Brain Computer Interface Game Controlling Using Fast Fourier Transform and Learning Vector Quantization

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***Abstract*—Brain Computer Interface (BCI) is a direct communication pathways which enables our brain to real time control a robotic movement or a game, which uses EEG signal to capture information of a human mind. In this research, we developed an arcade game that are controlled by BCI. Player sat and used their imagination to move the object in the game, in this case, they moved up or down. To achieve that, a wireless EEG device was used to record electrical activity in the player's brain; each action was segmented by two seconds per frame, and then extracted using Fast Fourier Transform. Continuously, the output was passed to Learning Vector Quantization networks to classify two different motor imagery-related brain patterns (imagination of limb movements: upward and downward). Before the game was used, we conducted training for ten people (subjects) with four repetitions of each thinking type. Then, it was tested with 10 other subjects in which resulted in 70% accuracy. The game was tested and then compared between the movement of the mouse and BCI of the same subject and great results were found in both conditions.**

***Index Terms*—Brain Computer Interface; Arcade Game; EEG Signal; FFT; LVQ.**

I. INTRODUCTION

Brain Computer Interface (BCI) develops augmented direct communication pathway between the brain and an external device. It translates the electric brain activities directly, bypassing the needs of muscular activity to control commands of external effectors such prosthetic hand or game. In medical application, BCI helps patients suffering from severe brain or muscular disorders in away prosthetic hand. In this research, we used BCI to send out external input of an attractive arcade games. It captures the imagination of the players and can stir a game that acts as a challenge to finish a particular stage.

A BCI has three fundamental components: brain as input, control command as output and an intermediate stage. The problems in the BCI is the intermediate stage.

Several devices are used such as Electroencephalogram (EEG), Electrocochleography (EcoG), and Electroretinography (ERG). EEG is the most common device used in BCI, and therefore used in this research. We used Neurosky wireless which supports the usage of BCI controller. Previous research has been done to use BCI to control mouse [1], game action [2]-[3], real time BCI [4], mobile robot [5]-[7], speech communication using EEG and EcoG [8], and control automating home appliances [9].

Processing EEG signals is not an easy thing to perform. An important issue is the variables of mental task imagined. Among them are attention [10]-[11], alertness [12], emotion [13] focusing thinking [14], and hand grasping imagination [15]. Modeling and classification system is important, according to the variables reviewed. EEG signal has low amplitude, weak signal to noise ratio, non-stationery, and no certain pattern that reflects brain condition. Even though, EEG signals in time domain, it has specific information when transformed into a frequency domain.

EEG signal consists of wave components differentiated by their frequency band, which are alpha wave (8-13 Hz). It very often appears in consciousness, closed eyes, and relax states; beta wave (14-40 Hz), highly observed during state of thinking; theta wave (4-7 Hz), and generally exists when people take a nap, sleepy, or are in emotional stress; and delta wave (0.5-3 Hz). The main feature of brain activity is when people are in deep sleep. Previous research extracted EEG signal in frequency components. It is also useful to eliminate noise, artifact or other noise information. Some of them in human attention using FFT [11] emotion state using power spectral density [13], influence of sound stimulation using wavelet [17].

Practical applications of BCI depend first on speed and accuracy. One problem example is the presence of artifacts in BCI. Hence, we have to explore techniques that can evade these issues. Frequency analysis for classification of the output action is quite helpful. Physiologically meaningful signal features can be extracted from various frequency bands of recorded EEG. For example, μ- and/or β-rhythm amplitudes serve as effective inputs for a BCI. Some research used frequency analysis to classify action of Packman game [3], three actions of single player game [18], and move Penguin using event-related desynchronization [4], and using FFT [19].

In Gaming's world, player's input devices are essential components to enable a player to actually play the game. Several studies have been designing games while utilizing BCI as their input device. They were used to control penguin's jump [4], movement of Pacman game [3], and developed of other purpose [20]. Others, measure the level of memory and attention [21], emotion, meditation and attention [22]-[23] while playing the game. The subject who use BCI game, have to learn how to voluntarily modulate the EEG oscillatory rhythms by performing the imagery tasks. Hence, the selection of appropriate subjects and prior training, determines the success of the development of BCI. Furthermore, the temporal dynamics and the accuracy of a BCI controlled depend on EEG signal processing and number of tasks imagination [4].

This research also developed an Arcade Game which is controlled using BCI. The brain information obtained through EEG, extracted using FFT in 4-40 Hz frequency range. The results of the FFT are array of spectral each frequency (4-40Hz) or frequency series, hereinafter became the input or features of classification system using Learning Vector Quantization (LVQ). The neural network architecture classifies the two actions, that upward and downward movement. Some research using Backpropagation to translate the three imagery signals [18] or hand grasping imagination [16], SVM the probabilistic neural network to control hand grasping imagination [24], and K-Nearest Neighbor (KNN) to distinguish two classes [25]. LVQ is a method JST development of Kohonen maps, which is simpler than Back-propagation. It is necessary to remember the action of a game required in a short time. Previous research using LVQ and frequency extracted [25], and LVQ to detect epileptic [26].

The combination of FFT and LVQ is intended to improve the differentiation of mind to move objects. Before the game is used, we conduct a series of training carried out on 10 people (subjects) with four repetitions of each movement (up and down). Beforehand, all subjects have been trained using BCI game.

II. Data Acquisition

EEG signals were recorded using NeuroSky EEG that has FP1 channel and 512 Hz sampling frequency. The sampling frequency makes the signal obtained at a frequency of 0-256 Hz, so that it covers all the frequency range of the EEG signal. EEG recording consists of two purposes, namely for training data and test data. Training data recorded four times each from 10 subjects with 20-25 years old and in good health. The number of subject was based on the availability health, which is voluntary.

Recording was performed during 30 seconds that was divided into two sessions. First, the subjects were asked to imagine to move the game character upward, followed moving downwards. It was a sitting position as shown Figure 1. Next, we tried the other ten subjects and carried out the test with the same conditions.

Figure 1: EEG Recording in 30 seconds

Recording of the 10 subjects were taken at four different times from 8AM-9AM, 12 (noon)-1PM, 5PM-6PM, and 9PM-10PM. The use of four different time intended to minimize the influence of other variables.

III. Game Controlling System

This BCI game controlling using FFT and LVQ is illustrated in Figure 2. EEG signals were recorded with a sampling frequency of 512 Hz during 30 seconds, which was then segmented into two seconds. It means that short time EEG signal is considered stationary. Then, the EEG signal extracted by the first FFT windowing passed with 50% overlap. The use of windowing method is intended to improve fluctuations in the lobes, which can interfere estimated spectral resolution. FFT converts the EEG signal from the time domain into the frequency domain within the range of 4-40 Hz. Then, the results of the FFT were classified by LVQ as a training data set.

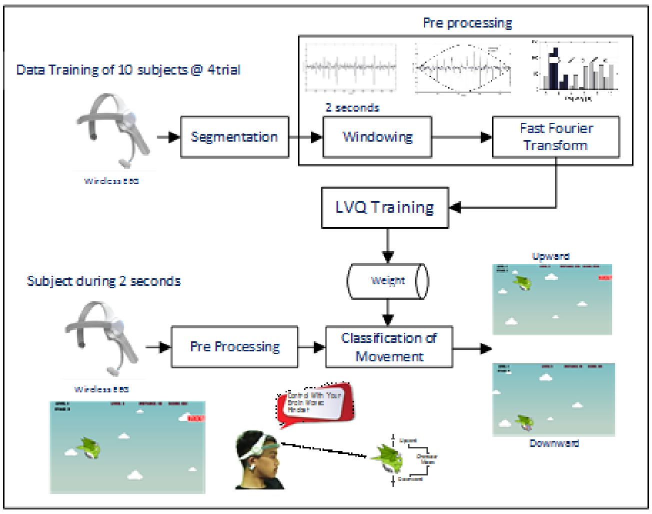

Figure 2: Design of BCI Game

A. Fast Fourier Transform

FFT is generally used for stationary signals. However, to minimize the influence of non-stationary signals such as EEG, the window was first used. It can improve the sidelobe fluctuations, which can interfere with the spectral resolution. For each frame, windowing was made, which was then averaged. The signal was divided on the same frame and overlapped 50% of data length to reduce the discontinuity. The signal in frame m=1 to M is as presented in Equation 1.

$$x_m(k) = x(k)w(k) \tag{1}$$

Each frame m with N data length, in the convolution with a window. There are several window functions, one of which is a function of Hamming as Equation 2.

$$w(k) = 0.54 - 0.46\, cos\left(\frac{2\pi k}{N-1}\right), \qquad 0 \le k \le N-1 \tag{2}$$

Hamming window has a marginally better sidelobe suppression, which is defined by its coefficients 0.54 and 0.46.

Fast Fourier Transform. Discrete Fourier transforms each m frame as given in Equation 3,

$$S_m(k) = \sum_{n=1}^{N-1} x_m(k) e^{-2\pi kn/N} \tag{3}$$

and spectral at k frequency S (k) as given in Equation 4.

$$S(k) = \frac{1}{M}\sum_{m=1}^{M} S_m(k) \tag{4}$$

B. Learning Vector Quantization

Learning Vector Quantization (LVQ) is a supervised version of vector quantization that can be used when we have each input data with class label. This learning technique uses the class information to reposition the weight vectors slightly, so as to improve the quality of the classifier decision regions, which is adapted from Kohenen Map. It is a two stage process of LVQ as shown Figure 3. Input of LVQ is FFT result with 4-40 Hz frequency range or 37 point number from the result of Equation 4, and two classes, upward and downward.

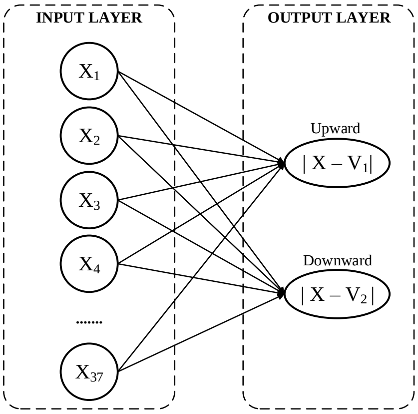

Figure 3: LVQ Architecture of two movement

If there were 40 set training data which consists of 20 sets and 20 sets of class 1and class 2 respectively, first, one set of each class was taken as a weight vector. The rest of 38 other training data set conducted the training, with the stages:

Each supervised training data, found distance for each class:

$$D_i = \sum_{j=i}^{n} \left\| x_{ij} - v_{ij} \right\|^2 \qquad (5)$$

where n = 37, i = 1 to 2.

The LVQ algorithm attempts to correct the winning weight Vi which has a minimum D under the conditions:

1. If the input xi and wining wi have the same class label, then move them closer by ΔV_i (j)=β(j)(x_ij-V_ij)
2. If the input xi and wining wi have different class label, then move them apart by ΔV_i (j)=-β(j)(x_ij-V_ij)
3. Weights vj corresponding to other input regions are left unchanged with ΔVi (t) = 0.

where β(t) is a learning rate that decreases with the number of epochs of training. In this way, we get better classification than by the SOM alone.

IV. Experimental Result

EEG signal recorded in two seconds with 512 sampling frequency, resulted in x = 1024. Thus, the results after the frame-based windowing are as shown in Figure 4.

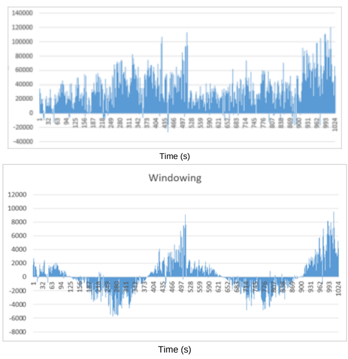

Figure 4: Frame based and windowing process

Fast Fourier Transfer of EEG signal in 4-40 Hz frequency range are as shown Figure 5.

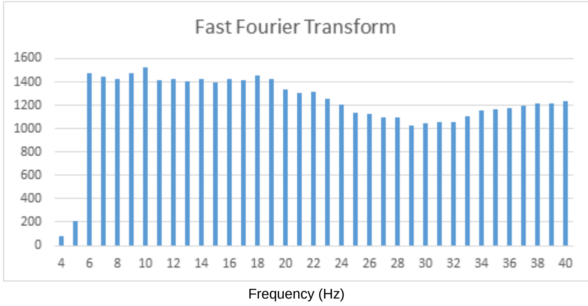

Figure 5: Fast Fourier Transform of EEG signal with downward imagination

Classification by LVQ with the training conducted with a minimum learning rate 0.0001, initial learning rate 0.05 and reduction of learning by 0.1 times, is as shown Figure 6.

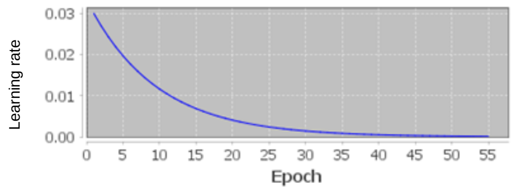

Figure 6: Decrease of learning rate

Before we used the game controlling, we tested the performance classifying to imagine moving upward or downward. Testing was conducted on the ability to distinguish imagination on action or movement of upwards or downwards comparing actual class. Testing conducted on 40 training data and 40 testing data with calculated number correct / 40 x 100% .

Table 1
Accuracy of Classification System toward Training Data and Testing Data

Subject	Accuracy (%)			
	Training Data		Testing Data	
	Without FFT	With FFT	Without FFT	With FFT
1	100	100	75	75
2	100	100	75	75
3	75	50	50	63
4	75	50	50	75
5	50	100	31	50
6	75	75	31	75
7	50	100	50	63
8	50	100	31	75
9	25	100	61	75
10	75	100	50	75
Average	68	88	50	70

The experiment result using FFT could improve the accuracy about 20%. There was an increase in accuracy of 68% to 88% of training data, and from 50% to 70% of testing data. These results are shown in Table 1.

Next, we tested the process on the system computing speed in moving the characters in the game based on the EEG data obtained in realtime.

Setting the game BCI performed for 30 seconds has generated 30 movements with an average of 0.014 seconds computing. While, the 1 minute setting produced 30 movements with an average of 0.024 seconds computing.

Both of the times were considered adequate to take action movement in an arcade game.

V. CONCLUSIONS

This research showed that the Fast Fourier Transform and Learning Vector quantization can be used as a method to control the motion of the arcade game of the imagination recorded EEG signals. The system gave 88% accuracy of training data and 70% accuracy of testing data.

Using FFT as a signal extraction can improve accuracy by 20%, from 68% to 88% toward training data and 50% to 70% of testing data.

Furthermore, the research also showed the computing time of using FFT and LVQ is quite brief, only 0.024 seconds to for one minute and 0.014 seconds to 30 seconds. The short time is realistic enough to be used as a control arcade game. The use of more data variance and more controlled state or conditions can also be seen as a suggestion to improve the outcome of this research in the near future.

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