Fast Brain Control Systems for Electric Wheelchair using Support Vector Machine

Ivan Halim Parmonangan[a], Jennifer Santoso[a], Widodo Budiharto*[a], Alexander Agung Santoso Gunawan**[a]

[a]School of Computer Science, Bina Nusantara University, Jakarta 11480, Indonesia

*wbudiharto@binus.edu, **aagung@binus.edu

ABSTRACT

This paper proposes a technology which enables healthy human brain to control electronic wheelchair movement. The method involves acquiring electroencephalograph (EEG) data from specific channels using Emotiv Software Development Kit (SDK) into Windows based application in a tablet PC to be preprocessed and classified. The aim of this research is to increase the accuracy rate of the brain control system by applying Support Vector Machine (SVM) as machine learning algorithm. EEG samples are taken from several respondents with disabilities but still have healthy brain to pick most suitable EEG channel which will be used as a proper learning input in order to simplify the computational complexity. The controller system based on Arduino microcontroller and combined with .NET based software to control the wheel movement. The result of this research is a brain-controlled electric wheelchair with enhanced and optimized EEG classification.

Keywords:electroencephalograph, optimization, support vector machine, wheelchair

1. INTRODUCTION

In this era, biomedical assistive devices are quickly developed. The widespread purposes make this field expand even faster. This research unleashed the potential in healthy-minded human; brain, no matter what their disabilities are as long as the brain is still healthy. Prior research has shown that human brain activity can be seen through electroencephalograph (EEG) and blood flow in the brain. This activity can be seen with technologies such as MRI. These days, researchers has succeeded to use brain to interact with computers which known as Brain-Computer Interface (BCI).

Vallabhaneni, Wang, and He defines BCI as "a method of communicating based on neural activity generated by the brain and is independent of its normal output pathways of peripheral nerves and muscles."[1] BCI is a potentially powerful communication medium which provides interaction between users and systems beyond the keyboard [2]. Brain neurons emit signals that will be captured, processed, converted, and classified as an instruction for computer system.

While most individuals with disabilities can be satisfied with manual wheelchairs, a segment of the disabled community finds that it is difficult or impossible to use wheelchairs independently [3], mainly people with a total paralysis with normal brain. However, these people are still able to use brain controlled wheelchair because they only need to use their mind to move around. Practically, the signal acquired by the EEG signal reader is raw EEG which is noisy and full of artifacts such as Electromyograph (EMG), Electrooculograph (EOG), Electrocardiograph (ECG), and also 50-60 Hz noise from electricity device hums as shown in Figure 1. Those noises change the amplitude and frequency of the pure EEG we want to obtain so that all kinds of noises have to be filtered in order to retrieve the purest possible EEG signals.

First International Workshop on Pattern Recognition, edited by Xudong Jiang, Guojian Chen, Genci Capi, Chiharu Ishii, Proc. of SPIE Vol. 10011, 100111N
 · doi: 10.1117/12.2243126

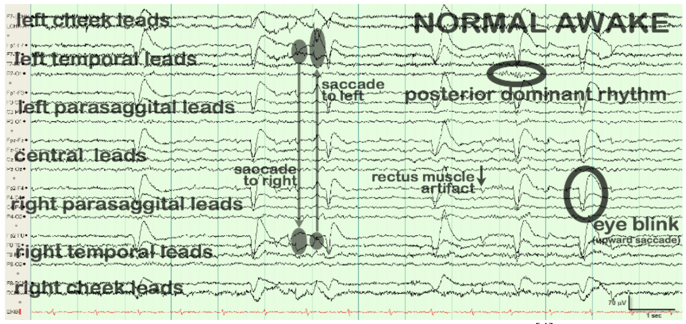

Figure 1. An image show raw EEG with noises [4]

The main problem of BCI system is the complexity of brainwaves which makes the accuracy of classification is not that much satisfying. Some algorithms to interpret thought based on EEG signals have been developed. Cheng-Wen Ko proposed that a thought can be interpreted by detecting spike from EEG signal combined with neural network [5]. Another research developed by Itturate et al. suggest a way to stimulate thought through virtual reconstruction of the scenario, continuously concentrating on the area of space to reach and finally controlling the navigation of electric wheelchair [6]. Galan et al. proposed an asynchronous EEG-based BCI to control a wheelchair with 64 channels [7]. However, the implementation is overly complicated and inefficient in channel usage, which can be reduced further.

The goal of the study is to create a brain-controlled wheelchair that will assist quadriplegic patients, who have very limited mobility, to be able to use their mind to control the wheelchair on their own. This study also has a purpose to optimize the brain control system on the wheelchair to minimize the effort exerted by the user to move the wheelchair. The optimization is done by finding appropriate commands to stimulate certain brain area with visual perception. Visual imagery and visual perception appear to engage frontal and parietal regions in more similar ways than occipital and temporal regions [8]. This finding may indicate that cognitive control processes function similarly in both imagery and perception.

Section 1 describes the background of the current condition and the introduction to the concepts of EEG, the main contribution of this study, as well as the problem statement, preliminaries, previous studies, and goal of the research. Section 2 explains our proposed method in solving this problem and a review of literature. Section 3 shows the analysis, process, and main result of the study. Section 4 concludes the study and explains further for future works.

2. MATERIALS AND METHODS

The system consists of three main components. The first component is the neuroheadset to capture EEG signal from the subject. The second component is a software application to receive the captured EEG signal from the helmet, convert the signal as a command for the third component, which is a microcontroller with motors to control wheelchair movement.

In this research, there are several key devices to support BCI and the electric wheelchair movement. Arduino UNO as the microcontroller operates two motors connected to the wheel of the wheelchair [9]. The device used to develop and run the application is tablet PC or laptop with Windows 7 or above installed and the software is written in C# with Accord. NET Framework library for the Machine Learning libraries [10]. Meanwhile, the brainwave reader device we are using is Emotiv EPOC+ as the newer version of the previous Emotiv EPOC that are bundled with extra libraries to retrieve raw EEG data from the device. Emotiv EPOC / EPOC+ features 14 EEG channels plus 2 references offering optimal positioning for accurate spatial resolution. Channel names, which are based on the international 10-20 electrode location system are AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, with CMS/DRL references in the P3/P4 locations. Since this study uses raw EEG data, digital signal processing is used to filter and preprocessed the captured raw EEG while SVM is used as the machine learning method to classify the preprocessed EEG signal. Figure 2 shows the image of Emotiv EPOC+ headset and the 14 channels of EEG.

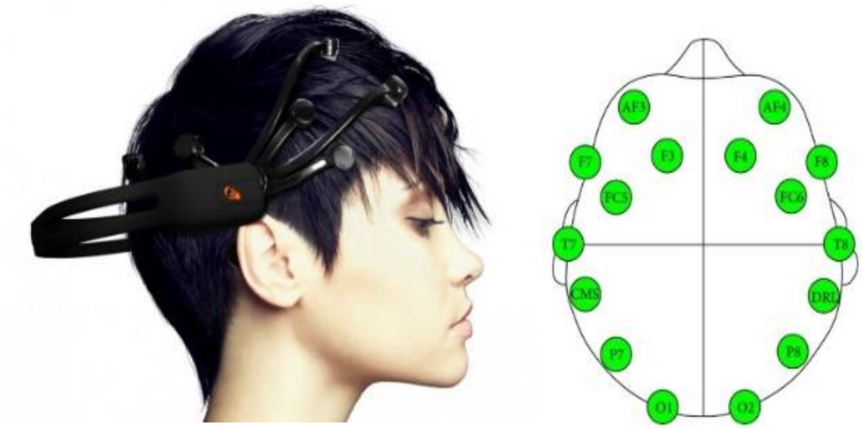

Figure 2. An image of Emotiv EPOC+ Headset and node placement [11]

In this study, the brain waves classified are only alpha and beta brain waves which represents relaxed activity and active thinking or concentration, respectively [12]. Then, captured EEG is to be filtered using Bandpass Filter [13] to keep in the desired frequencies (8 – 31 Hz), which will then result in filtered EEG in the range of the passband's frequencies.

Afterwards, the filtered EEG is then applied to windowing function [14], which convolutes non-periodic EEG signal into periodic signal to minimize spectrum leaks when applying FFT (Fast Fourier Transform). FFT itself is used to extract frequencies in EEG samples used for SVM input. The reason to use SVM as classifier despite of the complexity is the channels used as the input are only specific ones and preprocessed beforehand to compress the size. Therefore, SVM itself is suitable for EEG classification [15]. Block diagram of the whole system is depicted in Figure 3.

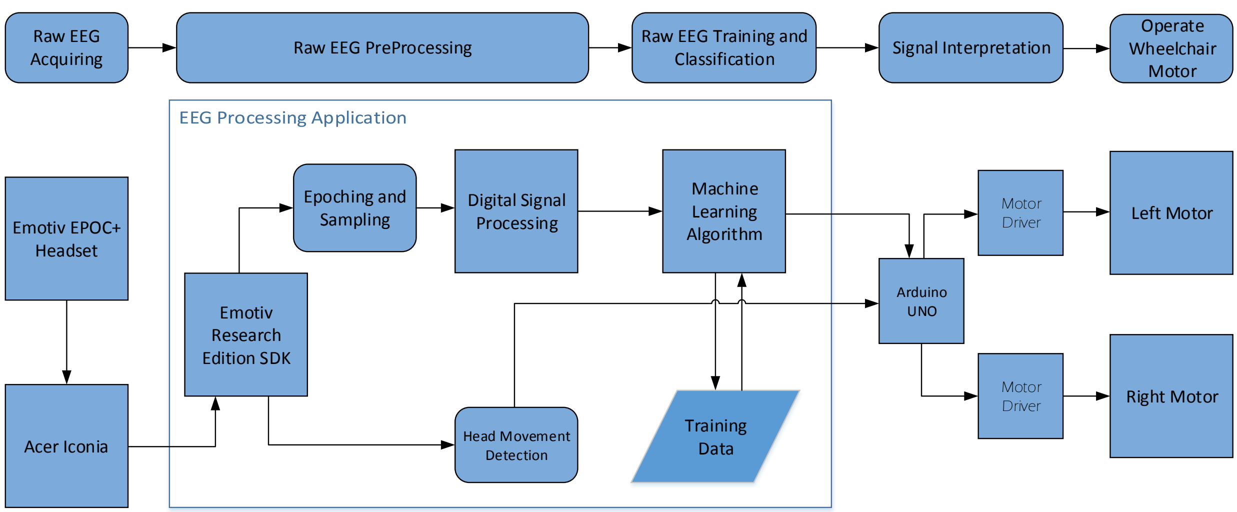

Figure 3. Block diagram of the system

The software uses multi-threading feature to do the classification of P8 and F3 independently. The preprocessed EEG is collected and inputted into SVM classifier continuously. The output is then collected and compared to the sensitivity. This process will give user a new experience that their focus is easily adjusted by changing the sensitivity control of each action. The P8 classification runs only when it is in neutral mode. Once the mode is changed into forward, the classification stops and user will no longer need to focus. To change back into neutral mode, user only need to blink either left or right eye. The F3 classification runs continuously after it has been trained or loaded and the EEG mode is chosen. The software also has a sensitivity control to ease user at maintaining their focus. The experiment will be done twice, with sensitivity adjusted and not adjusted. Meanwhile, the pseudocodes for the preprocessing, P8 classification and F3 classification can be seen below in Figure 4, 5, and 6 respectively.

```
Algorithm 1 Raw EEG Data Preprocessing
procedure EEGPreprocess
    if (P8.length ≤ 256 or F3.length ≤ 256) then
        Do GetRawEEG;
    else
        Do BPFilter;
        Do HannWindowing;
        Do FastFourierTransform;
    end if
    if (P8.trained) then
        Do P8Classification;
    end if
    if (EEGMode and F3.trained) then
        Do F3Classification;
    end if
end procedure
```

Figure 4. Algorithm for Raw EEG Data Preprocessing

```
Algorithm 2 P8 Classification
procedure P8Classification
    if FN.Flag = 0 then
        Get Preprocessed P8 EEG;
        Compute P8 SVM Classification Output;
        avg ← Average(P8Output)
    end if
    if avg ≥ N2F.Sensitivity then
        FN.Flag ← 1
    end if
end procedure
```

Figure 5. Algorithm for Neutral-Forward classification using channel P8

```
Algorithm 3 F3 Classification
procedure F3Classification
    Get Preprocessed F3 EEG;
    Compute F3 SVM Classification Output;
    avg ← Average(F3Output)
    if avg ≥ 0  and  avg ≤ Left.Sensitivity then
        LNR.Flag ← 0
    else if avg ≥ Right.Sensitivity  and  avg ≤ 2 then
        LNR.Flag ← 2
    else
        LNR.Flag ← 1
    end if
end procedure
```

Figure 6. Algorithm for Directional classification using channel F3

3. RESULTS AND DISCUSSION

The experiment shows that the brain activity is very distinguishable in parietal and frontal area. The data from those channels are good input for SVM that it could be separated linearly. The recording shows parietal and frontal lobe activities are easily separable which is good for machine learning input. To be precise, right parietal lobe is suitable for forward command and left frontal lobe is suitable for left-right command. Figure 7 shows the preprocessed, frequency-based EEG sample of the channels that best fit, P8 for forward command and F3 for left-right command.

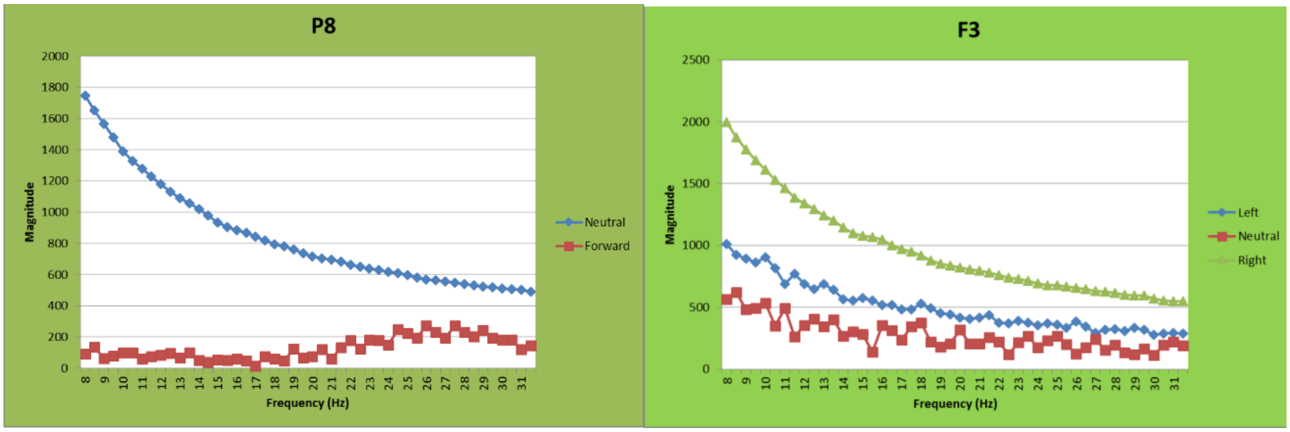

Figure 7. EEG Sample for Neutral-Forward Command from channel P8 and EEG Sample for Directional from channel F3

Figure 8 shows a wheelchair with brain control system and SVM that is successfully running.

Figure 8. Wheelchair with Brain Control System and SVM

The experiment is done to five subjects, each of different ages, genders, and physical disabilities excluding the brain. The five subjects are to test each command (move forward, move left, move right and stop) for 10 times randomly in full EEG mode except to stop which uses facial expression. To move forward, subjects imagine an object or focus at a point in front of them and imagine that object come closer. Whereas to move left or right, subjects determine the direction they want to go and focus at some object on the direction they want to move. Finally, to stop the wheelchair, subjects could just blink either left or right eye. The result of this experiment is counted from the number of true positive result from 10 tries per each movement. Table 1 below shows the results of the experiments without sensitivity adjustment:

Table 1. Result of experiment without sensitivity adjustment

Subject	**Actions (%)**				**Overall(%)**
	Forward	Stop	Left	Right	
1	90	80	80	70	
2	80	70	90	80	
3	90	100	70	80	
4	70	90	70	90	
5	100	90	80	90	
Average	86	86	78	82	83

Table 2 shows the experiment result with the same five subjects and the same random command procedure as before with the sensitivity adjusted:

Table 2. Result of experiment without sensitivity adjustment

Subject	**Actions(%)**				**Overall(%)**
	Forward	Stop	Left	Right	
1	90	80	80	80	
2	90	80	90	80	

Subject	Actions(%)				Overall(%)
	Forward	Stop	Left	Right	
3	90	100	80	90	
4	80	90	70	80	
5	100	90	90	90	
Average	90	88	82	84	86

4. CONCLUSION

Based on the current result, EEG signal is successfully captured by Emotiv and processed by applying Bandpass filter, Hann Windowing, and Fast Fourier Transform, making BCI implementation adequate. Out of 14 EEG channels in Emotiv EPOC, P8 is the most significant channel for which data can be used neutral to forward classification, while F3 is the most significant channel for directional classification (left, right, and neutral). There are some others like F5, F8, FC6, T7, and P7, but during the tests, P8 gave the best performance over the rest for neutral-forward classification, and F3 for the directional classification. The accuracy of the detection by SVM is 83% without sensitivity adjustment and 86% with sensitivity adjustment. This proves that using parietal and frontal lobe with visual perception gives a good result. The result also affected the user's ability to learn the new system. The more user are accustomed to the system, the better the result.

Future study would include testing more of other channel's performance and commands and therefore can be used as alternative for P8 and F3 whenever the subject has problems with the brain part associated with those two EEG channels that also opens a door to another usage of BCI. Possible further research would also include using optimized machine learning algorithm to increase accuracy of command classifications further.

ACKNOWLEDGEMENT

This work is fully supported by Toray Science and Technology Research Grant 2014-Japan.

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