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Implementation of Brain Computer Interface (BCI) as a Smart Wheelchair Motion Commands

Serly Yuliana[1], Maman Somantri[1], Teguh Prakoso[1,2] and Munawar A Riyadi[1,2*]

[1]Department of Electrical Engineering, Diponegoro University, Semarang, Indonesia
[2]Center for Biomechanics, Biomaterial, Biomechatronics and Biosignal Processing (CBIOM3S), Central Laboratory UNDIP, Semarang, Indonesia
Email : munawar@elektro.undip.ac.id

ABSTRACT. A wheelchair is a tool used to assist people with physical limitations in their legs. The most widely used are standard wheelchairs with a manual operating system by being pushed by hand. However, people with disabilities who have paralysis or suffer from neuromuscular and neurological conditions cannot use this wheelchair. Because of this, in this study focuses on implementing the Brain Computer Interface system to generate five commands to move a wheelchair. There are five important stages in the BCI system, that is signal acquisition, pre-processing, feature extraction, classification, and applications interface. Fast Fourier Transform (FFT) method used to extract brainwave features. The results of FFT are alpha (8-12Hz) and beta (12-30 Hz) waves in the frequency domain. For classifying brain waves into six classes as input commands to drive a DC motor used Support Vector Machine (SVM) method. Based on the test results, the average accuracy of the classification for the whole class reached 93,1%, the accuracy of class 0 (77,3%), class 1 (95,7%), class 2 (97,8%), class 3 (98,0%), and class 4 (97,5%).

Keywords: wheelchair, BCI System, FFT, SVM

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1. INTRODUCTION

A wheelchair is a tool to assist people with physical limitation in their legs, either due to illness, injury, or congenital disabilities [1]. The most widely used wheelchairs are standard wheelchairs with a manual operating system by being pushed by hand or another person's help [2]. Along with the times and technology, manual wheelchairs were modified by adding DC motor as a driver that can be controlled with a joystick [3], wheelchair instructed by head gesture[4], and voice commands [5]. So that, the user can move the wheelchair easily without power or another person's help. However, wheelchair with joystick controller used hand movements to operate it [6] and wheelchair with voice commands controller need clear pronunciations to operate it [5], so that people who have speech and hand disabilities e.g. who have paralysis or suffer from neuromuscular and neurological conditions such as amyotrophic lateral sclerosis, stroke, and spinal cord injuries cannot operate that wheelchairs. Because of this, in this research, the author develops the ability of a wheelchair that can move with brain wave commands by implementing a BCI (Brain-Computer Interface) system.

In this era, Brain Computer Interface (BCI) has become a very interesting topic among researchers in the fields of medicine, rehabilitation, health care, robotics, and entertainment [7]. BCI is a direct interface system from the brain to a computer or machine, which can receive commands directly from the brain. BCI converts electrical waves automatically extracted from EEG signals that can operate computers to control hardware that can be used to help people with motor dysfunction [8]. There are five important stages in the BCI system, namely signal acquisition, pre-processing, feature extraction, classification, and application interface [9]. The signal acquisition stage is capturing brain signals and performing noise reduction and artefact processing. Pre-processing is the stage to prepare the signal in a suitable form for further processing. Feature extraction is the stage to identify discriminative information on the brain that has been recorded. Classification is the stage of classifying signals into predetermined classes that take feature vectors into account [6]. The last stage is the application interface, which is the process of translating the classified signal into commands for connected devices such as bionic arms and wheelchairs [10]. To control a device that utilizes BCI, the subject must produce a pattern of brain activity with different characteristics. The pattern will be recognized and translated into commands. Most of the introduction of BCI relies on algorithms [11], where the algorithm is represented

[*] Corresponding author: munawar@elektro.undip.ac.id

by feature vectors [12]. In addition to classification, the selection of the EEG channel used and the selection of brain activity patterns are also important in developing BCI.

In a previous study on brain activity recognition patterns by Ivan Halim et al who conducted research on a fast brain control system for electric wheelchairs using the support vector machine (SVM) method. In this research, used of alpha (8-12 Hz) and beta (12-35 Hz) waves by using the EMOTIV sensor with 14 channels, the classification success rate reaches 83-86% in distinguishing 5 types of imagery motors. However, the implementation is a bit complicated and inefficient in terms of channel usage which can be reduced further [7]. Other previous research on brain activity patterns were also conducted by Munawar et al. In this research used Muse brain sensing which has four channels with the FFT method for feature extraction and the SVM method for classification which successfully classified five states to drive a wheeled robot with an accuracy rate of 91.78% [13]. Based on previous research, in this paper discusses the implementation of the BCI system which produces 5 classification classes for smart wheelchair motion commands using the Muse brain sensing sensor which has fewer channels than previous studies.

2. MATERIALS AND METHODS

2.1 System Design

The system design consists of hardware design that shown in Figure 1.

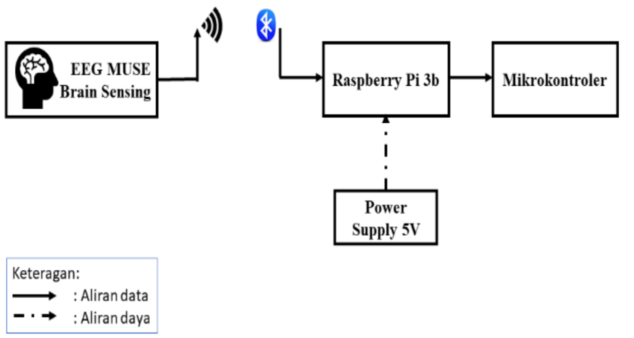

Fig. 1 Hardware design for implementing of BCI

In this research using Muse brain sensing to acquisition EEG signals. That is a product from Interaxon, Canada which is equipped with 5 channels (TP9, AF7, Fpz, AF8, TP10) with a sampling frequency of 256 Hz on each channel. The data acquired by Muse brain sensing include raw EEG, raw accelerometer, raw spectra (delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), gamma (30-44 Hz)), total power, artefact (eye blink, jaw clench), and Fast Fourier Transform (FFT) coefficients.

Raspberry Pi 3b is a mini computer that is used to perform signal processing that is feature extraction and classification. After signal computation is complete, raspberry pi will send the classification data to the microcontroller serially which is a wheelchair motion command.

2.2 Brain Computer Interface System

In this research focuses on the application of the BCI system to controlled wheelchair. as shown in Figure 2 that is flowchart of BCI system.

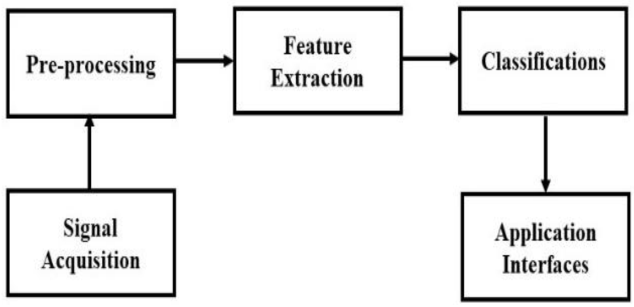

Fig. 2 BCI system

Signal acquisitions to stream EEG signals using the muse-lsl.py program that has been provided by the developer of Muse brain sensing, Alexander Barachant. Muse-lsl.py uses a function from the Streaming Layer Lab (LSL) adopted from the Python library that is `pylsl`. The program will scan and pair with the EEG Muse brain sensing that has been connected to the device via Bluetooth. After paired the program will send the detected EEG Muse brain sensing type and perform EEG data retrieval with a sampling frequency of 256 Hz. Then the data taken will be forwarded by opening a port using the function `outlet.push_sample(data[:, ii], timestamps[ii]`.

Then, the EEG signal will be windowed to reduce the discontinuity at the end of each frame due to the frame-based process. The type of window used in this study is the hamming window. The windowing process is done by multiplying the result of the window type with the frame-based result using equations:

$$w(n) = 0.54 - 0.46 \cos \frac{2\pi n}{N-1} \quad (1)$$

$$z(n) = x(n)w(n) \quad (2)$$

Where z(n) is window value N-sample, N is number of samples per frame, n is result of sample index of a frame, (n) is sample windowing result signal to n, x(n) is sample signal to N, w(n) is window type value to n.

After windowing process, signal will be extracted using FFT (Fast Fourier Transform). FFT used to convert the EEG signal from the time domain to the frequency domain using equations:

$$F(u) = \frac{1}{N}\sum_{x=0}^{N-1} f x \left[\left(cos\frac{2\pi ux}{N}\right) - j\left(sin\frac{2\pi ux}{N}\right)\right] \quad (3)$$

The FFT calculation produces a power spectral density for each brain wave namely, alpha, beta, gamma, and theta waves. Then the result of FFT becomes input for the classification process.

The next process after feature extraction is classification. In this study, a support vector machine (SVM) is used to classify EEG signals. SVM method can identify an object by finding the best hyperplane that serves as a separator between classes. hyperplane is a linear separator function, but non-linear hyperplane can be used for problems that cannot be solved using linear hyperplane. for a non-linear hyperplane, the data is transformed to a new feature space with a higher dimension so that the data can be separated linearly as shown in Figure 3.

The results of the classification are in the form of integer data 0,1,2,3,4 which are then sent to the microcontroller for wheelchair motion commands.

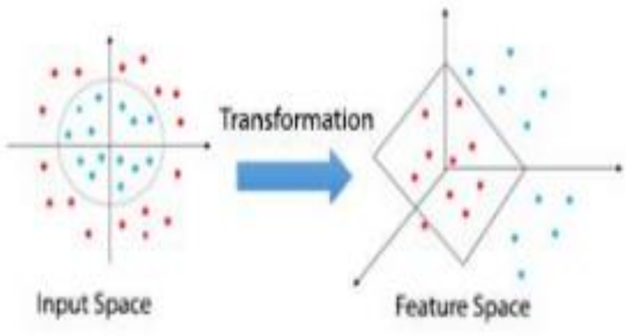

Fig. 3 Transformation from input vector to feature space

3. RESULT AND DISCUSSION

3.1 Signal Acquisition

The recording was done using a Muse brain sensing brainwave sensor with four channels, namely TP9, AF7, AF8, TP10. In the EEG data recording process, participants will be given 5 different motor imagery and combination of eye movements for approximately 4 minutes with details, recording duration for each condition for 40 seconds and a pause for each condition for 10 seconds.

The following are the requirements for participants in testing this Research:

1. Has no limitation of motion in the neck and eye muscles.
2. In a relaxed and focus state.

3.2 Pre-Processing and Feature Extractions

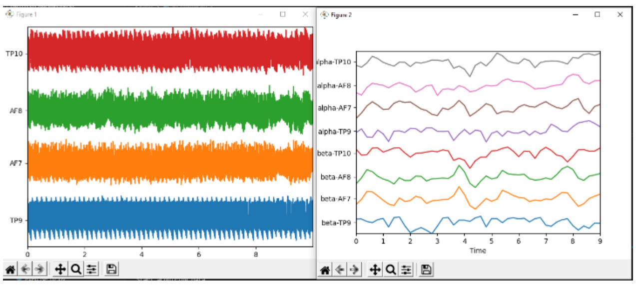

Fig. 4 The result of feature extraction

The results of pre-processing and feature extraction are in the form of certain types of waves that will be used as input for the classification process. In this research, 2 types of brain wave signals are used, namely alpha (8-12 Hz) and beta (12-35 Hz). Where, alpha and beta waves are EEG features that are active when humans perform motor movements. The results of pre-processing and feature extraction from the implementation of the program in this Research can be seen in Figure 4.

3.2 Classifications

Brain wave classification testing is carried out after obtaining the type of wave to be used and the combination of movements to determine certain wave characteristics for each class to be built. This research uses a combination of beta and gamma waves, as well as a combination of eye movements. During the testing process, participants are only allowed to carry out predetermined activities. In the test there was a "beep" sound for 2 times a sign to get ready before the recording process started, for the transfer of pattern recording, and at the end of the classification recording process there was a "beep" sound once.

Table 1
Overall Accuracy of Classifications

Participants	Iterations	Accuracy	F-Score
1	1	92,0%	0,917
	2	90,0%	0,898
2	1	96,9%	0,969
	2	93,8%	0,938
Average:		93,1%	0.930

In Table 1 shows the results of the overall classification test, it can be seen that the average overall classification success rate is 93,1%. The success rate of classification second participant is lower than the first participant, the accuracy rate of first participant is 94,4%, while the accuracy of second participant is 91,9%. The difference in success rates can be caused by the characteristics of the brain waves produced by each person differently. This type of eye motor movement is suitable for recognizing the pattern of brain wave activity for the first participant, but not suitable for second participant. So, from the results of these data, it can be said that the SVM algorithm as a brain wave signal classifier for wheelchair motion commands is able to classify brain wave patterns that appear with varying degrees of success reaches 93,1%. To increase the accuracy of the classifier, it can be done by looking for a combination of motor movements that are suitable for participants.

Table 2
Accuracy of Each Class

Partici-pants	Iterations	Accuracy of Each Class %				
		0	1	2	3	4
1	1	70,0	90,0	100	100	100
	2	70,0	100	90,0	100	90,0
2	1	92,3	92,3	100	100	100
	2	76,9	100	100	92,3	100
Average:		77,3	95,7	97,8	98,0	97,5

Table 2 shows the average success rate of EEG classification for each class. The success rate for class 0 is 77,3%, class 1 is 95,7%, class 2 is 97,8%, class 3 is 98,0%, and class 4 is 97,5%. From these data, the accuracy level of class 1 tends to be low, this is due to the characteristics of the brain waves that are captured for class 1 are less than optimal. Factors that affect the less than optimal detection of the EEG signal in each class are the user's lack of focus or fatigue. To improve classification accuracy, it can be done by combining motor movements that are more suitable for each class.

4. Conclusion

Best on the test result, the implementation of brain computer interface (BCI) system as a smart wheelchair motion command in the classification of real-time EEG signals. The level of accuracy generated in the classification of EEG reaches 93,1%. This means that the applied SVM algorithm can perform EEG classification quite well. The difference in accuracy in each class of EEG classification results is influenced by motor movements of the eye muscles, user concentration, and sweat attached to the Muse brain sensing sensor which can also reduce the level of accuracy. To get good accuracy in each class, the EEG classification can be done by looking for certain combinations of motor movements to produce certain activity patterns.

Acknowledgments

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References

[1] J. Utama and M. D. Saputra, “Design of electric wheelchair controller based on brainwaves spectrum EEG sensor,” *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 407, no. 1, 2018, doi: 10.1088/1757-899X/407/1/012080.

[2] A. M. Lokman, M. N. Ismail, N. A. S. Abdullah, and A. R. Omar, “Kansei Wheelchair Design Based on KJ Method,” vol. 23, pp. 4349–4353, 2017, doi: https://doi.org/10.1166/asl.2017.8329.

[3] T. Saharia and J. Bauri, “Joystick controlled wheelchair,” *Int. Res. J. Eng. Technol.*, vol. 4, no. 7, pp. 235–237, 2017, [Online]. Available: https://irjet.net/archives/V4/i7/IRJET-V4I740.pdf.

[4] M. Mudassir and A. Mujahid, “Modeling and Fabrication of Smart Robotic Wheelchair Instructed by Head Gesture,” *Indones. J. Electr. Eng. Informatics*, vol. 9, no. 3, 2021, doi: 10.52549/.v9i3.2892.

[5] M. Ilyas Malik, T. Bashir, M. Omar, and F. Khan, “Voice Controlled Wheel Chair System,” *Int. J. Comput. Sci. Mob. Comput.*, vol. 6, no. 6, pp. 411–419, 2017, [Online]. Available: www.ijcsmc.com.

[6] A. S. Junior and F. Arifin, “Prototipe Kursi Roda Elektrik Dengan Kendali Joystick Dan Smartphone,” *Elinvo (Electronics, Informatics, Vocat. Educ.*, vol. 4, no. 1, pp. 62–68, 2019.

[7] I. H. Parmonangan, J. Santoso, W. Budiharto, and A. A. Santoso Gunawan, “Fast brain control systems for electric wheelchair using support vector machine,” *First Int. Work. Pattern Recognit.*, vol. 10011, p. 100111N, 2016, doi: 10.1117/12.2243126.

[8] P. P. P. D. Negara, “Pengenalan Gelombang Otak Manusia Terhadap Rangsangan Impuls Suhu Air Dengan Brain Computer Interface (Bci),” *Tugas Akhir Univ. Sanata Dharma Yogyakarta*, pp. 1–66, 2018.

[9] M. B. Khalid, N. I. Rao, I. Rizwan-i-Haque, S. Munir, and F. Tahir, “Towards a brain computer interface using wavelet transform with averaged and time segmented adapted wavelets,” *2009 2nd Int. Conf. Comput. Control Commun. IC4 2009*, 2009, doi: 10.1109/IC4.2009.4909189.

[10] L. F. Nicolas-Alonso and J. Gomez-Gil, “Brain computer interfaces, a review,” *Sensors*, vol. 12, no. 2. pp. 1211–1279, 2012, doi: 10.3390/s120201211.

[11] D. J. McFarland, C. W. Anderson, K. R. Müller, A. Schlögl, and D. J. Krusienski, “BCI Meeting 2005 - Workshop on BCI signal processing: Feature extraction and translation,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 135–138, 2006, doi: 10.1109/TNSRE.2006.875637.

[12] R. O. Duda, P. E. Hart, and D. G. Stork, “Pattern Classification by Richard O. Duda, David G. Stork, Peter E.Hart .pdf.” p. 738, 2000, [Online]. Available: http://eu.wiley.com/WileyCDA/WileyTitle/productCd-0471056693.html.

[13] M. A. Riyadi, T. Prakoso, F. O. Whaillan, M. David Wahono, and A. Hidayatno, “Classification of EEG-based Brain Waves for Motor Imagery using Support Vector Machine,” *ICECOS 2019 - 3rd Int. Conf. Electr. Eng. Comput. Sci. Proceeding*, pp. 422–425, 2019, doi: 10.1109/ICECOS47637.2019.8984565.