

# Automatic Detection of Motor Imagery Movement for Neuro-Based Home Appliances System

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**Abstract—** This project of Automatic Detection of Motor Imagery Movements for Neuro-Based Home Appliances System aims to design a protocol of recording EEG signals for controlling electronic devices using brain activities and to detect motor imagery movement from EEG signals automatically. For the motor imagery movement detection, 2 different protocol was design for both real and imagery grasping hand movement. EEG signals will be recorded by placing the electrodes at C3 and C4 using the 10 – 20 international system. The raw EEG data from the Open BCI will be extracted and it will be filtered and transform to Fast Fourier transform for further analysis in time-domain and spectrogram. From the analysis, the threshold was set at both real-time data and spectrogram for automatic detection of motor imagery movement that can be apply on neuro-based home appliances system.

**Keywords—** EEG signals, Open BCI, Fast Fourier transform, spectrogram, threshold

## I. INTRODUCTION

Usually, people have a lot of works to do at their home such as cleaning and cooking. A lot of energy is needed to do these works. These issues can become quite a problem because it can affect our body condition especially when our body is already tired from our daily lives activities. However, with the help of emerging technology nowadays, a lot of works can be done more easily where a lot of machines and electronic devices has been created to help people to do their work. These technologies give a lot of advantages to the people because they do not need to use a lot of energy to complete certain works. For example, a washing machine to help people to wash their clothes with just only press a few buttons.

From the previous studies, this technology is proven that it can be achieved where we can control some electronic devices by using a communication with the brain signal. Some of the researches that has been done is Mind-Controlled Wheelchair using an EEG Headset and Arduino Microcontroller [1] and the second one is Cognitive Efficiency in Robot Control by Emotive EPOC [2]. Basically, these papers were related with neurology in the human body system.

Neurology is one of the important studies in our body system. It concerned about the study and treatment of

disorders of the nervous system. The nervous system in our body is a very complicated system that controls our daily body activities. It has two parts; which are the central nervous system and peripheral nervous system. The central nervous system involves the brain and spinal cord system while the peripheral nervous system involves all other neutral elements such as skin, ears, eyes and other sensory receptor [3].

There are a lot of recent methods that has been used in obtaining brain activity information such as magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), electroencephalography (EEG), electrocorticography (ECoG) and single-neuron recordings. However, MEG and fMRI are big and expensive apparatus which made only a few researchers use these apparatus for their research. EEG, ECoG and single-neuron recordings are the only methods that have cheaper cost, simple to use and have high resolution. Among these three methods, EEG is the least invasive method which is the electrodes are placed at the scalp of the user for recording elsewhere the electrodes of the ECoG are placed on the surface of the brain and the electrodes of the single-neuron recordings are placed invisibly within the brain [4],[5].

So, the main theory and concepts of this neuro-based smart system is to analyze the brain signal by doing several real and imaginary movement activities that can give a reaction to the brain system. Then the brain signal can be applied to the home appliances such as, blenders, fan or air conditioner so that it can be controlled by doing the brain activities.

This brain signal or also called electroencephalogram (EEG) contains activity of the human brain. By extracting a raw data from the EEG signal, it can be analyzed in many different ways such as in time-domain, frequency-domain or frequency-time domain or also called spectrogram. Theoretically, to get a spectrogram analysis, the technique of Short Time Fourier Transform (STFT) was used on the raw data which is normally in time-domain. The STFT is to perform a FT on the signal, then mapping the signal into a two-dimensional function of frequency and time [6].

One of the most important element for correct analysis of brain signals are the accuracy of the EEG signals measurement. Therefore, the brain structure and its function are important information in this study. The brain is composed with the occipital lobe, the temporal lobe, the parietal lobe and the frontal lobe [7]. The occipital lobe relates with sight and the temporal lobe relates with hearing and the parietal lobe relates with body and the frontal lobe relates with thinking. Especially, the somatic sensory cortex



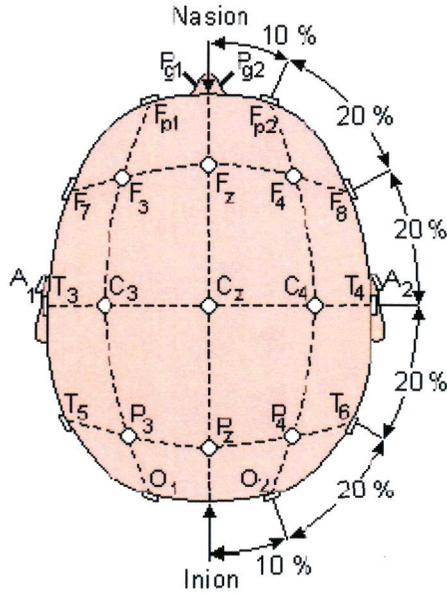


Figure 2: The International 10-20 system electrode placement

In this paper, only two electrode placement C3 and C4 were used because based on previous studies, electrode position at C3 and C4 were the brain area that associate with motor imagery movement. Both of the earlobes at A1 and A2 will be used as a reference point.

32 bit Open BCI board was used in the recording of brain signal activities in the EEG system. This board is compatible with Arduino microcontroller and has 8-channel neural interface with 32-bit processor. It implements the PIC32MX250F128B microcontroller at its core which is giving it more lots of local memory and fast processing speed [10].

The OpenBCI 32bit Board was used to sample brain activity (EEG), muscle activity (EMG), and heart activity (EKG). The board communicates wirelessly to a computer via the the OpenBCI programmable USB dongle, which is based on the RFDuino radio module. It can also communicate wirelessly to any mobile device or tablet compatible with Bluetooth Low Energy (BLE) [10].

The process is started by taking a real and imagery movement from the subjects by using an Open BCI hardware. All the subjects were asked to follow all the instruction in the protocol as in section II (B). All of the instruction were told by an instructor for each protocol. Then an EEG raw data was taken from the Open BCI saved data files that was stored in text file format. Next, all the raw data were imported to Matlab software for a signal analysis.

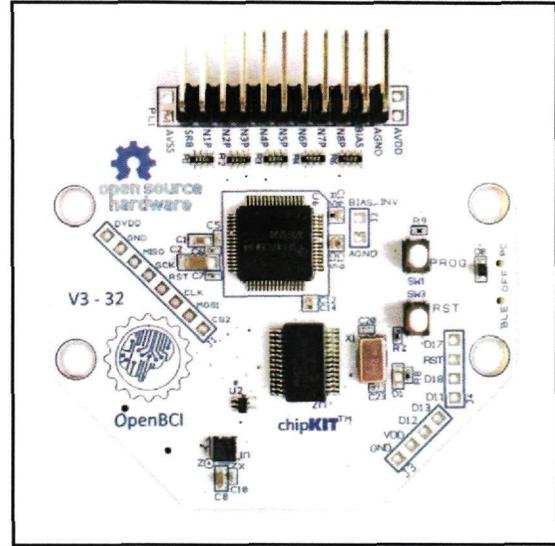


Figure 3: The 32 bit Open BCI Board

#### D. Signal processing and Analysis

Signal processing is one of the most important process to carry out before EEG data is analyzed. The data that was collected from Open BCI was stored as an unfiltered time-domain raw data. So, the raw data must be filtered first before it can be analyzed. In this case, the data was filtered with bandpass filter from 1 Hz to 50 Hz. Then notch filter at 50 Hz was used to remover power line interference.

Then to analyze the data in frequency-domain, Fast Fourier Transform (FFT) was computed using (1).

$$X_k = \sum_{n=0}^{N-1} x_n \cdot e^{-i2\pi kn/N} \quad (1)$$

Where  $X_k$  is the amplitude at the frequency,  $N$  is the number of time samples we have,  $n$  is the current sample we are considering,  $x_n$  is the value of the signal at time  $n$  and  $k$  is the current frequency we are considering.

In order to analyze the EEG in time-frequency domain, Short Time Fourier Transform (STFT) was computed using (2).

$$\text{STFT}\{x(t)\}(\tau, \omega) \equiv X(\tau, \omega) = \int_{-\infty}^{\infty} x(t)w(t - \tau)e^{-j\omega t} dt \quad (2)$$

Where  $w(t)$  is the window function. Usually, a Gaussian or Hann window is commonly used.  $x(t)$  is the signal that we want to transform and  $X(\tau, \omega)$  is the fourier transform of  $x(t)w(t-\tau)$ .

### E. Event Detection Algorithm

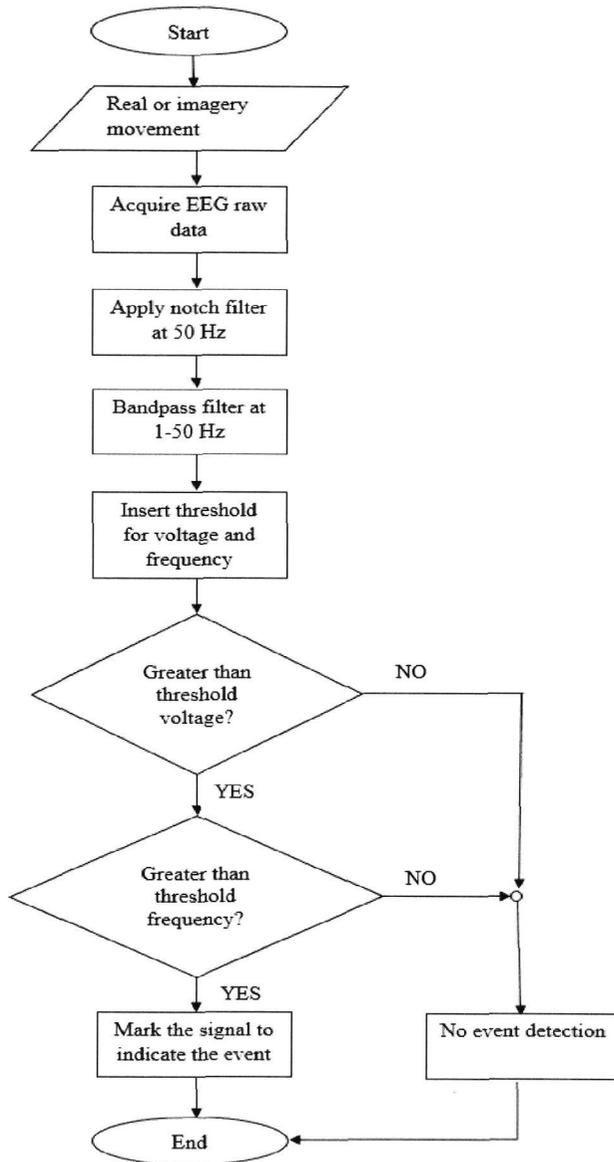


Figure 4: The event detection process

Figure 4 shows a flow chart of the event detection process for taking EEG signals data. It starts with taking a real and imagery movement that was taken from 10 subjects. All the subjects was doing 2 different protocol as told in Section II(B) that was guided by an instructor. 32-bit Open BCI was used during these processes and the live result was observed by interfaces the Open BCI with Processing software. The live result was showed in Graphical User Interface (GUI) from the Processing software where the real-time data and Fast Fourier Transform (FFT) plot was displayed.

The real time data from GUI was saved in a text file at the saved data folder as a raw data. Basically, the raw data reflects the DC offset that is present on top of the microvolt variations in EEG. To get an actual data, the EEG raw data was filtered by using Matlab software to remove the DC offset. A notch filter at 50 Hz was applied to the raw data and then it was filtered again with bandpass filter from 1 Hz to 50

Hz. After the filtering process, the raw data was transformed to real data just like the data that was displayed at the GUI.

From the Matlab software, a spectrogram also was plot so that the data was analyzed more detailed about the power/frequency (dB/Hz) of the signal. In other words, it shows the level of the frequency for every seconds throughout the EEG signal measurement. Then, threshold value was applied to signal for both at real-time data and spectrogram. So, if the voltage at the real time data did not surpasses the threshold value, there will be no event detection. If the voltage is higher than the threshold value, then it will be threshold again at frequency of the spectrogram. If the frequency is within the threshold, then the event detection will be mark at the signal. If not, there will be no event detection.

### III. RESULT AND DISCUSSION

Typically, the purpose of the protocol design in this research was to analyze whether there are any changes of signal when the subject start grasping the ball. That's why two protocol were designed where the first protocol ask the subjects to constantly grasp the ball for 10 seconds. The second protocol ask the subjects to grasp the ball quickly for 1 time, 2 times and 3 times. By doing 2 different protocol like this, the ideal case for the brain signal reaction when real and imagery grasping hand movement is occurred can be obtained. Then the threshold voltage can be set based on the ideal case of grasping hand movement.

From the previous study, reported by Ahmad Jais [12], there is change in the EEG signal for grasping movement. However, he only examined a few samples. In this work, the same finding is obtained from both protocols.

For the first protocol, the subject start grasping at 30<sup>th</sup>, 50<sup>th</sup>, 70<sup>th</sup> and 90<sup>th</sup> seconds. Other than that time, the subject was in relaxed condition. So, from the result shown in Figure 5 and Figure 6 below, it can be seen that an increase of amplitude when the subject start grasping especially at 30<sup>th</sup> and 70<sup>th</sup> seconds. The other grasping time at 50<sup>th</sup> and 90<sup>th</sup> seconds did not show much different due to several factors from the subject or the hardware itself.

For the spectrogram, there was a previous study state that the frequency range of the finger movement was around 16-21 Hz [11]. Since the grasping movement involving a fingers movement, this statement can be a reference frequency for the grasping movement. So, for the spectrogram in Figure 5 below, a slightly increase of power/frequency (dB/Hz) around 16-21 Hz can be observed (where there is a little red dot appear at the time of the grasping as shown in the red square mark). However, for the spectrogram result at the C4 in Figure 6, the power/frequency seem do not strong enough to reach 16-21 Hz. This is because all the subject use right hand for grasping. This result is in agreement with that reported by [8] which stated during the right hand movement, the left side of the brain (C3) in beta waves is increased and the right side of the brain (C4) will decreased [8].

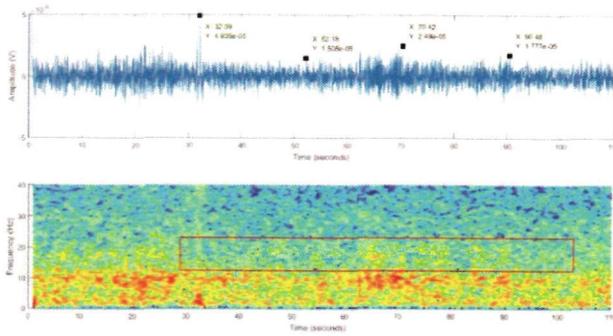


Figure 5: Real Grasping Movement with eyes closed at C3

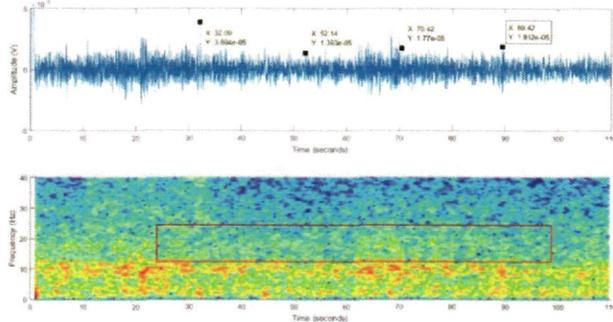


Figure 6: Real Grasping Movement with eyes closed at C4

Time \ Subject	30s	50s	70s	90s
1	49.35uV	15.08uV	24.90uV	17.77uV
2	51.19uV	10.13uV	16.48uV	14.83uV
3	10.92uV	10.33uV	10.53uV	14.30uV
4	156.2uV	20.40uV	10.98uV	17.34uV
5	8.45uV	11.78uV	13.12uV	12.95uV
6	38.28uV	27.04uV	32.8uV	23.77uV
7	23.77uV	18.15uV	20.29uV	17.06uV
8	44.55uV	36.12uV	41.21uV	71.78uV
9	21.16uV	141.3uV	148.7uV	29.45uV
10	51.64uV	47.59uV	25.1uV	18.67uV

Table 1: The amplitude of the EEG signal during grasping time for real movement with closed eyes at C3 for protocol 1

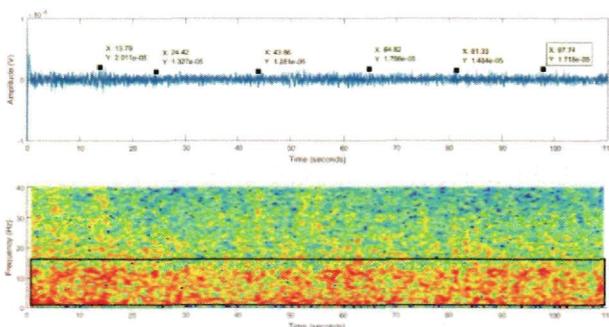


Figure 7: Relax condition with close eyes at C3

During relax condition, the reading of the EEG signal was around 10-20 uV with a frequency in Alpha band which is 7-13 Hz. Figure 7 shows a strong presence of power/frequency (dB/Hz) which is more than -103 dB/Hz at Alpha band range during a relax condition. So, from the result in Table 1, subject 3, 5 and 7 are still in the relax condition zone even during at the grasping time. Subject 1

had an increase of the amplitude during 30<sup>th</sup> and 70<sup>th</sup> seconds while subject 2 and subject 4 only had an increase of amplitude during 30<sup>th</sup> seconds only.

Subject number 8 shows an increase of the amplitude during all the grasping time which is the only subjects that achieved 100 percent result while subject number 6, 8 and 10 show an increase of amplitude 3 times only out of 4 which are still a good result.

The imagery movement results almost has no change at all because it is hard for the subject to grasp the ball for 10 seconds for real movement and it is even harder to concentrate for imagery movement. The poor result from the first protocol lead us to try the second protocol where the subject need to grasp the ball quickly for 1 time, 2 times and 3 times.

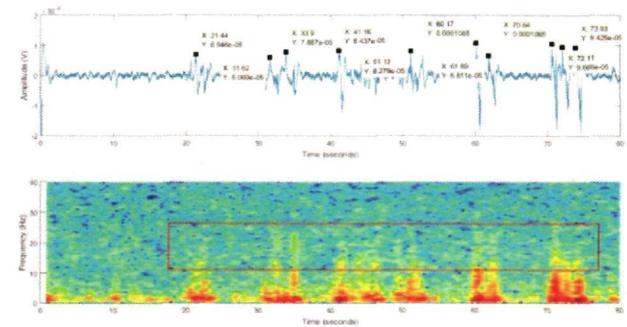


Figure 8: Real grasping movement with eyes closed at C3 for second protocol

For the second protocol, the subjects start grasping 1 time at 20<sup>th</sup> and 50<sup>th</sup> seconds, 2 times at 30<sup>th</sup> and 60<sup>th</sup> seconds and 3 times at 40<sup>th</sup> and 70<sup>th</sup> seconds. Other than that time the subject was in relax condition. So, the result in Figure 7 shows that the EEG signal amplitude is increased during grasping. During the grasping for 2 times at 30<sup>th</sup> and 60<sup>th</sup> seconds, it shows the signal amplitude is increased two times. For 3 times grasping, it show the signal only increase one time at 40<sup>th</sup> seconds but at 70<sup>th</sup> seconds, it shows 3 times change of signal

The spectrogram in Figure 8 also shows a positive result where the power/frequency (dB/Hz) is high around -103 dB/Hz at 16-21 Hz during grasping. However, only subject 1 shows the EEG signal changes during the grasping time as shown in table 2 below. Subjects 2 to 5 did not have much change in EEG signal during grasping.

Time \ Subject	20s	30s	40s	50s	60s	70s
1	69.46uV	60.69uV	84.37uV	82.79uV	68.11uV	94.25uV
2	15.04uV	16.77uV	14.56uV	14.65uV	22.46uV	13.89uV
3	16.88uV	15.56uV	19.98uV	17.97uV	16.61uV	18.81uV
4	14.51uV	13.17uV	12.80uV	12.36uV	15.36uV	13.41uV
5	16.86uV	15.83uV	21.39uV	18.45uV	12.85uV	19.95uV
6	61.06uV	37.24uV	52.86uV	59.71uV	42.84uV	45.36uV
7	52.51uV	50.89uV	28.37uV	48.22uV	40.89uV	36.76uV
8	45.95uV	43.22uV	61.25uV	43.95uV	62.33uV	36.72uV
9	4.496uV	1.466uV	45.13uV	74.42uV	12.02uV	32.07uV
10	29.67uV	35.71uV	34.34uV	11.83uV	7.236uV	19.9uV

Table 2: The amplitude of the EEG signal during grasping for real movement with closed eyes at C3 for protocol 2

There could be one explanation for subjects 2 to 5. It could be they did not understand the concept of grasping. Grasping means that to hold on tight onto something. So, maybe instead of grasping the ball, the subject just holding the ball which is not tightly grasping the ball. The second explanation could be the problem in the second protocol itself. In the second protocol, the subjects need to grasp the ball quickly for 1 time, 2 times and 3 times. One thing they need to remember, even they need to grasp the ball quickly, the fingers need to be fully stretch and then grasp the ball tightly and then the fingers need to be fully stretch back again. This will fulfill the condition of grasping.

Next, subject 6 to 8 give a positive response just like subject number 1. After subject 2 to 5 did not show a good result, the next 5 subjects was improvised in term of grasping methods so that the mistake was not repeated. Subject number 9 and 10 show quite a good result despite they not achieve 100 percent positive result but at least 50 percent from the grasping time they achieved positive reaction.

All the result shown only for real grasping movement with closed eyes at C3 for protocol 1 and 2. The C3 position was selected because all the subjects use right hand during the experiment which more affect left side if the brain which is C3 in beta wave [8]. The imagery movement result also did not show much change in the EEG signal.

. Since the relaxing condition for an EEG signal was around 10-20 uV and all the change of the EEG signal during the grasping time was above 24 uV, the threshold voltage can be set around 22 uV for automatic detection of motor imagery movements.

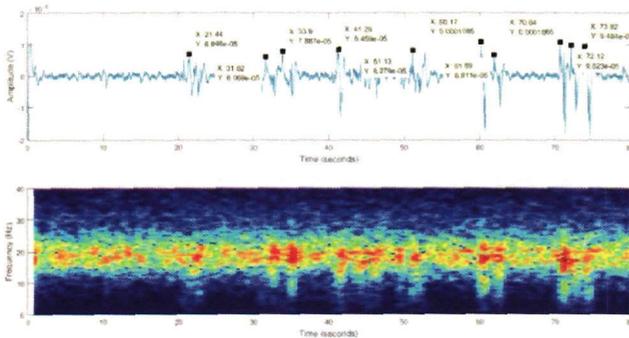


Figure 9: Real grasping movement with eyes closed at C3 for second protocol with threshold at spectrogram

Insert a threshold voltage alone is not enough because EEG signals recording is very sensitive even with a slightest change. So, not only 22 uV was set as a threshold, a frequency of 16 Hz to 21 Hz also was set as a threshold for event detection as shown in the spectrogram in figure 18 above. With this threshold setting, the event only occur when the amplitude is higher than 22 uV and within the frequency range of 16 Hz to 21 Hz with -103 dB/Hz.

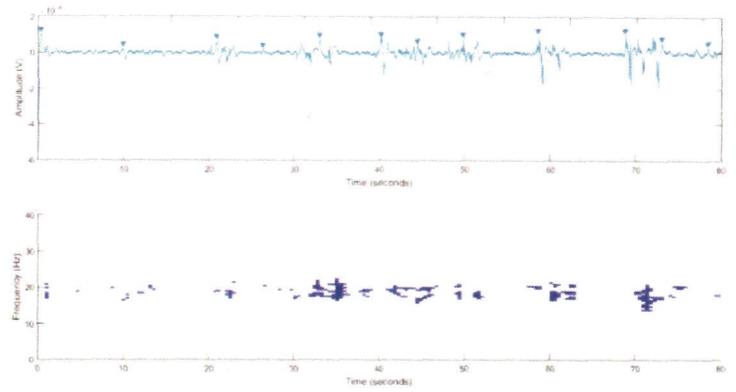


Figure 10: Real grasping movement with eyes closed at C3 for second protocol with threshold at both real-time and spectrogram

Finally, the threshold level was mark at both real-time and spectrogram data as shown in Figure 10. It is important to insert a threshold level at both real-time and spectrogram because if the threshold is set to real-time data only, it will also detect some a little increase of amplitude which is sometimes consists of noise. For example, between 0 and 20<sup>th</sup> seconds, there was a mark of event detection at the beginning and 10<sup>th</sup> seconds which is not during grasping time. But at the spectrogram, it shows weak power/frequency (dB/Hz) which shows the difference between grasping time or not. The result in figure 10 shows a strong power/frequency(dB/Hz) at above -103 dB/Hz and high amplitude during the grasping time at 20<sup>th</sup>, 30<sup>th</sup>, 40<sup>th</sup>, 50<sup>th</sup>, 60<sup>th</sup> and 70<sup>th</sup> seconds which are the requirement for the event detection.

#### IV. CONCLUSION

The protocol of recording EEG signals for controlling electronic devices using brain activities, the analysis of EEG signals and automatic detection of grasping movements in the EEG signals have been described in this paper. EEG signal has been taken from 10 healthy subjects that went through 2 different protocols. Both protocols contains both real and imagery hand grasping movements tasks. But the imagery movement data did shows a positive result for both protocols. So, only a real movement data has been analyzed. The EEG signals obtained from the protocol 2 allows grasping activity too be observed clearly, thus protocol 2 was used in this work to analyze more data to confirm these preliminary findings. For the automation detection of motor imagery movements, a threshold voltage around 22 uV for the real-time data and for spectrogram, a threshold between 16 Hz to 21 Hz were suggested to be used for event detection. But it can be only used in real grasping movements with closed eyes at electrode placement C3. The grasping method also should be done right by holding tightly with a right finger movements.

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