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Analysis of Arm Movement Prediction by Using the Electroencephalography Signal

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Abstract

Various technological approaches have been developed in order to help those people who are unfortunate enough to be afflicted with different types of paralysis which limit them in performing their daily life activities independently. One of the proposed technologies is the Brain-Computer Interface (BCI). The BCI system uses electroencephalography (EEG) which is generated by the subject's mental activity as input, and converts it into commands. Some previous experiments have shown the capability of the BCI system to predict the movement intention before the actual movement is onset. Thus research has predicted the movement by discriminating between data in the "rest" condition, where there is no movement intention, with "pre-movement" condition, where movement intention is detected before actual movement occurs. This experiment, however, was done to analyze the system for which machine learning was applied to data obtained in a continuous time interval, between 3 seconds before the movement was detected until 1 second after the actual movement was onset. This experiment shows that the system can discriminate the "pre-movement" condition and "rest" condition by using the EEG signal in 7-30 Hz where the Mu and Beta rhythm can be discovered with an average True Positive Rate (TPR) value of 0.64 ± 0.11 and an average False Positive Rate (FPR) of 0.17 ± 0.08. This experiment also shows that by using EEG signals obtained nearing the movement onset, the system has higher TPR or a detection rate in predicting the movement intention.

Abstrak

Analisis Prediksi Gerakan Tangan menggunakan Sinyal Elektroensefalografi. Berbagai pendekatan teknologi telah dikembangkan untuk membantu mereka yang menderita kelumpuhan dalam melakukan aktivitas kesehariannya secara mandiri. Salah satu teknologi tersebut adalah *Brain-Computer Interface* (BCI). Sistem BCI menggunakan elektro-ensefalografi (EEG) yang dihasilkan dari aktivitas mental seorang subjek sebagai masukan, dan mengubahnya menjadi perintah. Beberapa percobaan sebelumnya telah menunjukkan kemampuan sistem BCI untuk memprediksi gerakan sebelum gerakan tubuh aktual terjadi. Penelitian tersebut memprediksi gerakan yang akan terjadi dengan membedakan data pada kondisi *rest*, di mana tidak ada intensi gerakan, dengan kondisi *pre-movement*, di mana terdapat intensi gerakan sebelum gerakan aktual terjadi. Penelitian ini dilakukan untuk melakukan analisis sistem yang dihasilkan dari pembelajaran, yang kemudian diterapkan pada data dengan interval waktu kontinu, antara 3 detik sebelum gerakan terdeteksi sampai 1 detik setelah gerakan sebenarnya terjadi. Hasil percobaan menunjukkan bahwa sistem dapat membedakan kondisi *pre-movement* dan kondisi *rest* dengan menggunakan sinyal EEG pada frekuensi 7-30 Hz di mana letak Mu dan ritme Beta dengan nilai rerata *true positive rate* (TPR) sebesar 0.64 ± 0.11 dan rerata nilai *false positive rate* (FPR) sebesar 0.17 ± 0.08. Hasil percobaan juga mampu menunjukkan bahwa penggunaan sinyal EEG yang dekat dengan terjadinya gerakan, membuat sistem dapat mendeteksi intensi gerakan dengan nilai TPR atau tingkat deteksi gerakan semakin tinggi.

Keywords: brain-computer interface, electroencephalography, FPR, pre-movement intention, TPR

1. Introduction

Our brain has a vital function of coordinating and regulating various systems and organs in our body [1]. It does this regulatory function by sending millions of electrical signals, through the nervous system, to the targeted part of our body both consciously and un-consciously. This occurs continuously and the result can be seen in our daily activity, such as when we are walking or grabbing using our limbs. However, not all coordination of the brain can be delivered to other organs or limbs optimally. In various cases, transmission through the nerve might be distorted or even be outright disrupted due to damage in certain parts of the nerve system. This disruption can be caused either by diseases or accidents. This condition is commonly perceived as paralysis. Those with this condition will have one or more body part which cannot be moved according to their will.

Many researchers have presented various technological approaches to help those people who are unfortunate enough to be afflicted by paralysis in overcoming their limitation and performing their daily life activities independently. One of the proposed technologies is the Brain-Computer Interface (BCI). The BCI system uses electroencephalograph (EEG or a brainwave signal) as an input, which is generated by the subject's mental activity and it is converted into commands [2]. By associating these commands with a series of actions to be done by an assistive system, the subject (or in this case, the patient) can be leveraged by mechanical and electrical assistance to perform communications and activities independently. Figure 1 illustrates a common configuration of a basic BCI system.

If we take a deeper look towards the driving force behind the BCI system, which is the EEG signal, we will notice that there exist several different types of brain waves; the Alpha rhythm, Beta rhythm, Theta rhythm, and Delta rhythm. The Alpha rhythm is a brain wave with a frequency ranging between 8-13 Hz [3], while the Beta rhythm has a frequency range of 13-30 Hz [3]. In addition to those waves, researchers also found a rhythm which is closely related to the voluntary movement, which they dubbed as the Mu wave [4].

The Mu rhythm is defined as a brain wave having a frequency ranging between 8 and 13 Hz and could be measured at the motoric and sensory cortex area. Mu rhythm can be measured in the sensory-motoric cortex area, while a subject is not accessing the motoric or sensory nerves, or in other words while the subject is idle [4]. Some experiments have shown that Mu and Beta rhythms attenuate when the subject accesses the motoric or sensory nerves [4]. This phenomenon is called Event Related Desynchronization (ERD) [4].

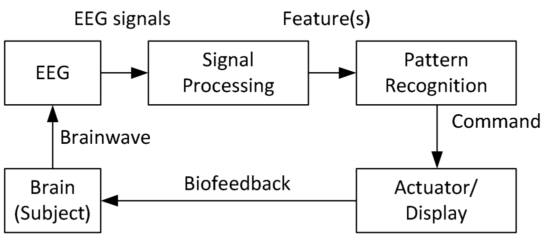


Figure 1. Basic BCI System

After the movement is completed and the subject no longer performs activities associated with sensory or motor nerves, the amplitude of the Mu and Beta rhythm bounce back. The increasing phenomenon of Mu and Beta rhythm amplitude is called Event Related Synchronization (ERS).

The ERD phenomenon has been used as features in several experiments associated with movement. Experiments conducted by Lew *et al*. [5] and Maoz *et al*. [6] have proven that when using an invasive EEG, the signal will decrease in amplitude before the movement is onset. Moreover, Pirez *et al*. [7], Lew *et al*. [5] and Planellas *et al*. [8] have shown that non-invasive EEG signal can be used to detect pre-movement before the movement is onset, also by detecting the ERD phenomenon. All of the above experiments were conducted using the self-paced (asynchronous) method, where the subject was given the liberty to move his arm at his own pace within a specific time interval. An experiment conducted by Pirez *et al*. [7] has shown that by using Readiness Potential [10] and ERD as features (where is the subject?) could make the system have accuracy of up to 96% for predicting the left or right finger movement before the actual movement is onset. Lew *et al*. [5] used the ERD phenomenon in the time domain as features, while Planellas *et al*. [8] used the same phenomenon in the frequency domain to extract its features based on power spectral by using Fast Fourier Transform (FFT). Both Lew *et al.* [5] and Planellas *et al.* [8] show that BCI can be used to predict the pre-movement by using movement intention from the EEG signal with average accuracy up to ±99%, for invasive measurement, and ±71%, for non-invasive measurement.

Another result which was also shown in the experiment conducted by Lew *et al*. [5] and Planellas *et al*. [8] is the ability of the system to detect the pre-movement intention during "rest" condition. Ideally, for safety reason, the movement intention during "rest" should not be utilized; however, the result of their experiment shows that the system was able to detect movement intentions during "rest" from 10% to 30%.

Lew *et al.* [5] tested the system in detecting continuous data 1 second before an auditory cue appears until 2 seconds after the cue appears. From their experiment, it can be shown that the prediction of movement intention at "rest" condition is below the random level. As it has been proven that by using the ERD phenomenon in time domain [5], classification can be done between the movement intention condition interval or "rest" condition interval; hence, this experiment aims to evaluate the arm movement prediction by using the same phenomenon in the frequency domain with the Burg's autoregressive (AR) method and Support Vector Machine (SVM) before actual movement onset. This experiment also evaluates the implementation of system pattern recognition in continuous time, from 3 seconds before the movement onset until 1 second after the movement onset by using a non-invasive EEG, in order to see the dynamics of system's decision (detection rate) in predicting the arm movement.

2. Experiment

This experiment was done using the self-paced method [5-8]. We illustrate the block diagram of this system which is used in the experiment in Figure 2.

Data from three healthy male subjects with an average of (30.3±2.5) years of age were obtained. The experiment was done to acquire EEG signals from each subject in 3 runs (sessions). Each run contains 50 epochs. Figure 3 illustrates the timing diagram for each epoch in the experiment. Each subject is allowed to move his arm only during "arm movement" interval. The system will display a "+" symbol to indicate that each subject is in the "rest" interval and a "." symbol to indicate that the subject in "arm movement" interval. Each subject is requested to move his arm voluntary as fast as he can during the "arm movement" interval and to do nothing during the "rest" interval.

Emotiv [9] is used to obtain the EEG signal with a sampling frequency of 128Hz. It has a resolution of 14-bits with the Least Significant Bit (LSB) having a voltage of 0.51 microvolt.

Emotiv collects 14 channels of the EEG signal on AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1, and O2. Since the movement correlates with neuron at sensory-motoric area [4], the electrodes on position AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, and T8 move near the sensory motoric area.

Two active applications had to be used in order to obtain the EEG signals. TestBench [9] was used by the system to acquire the EEG signal. The system also gives visual feedback to the subject through another application called Visual Stimulation Application (VSA). The VSA gives the subject visual cues to indicate the time interval ("idle", "rest", and "arm movement") in order to facilitate the self-paced experiment methodology. The system detects actual arm movement using a button located under the palm (normally-open-switch configuration). The button sends the movement's acknowledgement to VSA via a mouse click event. This button is built by using a mouse platform. The system sends all the metrics ("idle", "rest", "arm movement" interval, and actual arm movement acknowledgement) from VSA to TestBench via virtual serial (RS-232) protocol at 115200 bit/second (bps), with 8-bit of data, 1 start bit, 1 stop bit, and using no handshake.

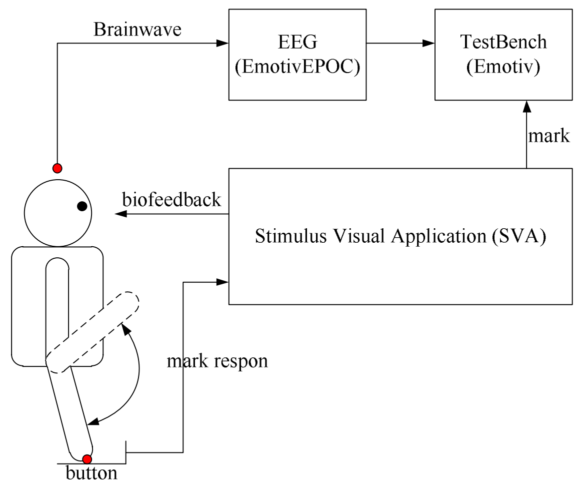


Figure 2. Block Diagram of Experiment the System

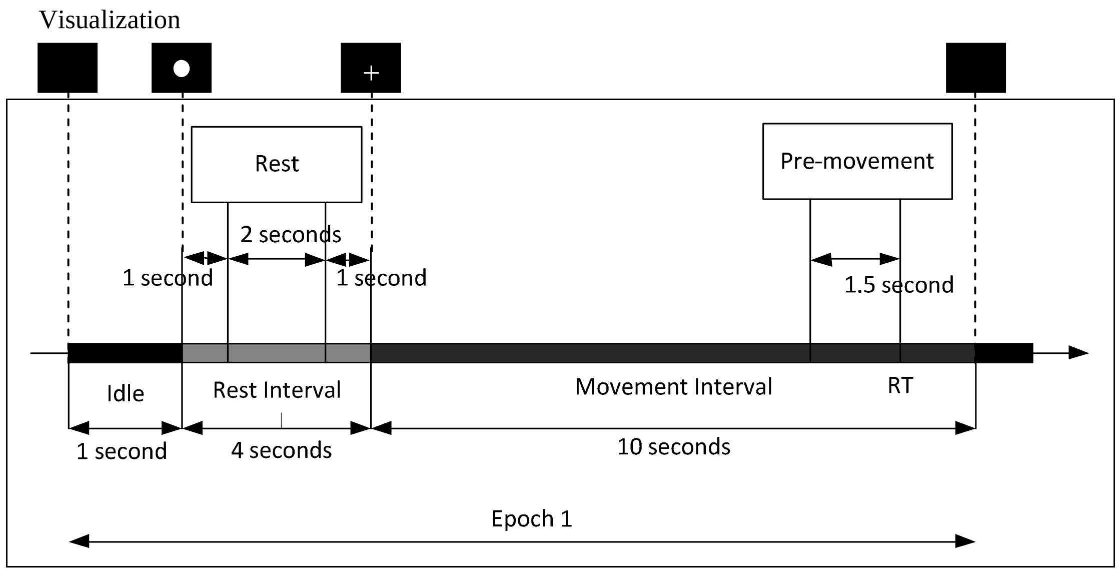


Figure 3. Time Diagram of Data Selection. RT Indicates the Arm Movement Onset

Data selection. In general, all of the data are divided into 2 classes or conditions, “rest” and “pre-movement”. The “rest” condition is the condition where there is no movement intention. On the other hand, the “pre-movement” condition is a condition where a subject has movement intention.

Data during the “rest” interval are taken one second after the “rest” mark appears. This consideration is taken to avoid the response of the EEG signal that arises when the subject sees the visual stimuli which appear on the screen [5,8]. The “rest” condition is processed using a 1 second (128 samples) window which is taken from the data between 1 to 3 seconds after the “rest” mark appears. By shifting the data every 125 milliseconds (875 milli-seconds overlap), for the “rest” class, we will have 8 pieces of data per second for each channel (16 pieces data per epoch).

Previous research conducted by Shibasaki and Harlett [10], Lew *et al.* [5], and Planelles *et al.* [8] shows that movement intention can be detected up to 2 seconds before the movement is onset. The data of “pre-movement’ which were taken for this class are the data from 1.5 seconds before the subject movement was detected by the system until the movement was detected by the system. Similar with the “rest” condition, the “pre-movement” class data were taken with a 1 second length window. The class “pre-movement” is obtained by shifting every 125 milliseconds, which starts from 1.5 seconds before the movement is detected giving 5 pieces of data of “pre-movement” class per epoch.

Aside from the “rest” and “pre-movement’ class, this experiment also captures the “continuous” class which is taken from 4 seconds before until 1 second after the movement onset. These data were then used for a probability density analysis on the pre-movement which is predicted using a model system which is generated from pattern recognition drawn from “rest” and “pre-movement” class. This “continuous” data selection is illustrated by Figure 4.

EEG signal processing. This experiment leverages the capability of the Common Average Reference (CAR) as a spatial filter in order to estimate and increase Signal to Noise Ratio (SNR) of the EEG signals from all channels. CAR equation is shown in Eq. (1) where X_i is an estimate of the EEG signal on channel i, x_i is the measured EEG signal on channel i, N is the number of channel used in the calculation, and x_j is the measured EEG signal on channel j.

$$X_i(t) = x_i(t) - \frac{1}{N}\sum_{j=1}^{N} x_j(t) \qquad (1)$$

Butterworth Band Pass Filter (BPF) with a passband range of 7-30 Hz was used as a temporal filter. The frequency range was chosen because the Mu rhythm and the Beta rhythm were said to be located in the mentioned frequency range [8]. This range also will reduce the artefacts in the EEG signals caused by visual stimulation response from the displayed cue marks.

$$P(f) = \frac{\sigma^2 T}{\left|1 + \sum_{i=1}^{p} a_i e^{-j2\pi fT}\right|^2} \qquad (2)$$

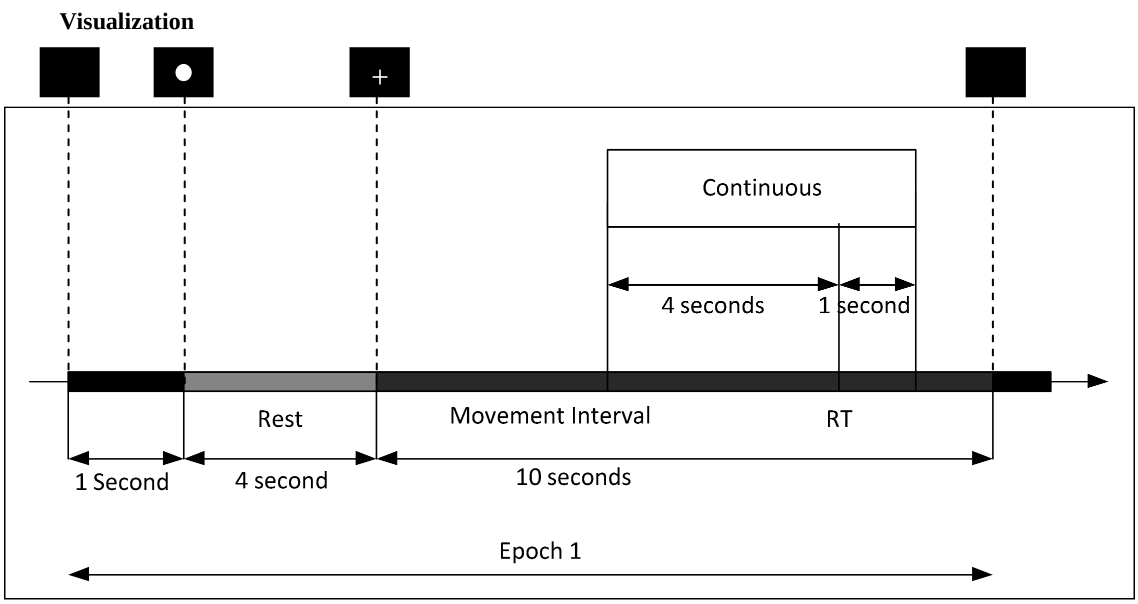


Figure 4. Continuous Data Selection. RT Indicates the Arm Movement Onset

The pattern recognition system uses Power Spectral Density (PSD) features which are calculated using a 6^{th} order Autoregressive (AR) Burg filter [11] as features. This method was chosen because it is suitable to be used for small data samples, giving a high resolution, and clear spectral values [11]. The equation for calculating the PSD of the EEG signal is shown in Eq. (2). The system uses the Coefficient of Determination (r^2) for channel and frequency selection of features [4], while Support Vector Machine (SVM) with Radial Basis Function (RBF) as kernel is used as the pattern recognition method.

Analysis and performance. The performance of this experiment is evaluated by using two metrics, True Positive Rate (TPR) and False Positive Rate (FPR). The TPR value indicates the system performance in correctly identifying movement intention; it is quantified by calculating the number of “pre-movement” occurrence correctly classified as “pre-movement” by the system, compared to the actual number of the intentions of “pre-movement” performed by the subject, as shown in Eq. (3). Meanwhile, the FPR value indicates the number of misclassification done by the system; it is quantified by comparing the number of “rest” condition occurrences which were wrongly classified as “pre-movement” condition with the actual number of “rest" condition occurrence during the experiment, as shown in Eq. (4).

Since the data from each class are limited, to calculate the TPR and FPR we first did a 3 fold cross-validation to the data, and we assume that the result of the cross validation is equal to 1 fold [8].

$$TPR = \frac{\sum pre-movement\ detected}{\sum all\ pre-movement\ in\ test\ data} \quad (3)$$

$$FPR = \frac{\sum rest\ detected\ as\ pre-movement}{\sum all\ rest\ in\ test\ data} \quad (4)$$

3. Results and Discussion

The experiment did not use all epoch which was acquired from the measurement. This decision is made because there were times when the subject did not move during “movement” intervals. Table 1 shows the total epoch in each run from each subject. This experiment also reduces the EEG channels from 14 to 8 channels that are near the sensory-motoric area (F3, F4, FC5, FC6, F7, F8, T7, T8).

The example of power spectral density of EEG signal in “pre-movement” and “rest” condition by using the AR method can be seen in Figure 5. Although Planellas *et al.* [8] state that ERD phenomenon occurring in the Mu rhythm and Beta rhythm is not easy to find, this experiment has shown that the ERD phenomenon occurs mainly at the Beta rhythm.

Channel and frequency were used as features to discriminate between the “pre-movement” condition and the “rest” condition. They were selected by using the Coefficient of Determination (r^2). Figure 6 illustrates the value of r^2 from channels AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, and T8 which move near the sensory motoric area. We can see that the value has the highest value at channel F8 and frequency 22-24Hz. Based on the value, we use PSD Alpha and Beta from channel F8.

Table 2 shows the result of the system in detecting the “rest” and “pre-movement” condition by using SVM with the Radial Basis Function (RBF) kernel.

From the results shown in Table 2, we can see that the system can correctly predict the “pre-movement” condition with the TPR value 0.64 ± 0.11. On the other hand, the misclassification of the “rest” condition to the “pre-movement” condition is 0.17 ± 0.08. This experiment produces an FPR of ±17% which is slightly lower from the FPR result shown by the experiment conducted by Planellas *et al.* [8] which was at ±30%. Based on this result, we should consider seriously the implementation of the BCI systems in real application.

Since Table 2 shows the system’s prediction only from two different time intervals (“rest” and “pre-movement”), a “continous” time interval was also tried. This implementation will decribe the “pre-movement” intention prediction phenomenon in continuous time interval from 3 seconds before until 1 second after movement is onset. Figure 7 illustrates the result of the prediction system in the “continuous” time interval.

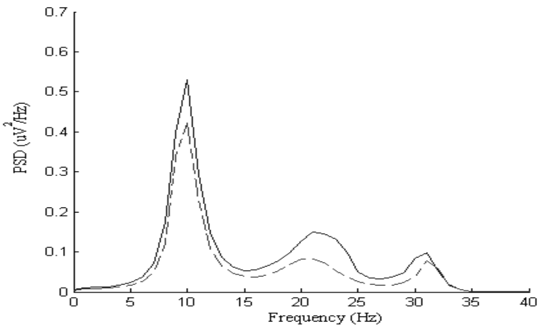
In Figure 7, the system predicts the movement intention every 125 ms. We can see that the system gives higher prediction of the movement intention when the data used are the data which are close in time to the actual movement onset. This prediction phenomenon in the continuous time interval is very interesting since the prediction of movement intention at 3 seconds before

Table 1. Total Epoch in Each Run

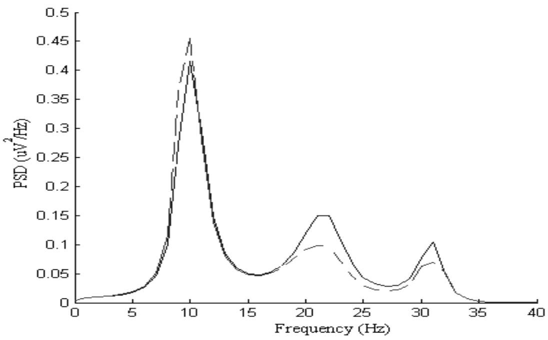
No	Subject	Run 1	Run 2	Run 3
1	A	50	50	50
2	B	49	49	46
3	C	50	49	48

Table 2. System Performance Metric Measured during the Experiment

No	Subject	TPR	FPR
1	A	0.65 ± 0.09	0.14 ± 0.04
2	B	0.64 ± 0.15	0.18 ± 0.16
3	C	0.64 ± 0.08	0.19 ± 0.03
Mean		0.64 ± 0.11	0.17 ± 0.08



(a)



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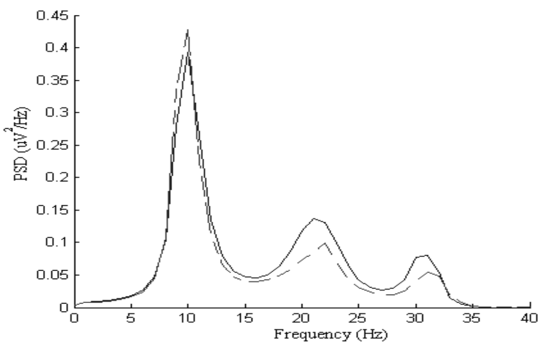

(c)

Figure 5. PSD of the "Rest" Condition (Solid) Compared to the "Pre-Movement" Condition (Dash) from Subject B at Channel F8 (a) Run 1 (b) Run 2 (c) Run 3

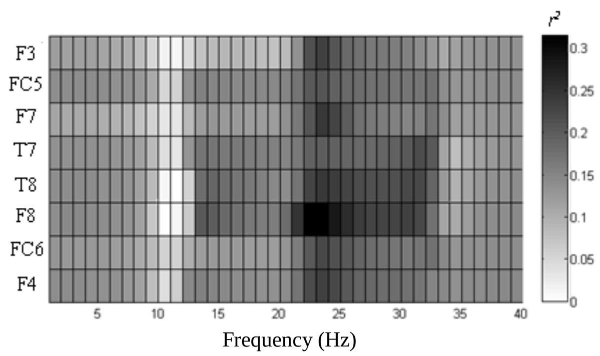

Figure 6. Coefficient of Determination (r^2) of 8 Channels from Subject B (Using Data Run 1 and Run 2)

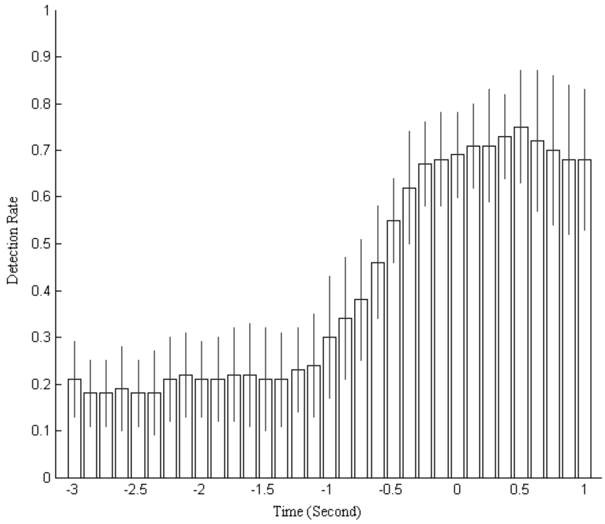

Figure 7. System's Decision Rate from 3 Seconds before Actual Movement Onset until 1 Second after Actual Movement Onset

actual movement onset until 1.5 seconds before actual movement onset has a detection rate of around 0.2. If we assume that the mentioned time interval is the "rest" condition, it can be assumed to be the FPR. By comparing the FPR value from the "rest" condition in the "rest" interval and the FPR value from the "rest" condition in the continous interval, we conclude that the difference of false prediction of the two conditions is not significant ($p > 0.05$).

4. Conclusions

This experiment evaluates the movement prediction phenomenon at the continuous time interval by using the non-invasive EEG signal with AR and SVM methods. From this result, the false prediction of movement intention in the continuous time interval compared to false prediction of movement intention in the "rest" interval is not significant ($p > 0.05$). On the other hand, this experiment shows that the system has higher accuracy (TPR) for predicting pre-movement intention when the system is using the signal which is close in time to the actual movement onset. Further experiment with a longer period in continuous time needs to be conducted in order to see the reliability of the BCI system in continuous time. We also consider the high and dense brain activity during continuous long time interval observation, which might give significant findings to enhance the application of the EEG signal in assistive technology, especially in the BCI system.

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