Electroencephalogram (EEG) Signal Classification Using Artificial Neural Network to Control Electric Artificial Hand Movement

A S Saragih\textsuperscript{1,}, A Pamungkas\textsuperscript{1}, B Y Zain\textsuperscript{1}, W Ahmed\textsuperscript{2}

\textsuperscript{1}Department of Mechanical Engineering, Faculty of Engineering, Universitas Indonesia, Depok, 16424, Indonesia.
\textsuperscript{2}Engineering Requirements Unit, College of Engineering, Al Ain, Abu Dhabi, United Arab Emirates University

*Corresponding author’s : ashamsuddin@ui.ac.id

Abstract. All due to the complex nature of the electroencephalography (EEG) signal, it is a challenge to be able to use it as the driver of an electric artificial hand. By using EEG signal, the command for artificial hand movements becomes more intuitive and natural. This study aims to classify EEG signals to serve as electronic hand control. Classification is conducted using artificial neural networks (ANN), in which EEG signal datasets are obtained from a commercial brain computer interface (BCI). The ANN model obtained is expected to be able to determine that the EEG signal is one of the five EEG signals generated from five predetermined hand movements. This study proposes feature extraction and processing that is very simple but performs well, indicated by its small error value. The results show that ANN can classify five hand movements tested with an overall accuracy rate of 80%.

1. Introduction
Prosthetics are artificial devices that replace lost body parts, which are caused by trauma, disease or congenital conditions [1]. Prosthetic hands or artificial hands are grouped into two main groups, namely cosmetic and functional artificial hands. Cosmetic hands are made to resemble the looks of the original arm without any basic hand functions. Functional artificial hands are artificial arms that can perform several arm functions, ranging from simple functions to complex functions [2].

The development of artificial hand technology lies in the fields of actuators, sensors, controllers and fabrication. Hand control systems that have been developed include electromyography (EMG) and the EEG. Control systems using EMG contractions of the muscles in the arms produce raw EMG signals, in which raw EMG signals are manifestations of neuromuscular activity associated with muscle contraction [2]. Artificial hand control using EMG signals has limitations in some cases such as inconsistency problems, less intuitiveness or must be done in a patient state and requires muscle work. Research on the use of EEG signals as artificial hand controls uses facial expressions [3, 4]. Certain facial expressions such as blinking will generate an EEG signal that will be recorded by the sensor. Then this signal is processed to move the artificial hand.

This control system has weaknesses, including facial expressions having limitations which therefore limits the artificial hand control. The EEG signal produced by facial expression, in principle, is not an EEG signal to move an artificial hand. Thus, the control system is less natural. The EEG signal from facial expressions that has been processed by the system in the headset EEG becomes a
mature signal. To get control of natural limbs originating from the brain, user factors and design preferences are a priority in the process of translating brainwaves into commands in moving artificial hands. Therefore, the purpose of this study was to classify electroencephalogram (EEG) signals originating from hand movements using artificial neural networks. After the classification is successfully carried out, the network can determine the type of hand movements that are tested randomly. The output of this network is expected to be used as an input command to move artificial hands, so that electronic artificial hand control can be achieved using EEG signals. By using EEG signals, the command for artificial hand movements becomes more intuitive and more natural.

2. Materials and methods
The research method consists of two stages, training and testing. At the training stage, the subject performs hand movements in accordance with medical rehabilitation procedures. Five commonly used hand movements; cylindrical grip (CG), power handgrip (PG), tripod pinch (TP), index point (IP), and resting (open grip-OG) are performed. A movement produces an EEG signal, which is then captured by EEG sensor OpenBCI® Cyton to obtain raw signals. This raw signal is processed through feature extraction stages, in which the obtained EEG signal is divided into training data and test data. Training data is used as input in the classification training process. The method used for the classification process is artificial neural network (ANN). The classification class target is determined based on the type of hand movement according to Table 1. The output parameters obtained by the network from the EEG signal classification process are used for the testing process.

| Item  | CG       | PG       | TP       | IP       | OG       |
|-------|----------|----------|----------|----------|----------|
| train data | 1-9    | 10-18   | 19-27   | 28-36   | 37-45   |
| target | 0.00    | 0.25     | 0.50     | 0.75     | 1.00     |

The design of the ANN architecture begins with de-signalization process, then changes are made to the training parameters such as the number of hidden layers, the number of epochs / iterations and the rate of learning. Evaluation of classification results is done by determining the accuracy value according to the following equation [5]:

$$\text{accuracy} = \frac{\sum_{i=1}^{t} tp_i + tn_i}{tp_i + fn_i + fp_i + tn_i}$$  \hspace{1cm} (1)$$

Where $tp_i$, $tn_i$, $fn_i$, and $fp_i$ are obtained from the confusion matrix shown at table 2 as follows:

| Data class | classified as positive | classified as negative |
|------------|-------------------------|------------------------|
| Positive   | true positive (tp) | false negative (fn) |
| negative   | false positive (fp) | true negative (tn) |

The ANN used for the classification of EEG signals is multi-layer neural network backpropagation. The input pattern used in the network is a dataset of five movements carried out by the test subjects as shown in Figure 1. The network is designed using one input layer consisting of 48 neurons obtained from the extraction of six features and each represents the 8 channels of EEG sensor OpenBCI® Cyton. There are three hidden layers, with the number of neurons determined by trying several configurations until high performance or a low error value is achieved. One output layer consists of one neuron. The activation function used is a binary sigmoid function.

The next step is to determine the network training function. Perfect performance is achieved if the error value is zero. Since that is difficult to achieve, the error value close to zero can be categorized as having a good performance. Experiments have been conducted using nine training functions from Matlab® software.
The previous experimental results showed that the optimal training function to be used in the classification process is the function of trainlm. Trainlm is a Levenberg-Marquardt (LM) algorithm that is classified as a high-order adaptive algorithm that can minimize Mean Square Error from a network. The function ‘trainlm’ is also widely used in several studies and has proven effective as a learning function. By using the training function and the same training parameters, the EEG signal classification process is carried out on 10 subjects.

3. Results and discussion
The others training functions of traincgb, traincfg, traincgp and trainrp have low performance that during the training process, the training function gradient value or minimum step has been reached before the performance goal is reached.

Figure 2 shows that the training function traingda produces similarly low performance even though the maximum epoch value has been reached. Traingdx and trainlm managed to get a pretty optimal performance. Based on the results of this experiment the ‘trainlm’ will be used on the network for the process EEG signal classification for 10 subjects.
By using the training function and the same parameters, the EEG signal classification process is carried out on 10 subjects. Figure 3 shows that out of 10 subjects who were trained, the network training error value was almost close to zero. There is a significant deviation in some data as happened in subject 3 and subject 9, but still within tolerable limits. The 13th data of subject 3 has an error value of 0.00618, while the 8th data of subject 9 has an error value of 0.00512. The cause of the error is because the data has a small suitability with the target data that has been set. In the picture it can also be seen that subject 1 and subject 8 have an error value close to zero which is relatively stable.

3.1. Network testing

The results of network testing using test data are shown in Figure 4. Overall, the simulation results on the test data are quite successful. For example, in the first test subject, the first movement test data was identified by the network according to the movement class ‘cylindrical grip’. The second movement test data that should have been recognized as a ‘power grip’ movement by the network, is recognized as the ‘index point’ movement. The third movement test data is also able to be correctly recognized as a ‘tripod pinch’ movement, as well as the fourth movement test data that can be correctly recognized as an ‘index point’ movement, even though there is a difference in the output value compared to the target value. The fifth movement test result, the ‘open grip’ movement, is very well recognized with an output value that is very close to the target value.

3.2. Artificial hand testing

The design of artificial hand is developed by improving the anthropomorphically. The actuation of the artificial hand fingers is achieved by tendon mechanism. The servos are controlled by microcontroller with custom proto shield located near the back of the hand.

The dimension of the hand, with all fingers open, is 143 mm long, 120 mm wide, and 15 mm thick. For the forearm, it is 274 mm long, 79 mm wide, 49 mm thick, and 76 mm thick at battery slot. The weight of the prosthetic hand with servo and microcontroller is 463 grams, while the total weight
including batteries is 625 grams. The prosthetic hand is manufactured through FDM 3D printing using PLA+ material. Here, 3D printing manufacturing method is given a special emphasis, especially in relation to production of prostheses. Human hands can greatly differ from one person to another, according to gender, age, race, and any other factors. In relation to the production of prosthetic hands and prostheses devices in general, 3D printing increases versatility of the production process of prostheses devices, especially even though they are complex and highly customized objects, designing and production time can be greatly shaved.

![Figure 7. Attempt to perform open grip (top left), power grip (top middle), tripod pinch (top right), index pointing (bottom left), cylindrical grip (bottom right) by artificial hand.](image)

After all the hand components, tendon, servo motor, cables and microcontroller have been installed, the created artificial hand is ready for experimental functionality testing. The tendon used for the artificial hand is a 0.14 mm diameter-fishing line. Fishing line is used as the tendon since it does not stretch when it is pulled, rather, it keeps its tension. In comparison to the predetermined grip postures, the created artificial hand can perform all of the 5 postures as shown in Figure 7.

4. Conclusions
Classification of electroencephalography (EEG) signals generated from hand movements was carried out using artificial neural networks (ANN). The test results show that the ANN model obtained is able to determine the type of hand movement tested from randomly determined test data. The classification of five hand movements tested has a total accuracy level of 80%. Thus, it shows that the classification of EEG signal hand movements can be done through a simple process without needing long signal processing procedure. The Classification was using backpropagation artificial neural networks with trainlm as the training function. The feature extraction used are minimum value, maximum value, mean value, median value, mode value and standard deviation value. The result lay on a specific electrodes configuration of the EEG sensor. Change of the configuration may result different accuracy.

5. References
[1] M. C. Mohan and M. Purushothaman, "Design and fabrication of prosthetic human hand using eeg and force sensor with arduino micro controller," in 2017 Third International Conference on Science Technology Engineering & Management (ICONSTEM), 2017, pp. 1083-1086.
[2] O. B. Lörinczi and P. Aradi, "Development of a prosthetic hand regarding complex motion and controllability" J Periodica Polytechnica Mechanical Engineering, vol. 55, no. 2, pp. 101-104, 2011.
[3] D. Bright, A. Nair, D. Salvekar, and S. Bhisikar, "EEG-based brain controlled prosthetic arm," in 2016 Conference on Advances in Signal Processing (CASP), 2016, pp. 479-483: IEEE.
[4] M. A. A. Kasim et al., "User-friendly labview gui for prosthetic hand control using emotiv eeg headset," Procedia Computer Science, vol. 105, pp. 276-281, 2017.
[5] M. Sokolova, G. Lapalme, and Management, "A systematic analysis of performance measures for classification tasks," Information Processing and Management, vol. 45, no. 4, pp. 427-437, 2009.

Acknowledgments
This initial research works was funding by Direktorat Riset dan Pengabdian Masyarakat (DRPM) Universitas Indonesia under PITTA-A program no.NKB-0453/UN2.R3.1/HKP.05.00/2019.