EEG Analysis on Actual and Imaginary Left and Right Hand Lifting using Support Vector Machine (SVM)

Nabilah Hamzah, Norliza Zaini, Maizura Sani, Nurlaila Ismail

***Abstract*— Brain Computer Interface or BCI is a technology that creates new communication channel where human brain (via Electroencephalography) can communicate with electronic devices.EEG signal is produced by the neurons, where every thought, emotion and movement can generate different patterns of EEG signal. There are two objectives defined for this research. The first objective is to compare the EEG data generated for actual and imaginary motor movement when lifting the left and right hand by using Support Vector Machine (SVM).The second objective is to find the correlation in EEG pattern between the actual motor movement and imaginary motor movement data, which is also based on SVM classification analysis. From the classification analysis, the accuracy for actual left and right-hand lifting movement is obtained at 90%. Meanwhile, the accuracy for classifying EEG data of imaginary left and right-hand lifting movement is obtained at 75%. In finding the correlation between the actual and imaginary EEG data, a classification analysis is also done by combining the actual and imaginary data. In this experiment, the accuracy in classifying the left and right-hand lifting activities is obtained at 78.8%. The significant accuracy measures obtained means that there is some correlation in EEG patterns between the actual motor movement and imaginary motor movement of lifting either left or right hand.**

***Index Terms*—EEG, Power Spectral Density, Support Vector Machine**

I. INTRODUCTION

Encephalography or EEG is an electrical signal produced by the neurons within our brain. This electrical signal is produced when the neurons communicate with each other. The study of EEG signal and its proper analysis can bring large advantages in medical and engineering application area because EEG signal is a signal that contains most of the information explaining what is happening in our body such as the emotion that we are feeling or the motor movement we are currently doing. Due to this fact, by analyzing the EEG data, it can lead us to a better understanding of our brain function[1], in correlation of what happened in our body. We can make use of this technology to build a better world by proposing new techniques in interpreting the EEG signal to acquire its meanings. This aim is covered under the scope of brain-computer interface (BCI) domain, which promotes technology that utilizes EEG signal to control electronic peripherals. Based on this BCI technology, individuals will have the privilege of controlling electronic devices just by using their brain. This is especially beneficial in the context of medical and health, where BCI technology can help to support the disabled people to live their life.

Due to the significant benefits it can offer, this technology becomes more popular and has been rapidly growing from time to time. There are many researchers that have published on the BCI techniques and systems. More recently, BCI technology is highlighted to become one of the revolutionary technologies used in the communication channel[2]. In this sense, analyzing EEG signal is not an easy task and a big challenge because EEG signal has very small amplitude and always contaminated with noises and artifacts. These noises and artifacts generate larger amplitude around 230 – 350 microvolt in comparison to EEG Event-Related Potential (ERP), which is around 7-20 microvolt[3].

In general, analyzing EEG signal takes four general steps, namely i) collection of EEG raw data, ii) preprocessing, iii) feature extraction and iv) classification. For data collection process,Emotiv Epoch Neuroheadset was chosen as the recording device. After data collection, the raw EEG data will undergo the preprocessing stage. Signal preprocessing is a process to remove all noises and artifacts from the EEG raw data. There are two types of artifacts, namely biological artifacts and non-biological artifacts. Examples of biological artifacts include Electrooculogram (EOG) and Electromyogram (EMG). EOG signal occurred when there are some eye movement or eye blink. EMG signal occurred when there is muscle movement. EOG is the biggest problem in EEG signal analysis because EOG will generate greater amplitude and make it difficult to detect the EEG signal. There are several methods which can be used for removing noises

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and artifacts[3-6]. Most researchers rely on manual cleaning but this process is time-consuming and lengthy [5].

EEG feature extraction is a process to extract the important feature without losing any crucial information. EEG feature extraction can be divided into two models, parametric and non-parametric. There are some advantages and disadvantages of these two models. It was found that parametric model does not provide good performance and for then on-parametric model, there was alack of detailed information in EEG analysis[7]. There are some methods of feature extraction that arebased on estimating the signal energy distributed in the frequencyeither in frequency or time domain[8], e.g Power Spectral Density (PSD) and Energy Spectral Density. [9-12] used either PSD or ESD to extract the important feature and shows a good result with higher accuracy value.

EEG classification is an analysis that uses a particular type of classifiers to separate the EEG data into its own classes. Support Vector Machine (SVM)[13-16], Artificial Neural Network (ANN)[17-23] and K-Nearest Neighbor (KNN) are examples of classifiers that are mostly used in classifying the EEG signal. All classifier performance actually dependon the data that are being provided. If the data provided is good or clean without noises/artifacts and the extracted features are also good, then the classifier can easily differentiate between the two classes. In this regard, there are many researchers who had published their methods on how to classify EEG imaginary data.

II. METHODOLOGY

This section discusses the sequences of activities performed to analyze EEG signal. Figure 1 shows a flow diagram of the overall steps to analyze EEG signal.

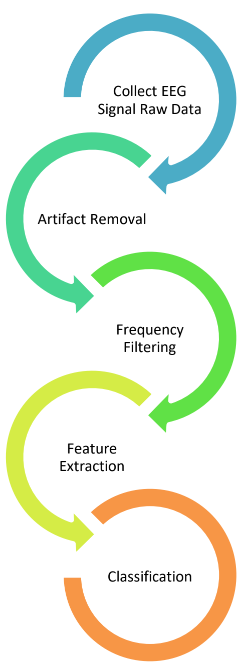

Figure 1: Flow Diagram for EEG Signal Analysis

A. *Collect EEG Signal Raw Data*

To acquire the raw EEG data, an experimental procedure is designed to record the EEG signals from a number of subjects. Emotiv Epoc Neuroheadset is used as the recording devices. Emotiv Epoc Neuroheadset consists of 14 electrodes (AF3, AF4, F7, F8, F3, F4, FC5, FC6, T7, T8, P7, P8, O1,O2).Emotiv Epoch Neuroheadset electrode placement is according to the world 10-20 electrode placement system. Figure 2 shows Emotiv Epoch Neuroheadset electrode placement from P1 to P14. Emotiv Epoch Neuroheadset is chosen as the recording device because it is very reliable for most application and inexpensive rather than other recording devices [19].

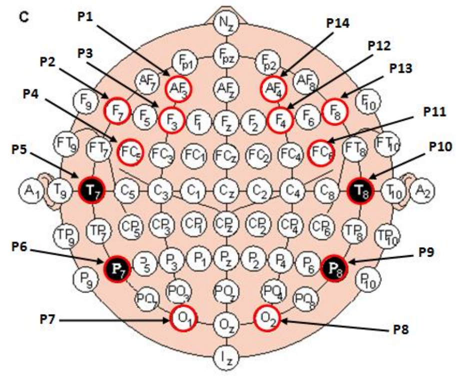

Figure 2: Emotiv Epoch Neuroheadset Electrode Placement

There are two experimental procedures thatwere carried out by each of the subjects, one for actual motor movement and another for imaginary motor movement (i.e. to lift right and left hand). Subjects were equipped with Emotiv Epoch Neuroheadset before starting the recording sessions. Each subject is asked to sit comfortably on a chair and to stay focus and relax. For actual motor movement, the subject is required to kinesthetically lift his/her hand. For imaginary motor movement, the subject is required to imagine that they are lifting their hand, either right or left. After completing the two sessions, the raw data were converted to ".csv" file (Microsoft excel) and then processed offline using the Matlab software.

B. *Preprocessing*

Signal preprocessingis a stage that consists of two different operations, specifically artifacts removal and frequency filtering. This is the first stage that the raw EEG signal needs to undergo. In this stage, the raw EEG signal will first be analyzed and processed to get a clean EEG data. While recording the EEG signals,all noises and artifacts (EMG and EOG)are also recorded. So, the recorded EEG signal will become a complex signal that contains all the information including the meaningful data, noises and also artifacts[1, 4]. Noises and artifacts need to be removed from the EEG signal without losing any crucial data.EEG signal is recorded in microvolt unit. Usually, the noises and artifacts will generate 10 to 100 times bigger amplitude when compared to the EEG signal [24].Due to this fact, any amplitude that exceeds±100μV is assumed as artifacts and will be rejected automatically[9, 11].

In EEG data, there are four major brain rhythms, namely Delta, Theta, Alpha and Beta. Delta wave is the one with the highest amplitude and slowest frequency range (below 4Hz). Theta wave is typically of lower amplitude than delta but has a higher frequency, i.e. around 4Hz to 7 Hz. Alpha and Beta wave usually occurred during awake state. Alpha wave occurredduring relaxed state and the frequency range around 7 Hz to 13 Hz. Beta wave usually happened when people are thinking. Beta wave has very low voltage or amplitude but higher in frequency, i.e. around 13 Hz to 30 Hz [25]. Table 1 shows the frequency range for every brain rhythms. In frequency filtering process, the EEG signal will be divided into the four major brain rhythms or can also be called as sub-bands. After dividing the signal into four major sub-bands, the filtered EEG signal will undergo Fast Fourier Transform (FFT). FFT is used to convert the EEG signal from time domain to frequency domain. This conversion is implemented by using FFT function in Matlab software. This conversion is very important because it will be used later in feature extraction process.

Table 1: Four Major Brain Rhythms Frequency Range

Brain Rhythms	*Frequency Range (Hz)*
Delta	1Hz – 4Hz
Theta	4Hz – 7Hz
Alpha	7Hz – 13Hz
Beta	13Hz – 30Hz

C. Feature Extraction

Feature extraction is a process where the important feature or information is extracted from the EEG signal. There are many methods that can be used to extract the important feature e.g. Power Spectral Density, Wavelet Transform, Independent Component Analysis, Autoregressive Modeling and Energy Spectral Density. EEG feature extraction can be divided into two model parametric and non-parametric [7]. These two models parametric and non-parametric have their own advantages and disadvantages. The most common method used for analyzing EEG is then on-parametric method. PSD is one example of then on-parametric methods.

For this study, Power Spectral Density (PSD) feature extraction is chosen to be used. PSD extraction is one of the popular methods commonly used in EEG feature extraction process. The PSD extraction technique detects the power/energy at the highest peak of the frequency.

D. Classification

After PSD features areextracted from the EEG signal, the PSD data will be classified into its own group. This process is called as the classification process. There are many methods that can be used to classify the EEG signal e.g. Support Vector Machine, Artificial Neural Network, K-Nearest Neighbors. But for this study, Support Vector Machine (SVM) was chosen as the classifier. SVM is one of the popular methods used to classify EEG signal. There are a few articles related to the application of this method [13-16, 26].

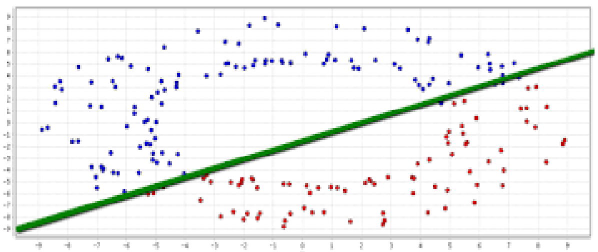

Figure 3: Linear SVM

SVM classifier performs classification by using a hyper-plane that will divide the data into two categories [15]. SVM can be divided into two groups, linear SVM and non-linear SVM. Figure 3 above shows the example of how linear SVM divides the data into two different groups by using hyper-plane. As mentioned above, EEG signal is a complex signal and most of the data cannot be divided by linear SVM classifier. Thus, for better classification result, we are using a non-linear SVM technique. The general idea for non-linear SVM is to map the data into much higher dimensional space (“feature space”) where the data can be divided by using hyper-plane.

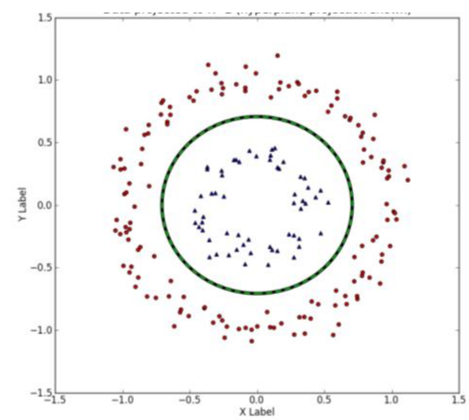

Figure 4: Non-Linear Data Set

Figure 4 above shows anon-linear data SVM. From the figure, it shows that the data cannot be divided by hyper-plane. While Figure 5 shows how SVM separates the data in the higher dimensional surface so that the data can be separated by hyper-plane. Non-linear SVM is a more reliable classifier than linear SVM because most of EEG data are non-linear data. Non-linear SVM uses a clever algorithm with a kernel trick to construct the higher dimensional space. SVM concept is the same as ANN where SVM need to be trained first. After training the SVM, the data will be validated and tested. From the training, validation and testing, the accuracy for classifying the data of right and left-hand lifting will be acquired.

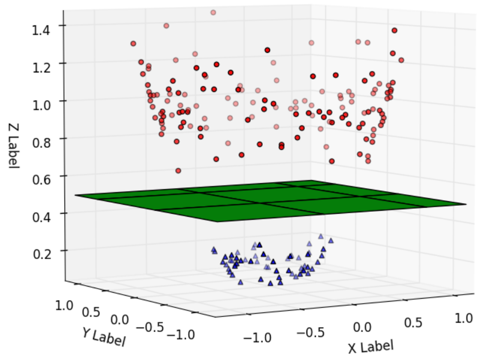

Figure 5: Non-Linear SVM

	p' (Predicted)	n' (Predicted)
p (Actual)	True Positive	False Negative
n (Actual)	False Positive	True Negative

Figure 6: Example of Confusion Matrix

Figure 6 shows a table to illustrate the confusion matrix. There are a number of terms used in the confusion matrix; i.e. True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN), actual value and predicted value. The actual value is a value that SVM supposed to get, while the predicted value is a value that was predicted by the SVM. From the figure above, there are four coefficients p, n, p', and n'. P and n are the actual value, while p' and n' are the predicted value. There will be two types of data, specifically i) lifting left-hand and ii) lifting right-hand. We label the right-hand lifting data as "1" (positive), while left-hand lifting data is labeled as "0" (negative). For True Positive (TP) case, it means that SVM has correctly predicted the data as right-hand lifting. True Negative (TN) refers to correct prediction of left-hand lifting data. False Positive (FP) occurs when SVM has wrongly predicted the left-hand lifting as right-hand lifting. Lastly, False Negative (FN) means SVM has wrongly predicted the right-hand lifting as left-hand lifting.

Accuracy value can be calculated by using this formula:

$$Accuracy = \frac{TP + TN}{p + n}$$

Where TP is True Positive Value, TN is True Negative Value and p and n are the total value of the data.

There are three types of data for this research that have been classified by the SVM: (1) Actual Motor Movement for lifting left and right hand, (2) Imaginary Motor Movement for lifting left and right hand, (3) Combining Both Motor Movement for lifting left and right hand. Actual motor movement for lifting left and right hand is a data where subjects are actually lifting their hands. For imaginary motor movement,the subject imagines lifting their hand. Combining both data for actual and imaginary means that the data from (1) and (2) will be combined together. Table 2-4show the total data set used for each type of data:

1. Actual Motor Movement

Table 2: Actual Motor Movement Data Set

Type of Motor Movement	Total Data Set
Left	20
Right	20
Total	**40**

2. Imaginary Motor Movement

Table 3: Imaginary Motor Movement Data Set

Type of Motor Movement	Total Data Set
Left	20
Right	20
Total	**40**

3. Combining Both Actual/Imaginary Motor Movement

Table 4: Combining Both Motor Movement Data Set

Type Of Motor Movement	Total Data Set	
Left Actual Motor	20	Combine
Left Imaginary Motor	20	
Right Actual Motor	20	Combine
Right Imaginary Motor	20	
Total	**80**	

III. RESULT AND DISCUSSION

This section shows the results obtained from the EEG analysis based on the recorded EEG signals when the subject is doing the actual (kinesthetic) movement and imagining lifting their hands. In this experiment, 80 set of EEG data is recorded for left and right hand. Table 5 shows the total data set for every type of hand motor movement.

Table 5: Total Data Set

Type of Hand Motor Movement	Total Data Set
Actual Left Hand	20
Actual Right Hand	20
Imaginary Left Hand	20
Imaginary Right Hand	20

Table6 shows the accuracy value for classifying the actual (kinesthetic) hand lifting data for all subjects. The accuracy rate of the classifier for lifting left and right hand obtained from the experiment is found at 90%. From this high accuracy value, it is shown that the classifier has successfully classified the actual(kinesthetic) motor-movement data.

Table 6:Classification Accuracy Value for Actual Motor Movement

Type of Motor Movement	EEG Data	
	Accuracy (%)	Confusion (%)
Left Hand	45%	5%
Right Hand	45%	5%
Total	**90%**	**10%**

Figure 7 shows the confusion matrix for actual (kinesthetic) hand lifting. The confusion matrix shows how many data are misclassified by the SVM. From the 40 data set, only 4 data are being misclassified by the SVM.

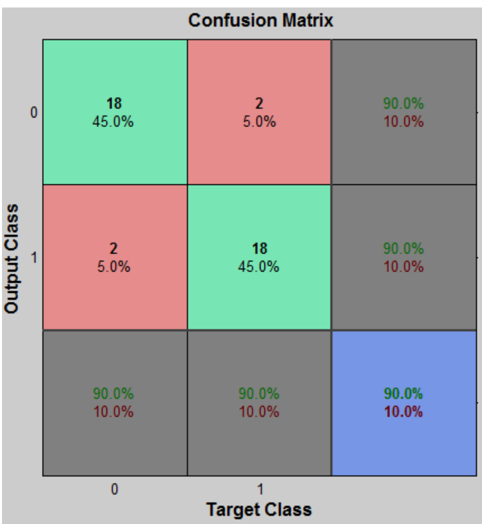

Figure 7: Confusion Matrix for Actual Motor Movement

Table7 shows the accuracy value for classifying imaginary left and right-hand lifting data. The accuracy value obtained is 75%. It is shown that this accuracy value is slightly lower than the accuracy for classifying the actual movement of the right and left-hand lifting. Figure 8 shows the confusion matrix for the imaginary motor movement, where 10 data can be seen to be misclassified.

Table 7:Classification Accuracy Value for Imaginary Motor Movement

Type of Motor Movement	EEG Data	
	Accuracy (%)	Confusion (%)
Left Hand	32.5%	7.5%
Right Hand	42.5%	17.5%
Total	**75%**	**25%**

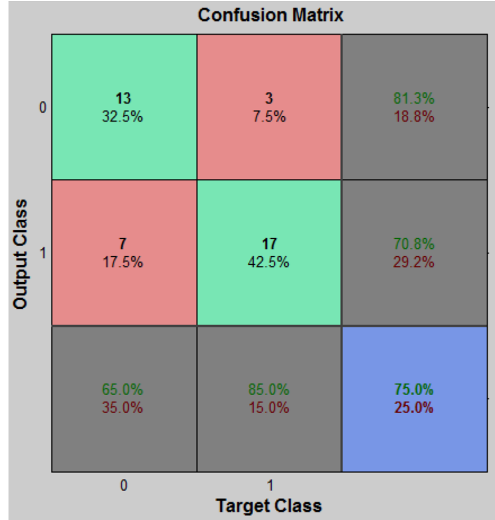

Figure 8: Confusion Matrix for Imaginary Motor Movement

Table 8 shows the accuracy measure for a classification analysis that combines both actual and imaginary data. The accuracy for classifying left-hand lifting and right-hand lifting from the combined actual and imaginary data is obtained at 78.8%. From the obtained accuracy value, it can be deducted that SVM is able to classify data between right-hand lifting and left-hand lifting with a significant accuracy. Thus, we can conclude that there are similarities in EEG pattern between the actual and imaginary hand lifting data. Actual and imaginary data for right-hand lifting data are assumed to have similar patterns, while this assumption is also true for the left-hand lifting data. Figure 9 shows the confusion matrix for the SVM classification that combines both actual and imaginary hand lifting data. From the figure, it is shown that there isa total of 17 data that have been misclassified.

Table 8:Classification Accuracy Value for Combined Actual and Imaginary Motor Movement Data

Type of Motor Movement	EEG Data	
	Accuracy (%)	Confusion (%)
Left Hand	35%	6.3%
Right Hand	43.8%	15%
Total	**78.8%**	**21.3%**

IV. CONCLUSION

From the performed analysis and findings, we can conclude that PSD is shown to be a good feature of EEG data to be used as inputs for classifying different hand lifting for bothactual and imaginary motor movement data. As for the classification analysis, SVM is found to be a good classifier, where it has obtained high accuracy value in differentiating and classifying the right and left-hand lifting activities either based on actual or imaginary data. Correlation is also found between the right-hand lifting of actual and imaginary data, while the left-hand lifting of actual and imaginary data is also found to correlate with each other. This assumption is made based on the high accuracy measure obtained by the SVM classifier based on the combined actual and imaginary motor movement data as inputs.

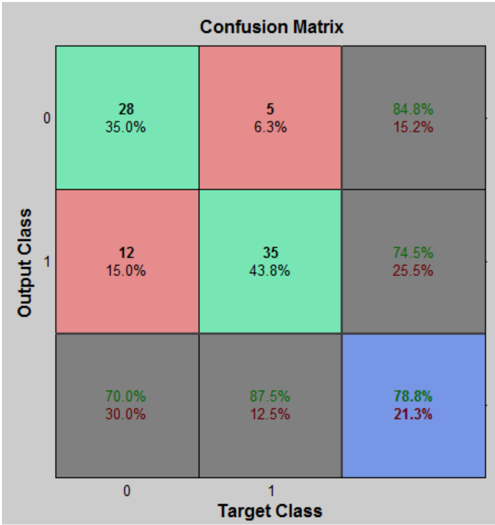

Figure 9: Confusion Matrix for Combining Both Actual and Imaginary Motor Movement

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