the left motor imagery, right motor imagery and rest. These tasks correspond to the desired values of[1; 0; 0];[0; 1; 0] and[0; 0; 1].

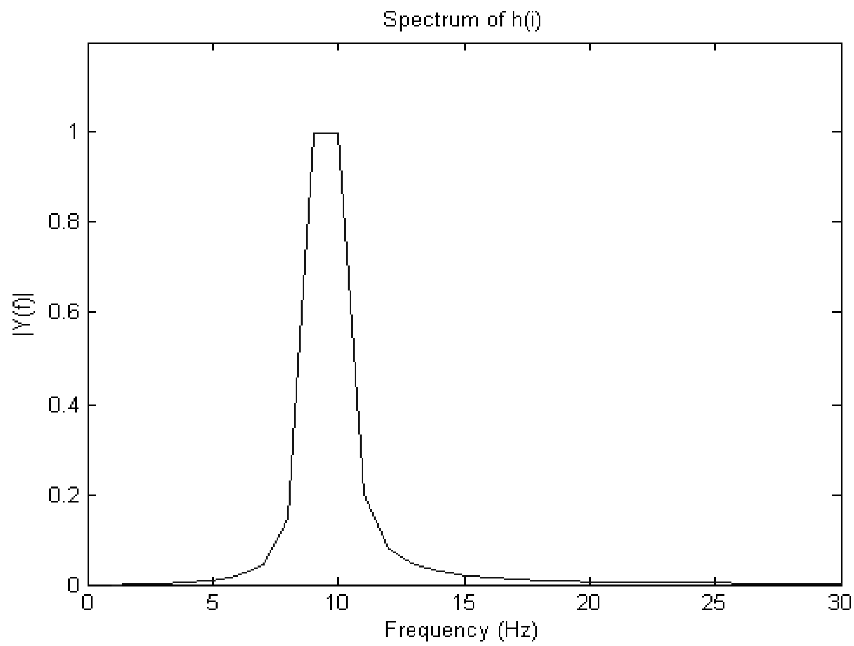
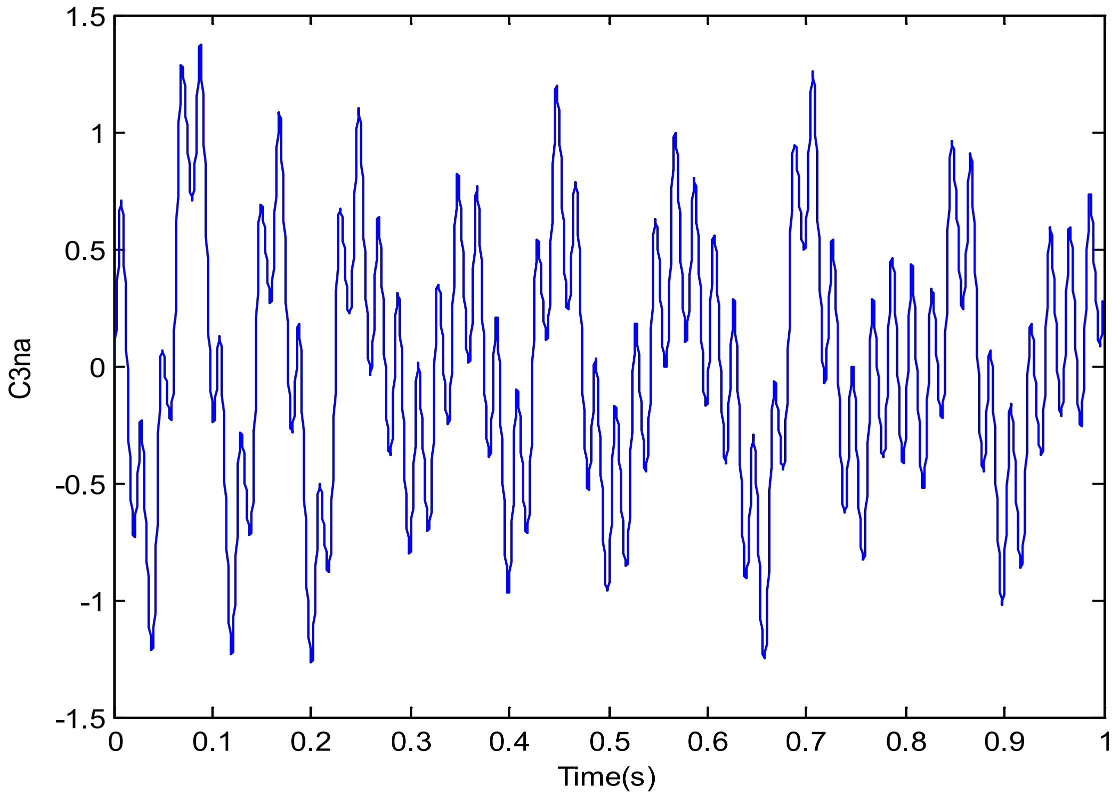
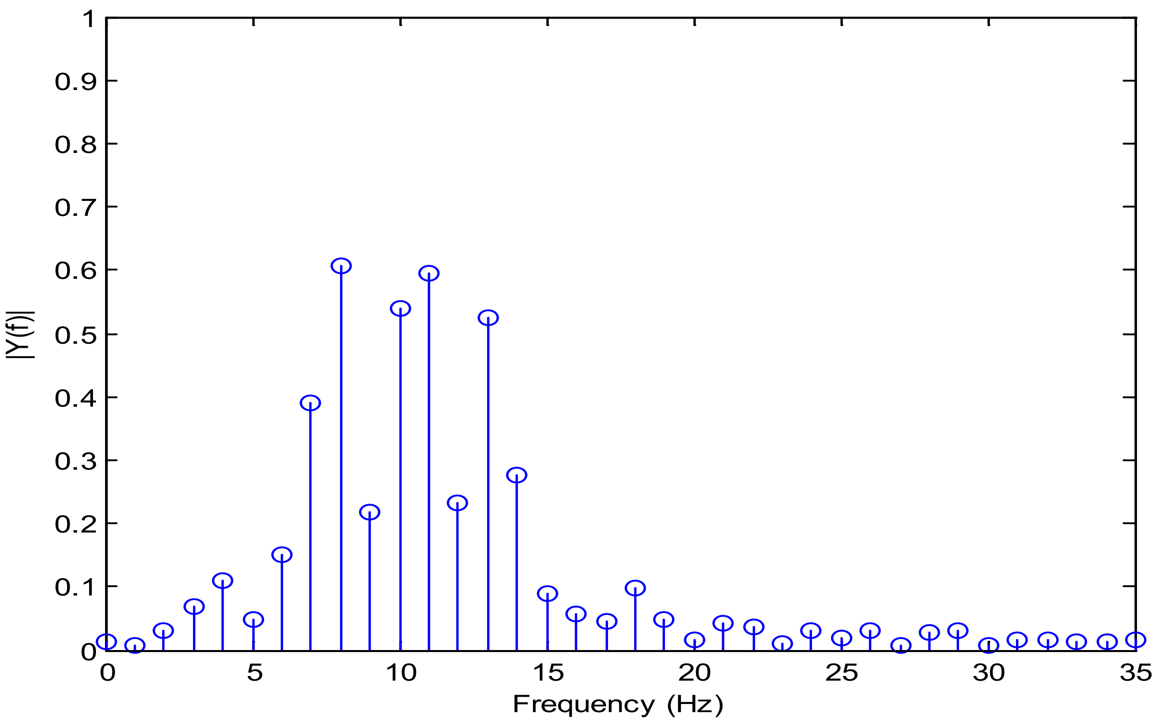


Figure 6. Amplitude response of the 2 Hz bandpass filter. The pass-band is from 8 to 10 Hz



(a)



(b)

Figure 7. One output of bandpass filter with C3na input, in which (a) signal on time domain, (b) spectrum. There are 11 different spectra corresponding to 11 parts 8–10 Hz, 10–12 Hz, …, 28–30 Hz, respectively. The average value in each part is used as input for classification

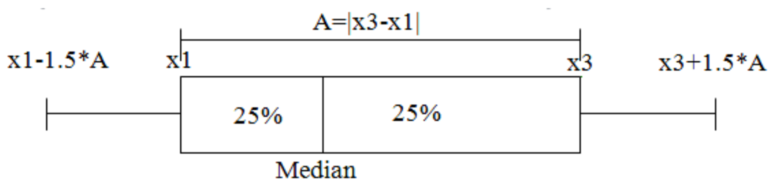


Figure 8. Representation of calculating outliers. The samples have value out of (x3-x1+3A) is removed from the data set

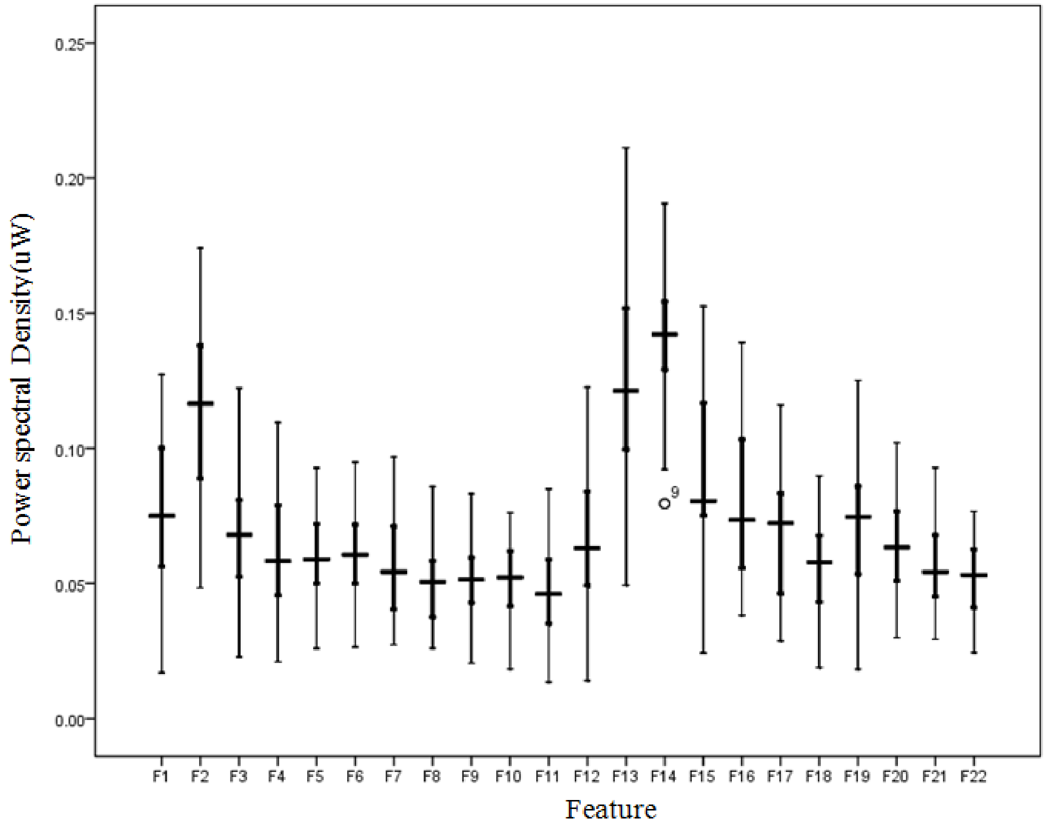


Figure 9. Box plot of features of $C3_{na}$ and $C4_{na}$. The average values of F1 – F22 have different max, min, and average values. For example, F14 has the greatest value while F13 is available with the maximum value

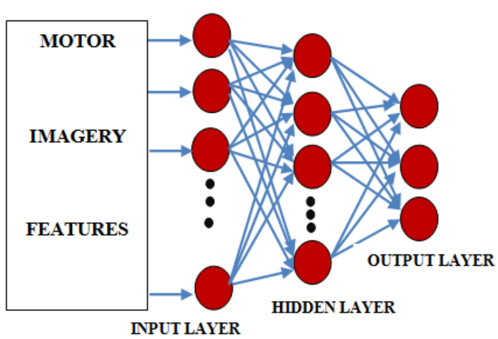


Figure 10. The network has 22 nodes of the input layer, 10 nodes of the hidden layer and 3 nodes of the output layer

3. Results and Discussion

For the objective of investigating brain activity through hand movements, two subjects were invited to attend experiments, in which each participant worked out 200 runs of mental tasks. The feature set consists of 100 samples of the right hand movement, 100 samples of left hand movement and 200 samples of the rest. The training set is divided equally to the testing set. This means that the set of samples was separated into 2 subsets, training set and testing set, N1 and N2, respectively. N1 has 50 samples of the left motor imagery, 50 samples of the right imagery and 100 samples of the rest. N2 contains the rest of the data set. From this separation, N1 is inserted the network for training, while the testing samples were taken from N2. Because there is difference in EEG signal regarding to each subject, the ANN training and classification were perform on each subject. The accuracy is got by calculating the exact classification samples over the population of each mental task.

In the mental task of right hand movement imagery, the result of the APPSD of subject 1 is shown in Figure 11a.

Figure 11b is the result of the left hand movement imagery.

Figure 11c represents the rest status of the participant.

In the training set N1, the outliers were discarded due to the defined condition. Therefore, the practical population of N1 is equal or less than 200 samples. Table 1 shows the result of 200 testing samples of N2 with the ANN from the obtained training set N1.

Table 1. Accuracy for Subject-1

Testing sample	Results of mental task that ANN recognized			
	Left hand movement	***Right hand movement***	***Rest***	***Accuracy (%)***
Left hand movement	47	2	1	94
Right hand movement	3	46	1	92
Rest	4	0	96	98

The accuracy in the case of the left hand movement imagery of Subject-1 is 94% as shown in Table 1. With 50 left hand movement imagery samples, the network detects 47 samples. The accuracy for right hand movement is 92% and this is 98% in the rest task. The average accuracy for 3 mental tasks is 94.7%.

The participant 2 did the same protocol of subject 1. In this case, the results of mental task were represented in Figure 12a, Figure 12b, and Figure 12c.

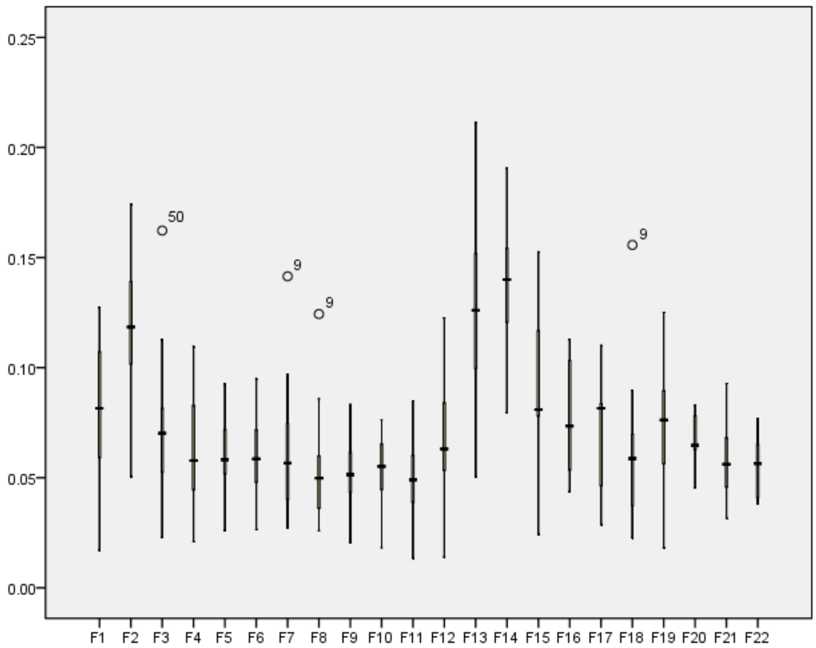


Figure 11a. The APPSD of the right hand movement imagery of subject-1 and two outliers were discarded. The samples 9th, 50th were discarded

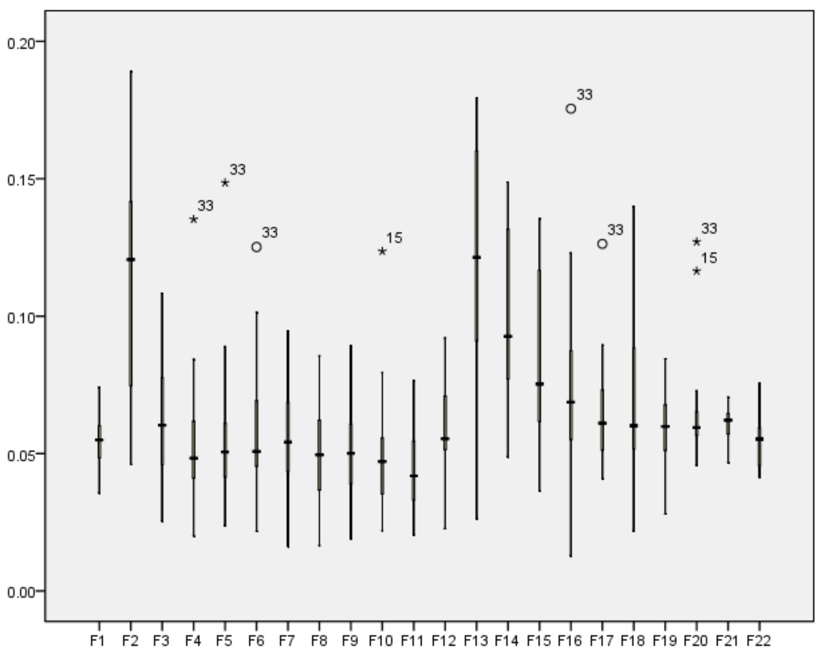


Figure 11b. The APPSD of left hand movement - subject 1. Two outliers were discarded: 33, 15

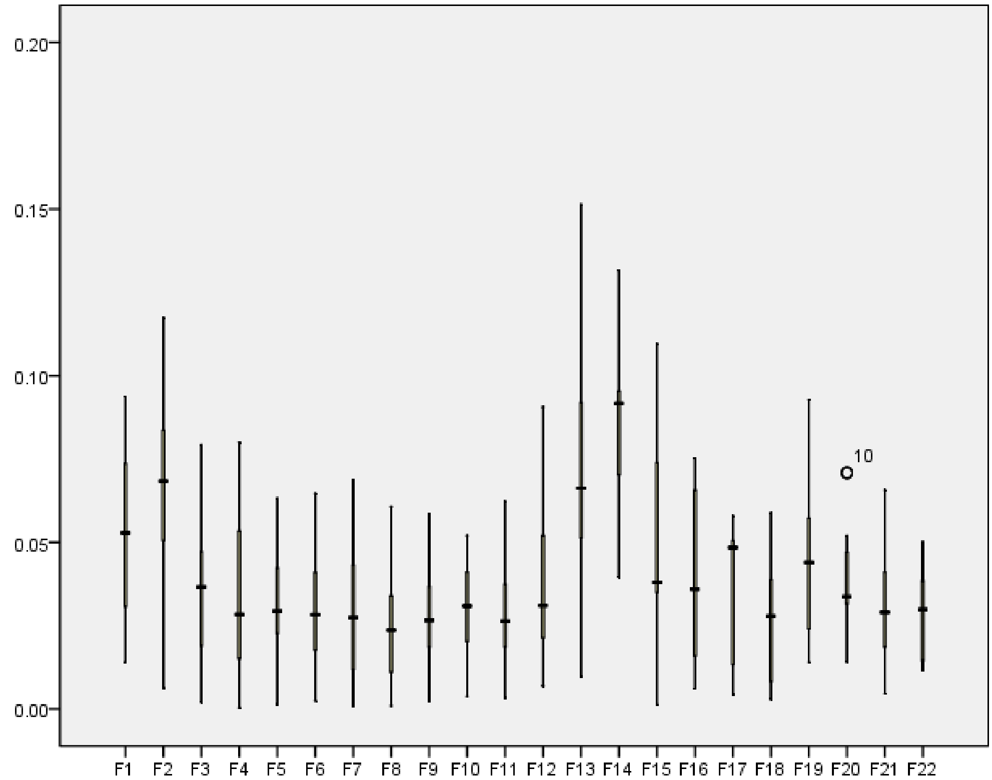


Figure 11c. The APPSD of the rest time - subject 1. One outlier was discarded: 10

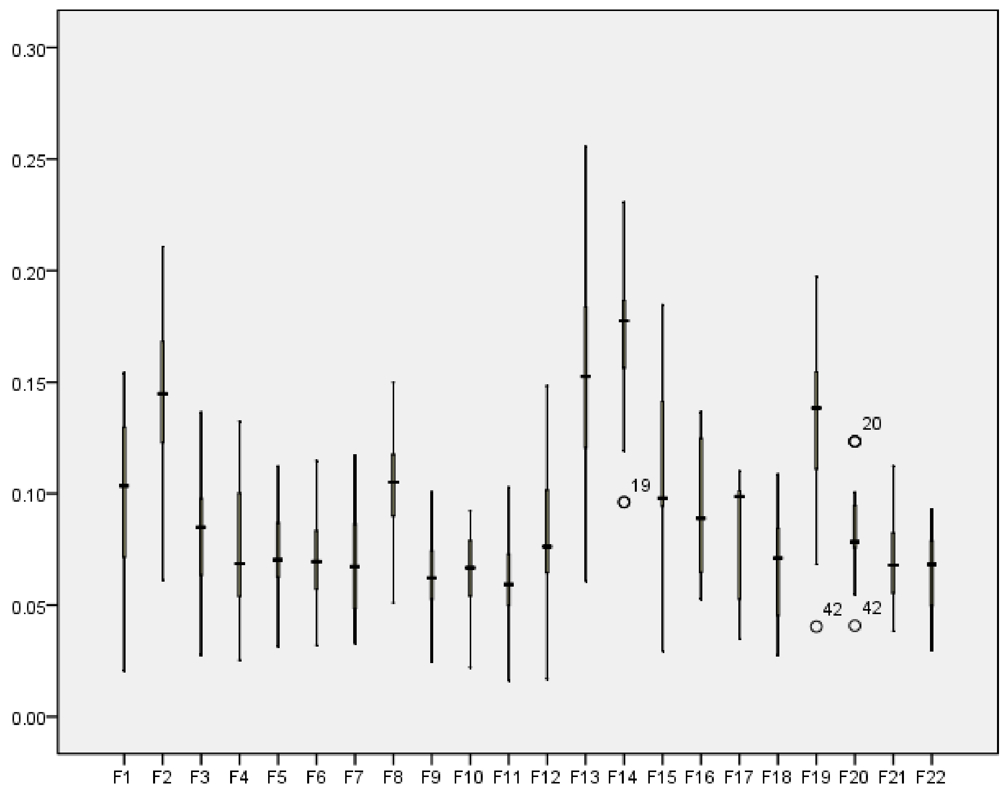


Figure 12a. The APPSD of the right imagery of subject-2. Three outliers were discarded: sample 19, 20, 42

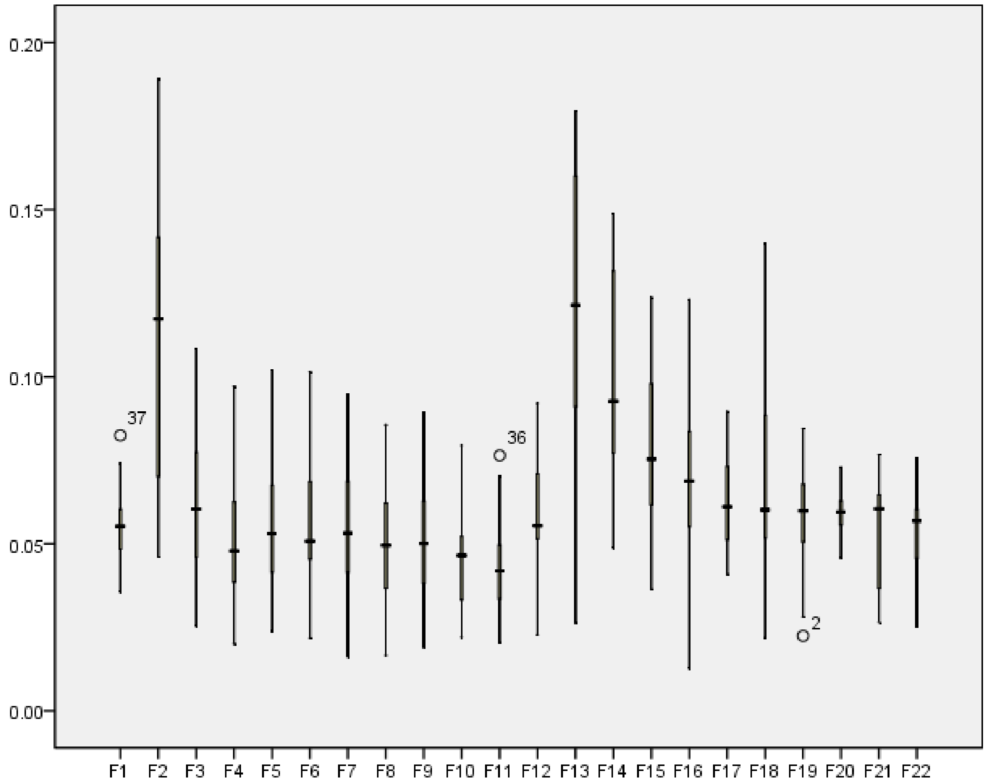


Figure 12b. The APPSD of the left imagery of subject-2. Three outliers were discarded: 37, 36, 2

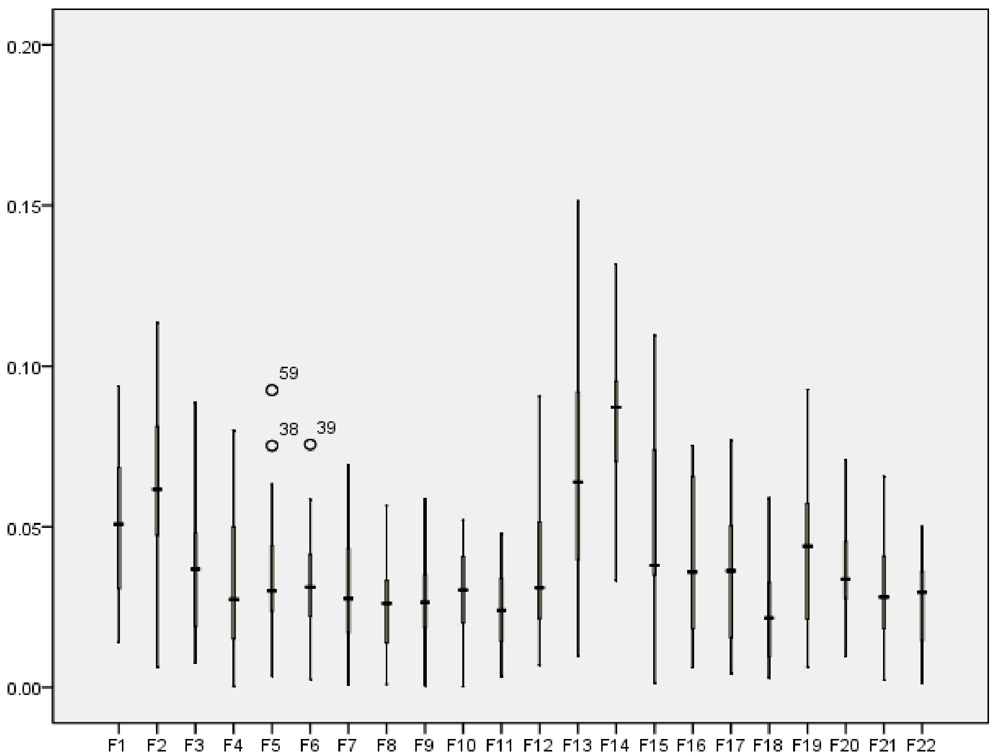


Figure 12c. The APPSD of the rest time of subject-2. Three outliers were discarded: 59, 38, 39

The figures (11, 12a, 12b, 12c) show that with 2 subjects, the values of the APPSD are different. Their changes depend on different subjects. Therefore, data collected from subject-1 are more concentration than subject-1 because of the number of outliers.

In this case, only 191 N1 samples of Subject-2 were applied for training because of removed outliers. In Similarity to subject-1, 200 samples of N2 set of subject-2 were tested.

The experiment shows that the accuracy of right hand movement of subject-2 is 88%. It is less than the result of subject-1. The average accuracy is just 87.5 %, in which the accuracy of each imagery task (left, right, or rest) is all less than subject-1. In addition, subject-1 has the best accuracy of 98% when performing rest. Subject-2 gets 84% accuracy of left hand movement mental task. In brief, the result of both subjects showed that the proposed approach is reliable, although there is the tiny difference between two subjects due to noise or artifacts.

Furthermore, despite of classification methods, outliers must be reduced or removed. The authors proposed the Common Spatial Pattern Ensemble Complex Spectral Phase Evolution (CSPE) to overcome the sensitivity of the Common Spatial Pattern (CSP) to outlier[21]. The task consists of performing motor imagery of the left hand, right hand, foot, or tongue in response to a cue of 3 volunteers. The average accuracy of 3 subjects (measured on CB channel- channel bank) is 83.02 %.

Table 2. Accuracy for Subject-2

Testing sample	Results of mental task that ANN recognized			
	Left hand movement	***Right hand movement***	***Rest***	***Accuracy (%)***
Left hand movement	42	5	3	84
Right hand movement	2	44	4	88
Rest	10	1	89	89

Imagery features can also be classified with the Support Vector Machine (SVM) method. On sensorimotor channels (SC) channel, the average accuracy is 80.35%. The change in μ and β rhythmic patterns varies from one subject to another. This causes an unavoidable time-consuming fine-tuning process in building a BCI for every subject. To address this issue, a new method called Sub-band Common Spatial Pattern (SBCSP) was proposed to solve the problem [22]. The EEG signals were decomposed into sub-bands by filters. By using discriminate analysis, SBCSP features were extracted. The average error using Linear Discriminant Analyzers (LDA) and Recursive Band Elimination method is 10%.

Ahmed developed the neural network algorithm with the wavelet-based feature extraction for controlling an electrical wheelchair using EEG technology[23]. The author worked out classifying eye blinks of user to control the wheelchair. However the author's method is not clear, in which there were not any mathematic equations and numeric results of the wavelet algorithm for feature extraction as well as the NN for training data. With the APPSD feature, we can conclude that high frequency bands are more effective for classifying happy and unhappy emotions than low frequency bands[24]. In this paper, from experiments on 2 subjects, we applied the statistical box plot to discard outliers which are the important problem in the accurate calculation of this approach. The accuracy is greater than 80% with many trials for classification of mental tasks. It means that the proposed methods can be improved the recognized performance.

4. Conclusions

This paper represented an Average Partial Power Spectral Density (APPSD) approach for classification of mental task - motor imagery using EEG technique. EEG signals obtained were processed to produce pass bands of frequencies for feature extraction. Signal features were determined using the APPSD approach, in which outliers were removed for accurate feature extraction. Then these features were inserted the input layer of the network for imagery recognition. Experimental results with high accuracy showed to illustrate the effectiveness of the proposed approach. These results may be developed for rehabilitation applications.

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