The Bionic Hand Movement Using Myo Sensor and Neural Networks

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***Abstract*— One part of human body in which very useful in this life is a hand. This life will be disrupted if one or both of these hands do not work, due to disability or amputation. One of the contributions that help this condition is the bionic hand. This study have developed a bionic hand that consist of six servo motors to drive the fingers movement. Myo sensor is used in this bionic hand, it is located in the forearm. It has been used to record the muscle signals. Feature extraction of the muscle signal was formulated by using root mean square (rms). Kind of the bionic hand movement was found by identifying the movement signal pattern using back propagation through the artificial neural network. The output data obtained from back propagation was processed by microcontroller and transmitted to the servo motors for getting a movement of the bionic hand. Based on experimental data, five kinds of movement were tested in this system, average of recognition for each movement: handful accuracy movement 65%; pointing-fingers 75%; wave in 100%; wave out 75%; and spread 100%. Testing for the whole movements (five kinds) were performed with the average error 17%.**

***Keywords*— bionic hand, myo sensor, root mean square, back propagation, microcontroller, servo motor.**

I. INTRODUCTION

Along with the development of robotics technology in the field of robot, a lot of researches have done to help people in everyday life. One of these studies are still currently being developed is the bionic robot. Bionic robot is a robot that is implanted in humans to replace the function and role of missing human body parts such as the hands or feet. The human body parts are very important for people to perform daily activities one of which is a hand. Losing a hand due to an accident or paralysis will cause men to have difficulty in carrying out their daily activities. For example, a person who lost his hand, will be difficult to perform tasks related to the function of the human hand. Researchers are trying to develop a bionic arm robot to solve the aforementioned problems. The bionic hand will be controlled via myoelectric signals generated by human muscle. Basically, the human body has electricity, including one containing the muscles. Although muscle has electrical signals, but the strength of the resulting voltage is very small. A small electric can be catched up using a set of electronic devices (sensors). In this study, the Myo sensor limited only to the EMG (electromyogram) sensor has been used to get the EMG signals generated by muscle movement on the human hand [1] [5]. Data is read by EMG then sent via Bluetooth to a Personal Computer (PC) to be processed and then sent to the bionic arm robot which was equipped with a special microcontroller. All functions in Myo sensor is processed by ARM Cortex M4. Meanwhile the processor of the arm robot is one of ATMega series. The data received will be processed, then ordered to drive the six servo that is embedded in the arm robot mechanics. All of the above processes will produce a new function that is a similar to real human hands.

Study on the Myo sensor to move the hand robot has been done in some previous researchers [1], but there are still many shortcomings regarding the method of introduction of the signal. The previous research using binary control algoritm method for classifying signals, meanwhile this research using artifical neural network is back propagation as a method for classifying signals.

Based on this condition, many researchers [2], [3] have been trying the other method for identifying the signal including in this study, namely back propagation through the artificial neural network to produce the better output.

II. PREVIOUS WORKS

Previous researchers have shown some results and developments that can be used as references for this study. Related studies that have been carried out as follows:

The research conducted by Cahyo Setiawan suggested the use of spring on finger parts of the robot make it more difficult to do a clenching movement. Because when the spring is pulled, then there will be a repulsive force of the spring [1]. Changing the position of Myo sensor that is placed on the arm will result in changes to the data [6]. The only movements that can be used are the ones with unique data compared to the others. Movements with similar data cannot be used as a reference to the input of the hand robot.

Research conducted by Iqbal Maulana Malik suggested that back propagation network can be used to classify 6 movements that will be used to control the slide. Back propagation network that is most ideal for the system is the one using hidden nodes twice as much as the input nodes [2]. More natural and flexible interactions have been achieved since the availability of user who can control slide from a distance with a more complex features such as next, previous, zoom in and zoom out commands, dragging the slide while zooming, giving highlights, and free drawing. Calibration to the user can be done by recording every movement pattern.

According to research by Suresh M., Krishnamohan P. G. and Mallikarjun S. Holi, the EMG signal is the sum of the disposal of all motor units in the range of pick-up electrodes. Nervous system always controls muscle activity (contraction/ relaxation) [3]. Therefore, the EMG signal is a complex signal, which is controlled by the nervous system and depends on the nature of the anatomy and physiology of muscle.

According to the study by Nomiyasari, EMG is a bioelectric recording instrumentation used to determine the signal caused by skeletal muscle activities. This muscle is one of human organs that move the skeleton [4]. Skeletal muscle has the nature of conscious, unconscious, and irregular because these activities depend on the will of the user. In general, the working principle of the skeletal muscle is relatively similar to the heart muscle, with the difference is the origin of the stimulus. The motion of the muscle does not possess automaticity. Stimulus originates in the brain and transmitted through nerves. To determine the EMG signal, electrode is placed as a medium of interaction.

III. Methodology

Design of the whole system for this research is shown in Fig. 1.

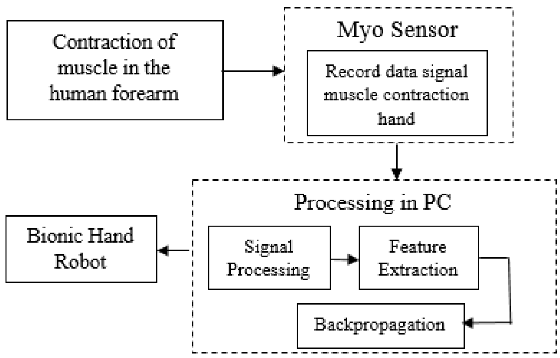

Fig. 1. Diagram of the system design

In this study, the first thing to do is to get the signals from muscle contractions in human hands using Myo sensor. The placement of Myo sensor should not be arbitrary because it has eight electrodes that will be used to record the activity of several muscles located on the human forearm. These sensors record data from muscle contraction, and then the data is processed on a PC to extract the features that will be established as patterns and be classified by method of back propagation. From this classification, it will generate the type of movement that is already recognizable from the input signal, then take a decision and sent it to the bionic hand robot to perform the same movement with user's hands.

A. Signal Processing

In this research tested the input signal to the system is still in a short times (50ms) per data retrieval. The signals are still in the time domain because if using preprocessing like Fourier transform in order to produce a better signal feature turn out happened is a slow response to the performance of the system should be running close to the real time.

While there is no movement, human muscles still emit signals recorded by EMG sensor, it is evident from the persistence of the value of the amplitude of the electrical muscle, although very small. In this study, the signals are called noise, so it needs a way to distinguish the active signal and noise. Active signal is obtained from an average of idle data which then calculated to find the value of the standard deviation to produce a maximum value of idle data. If the data is larger than the maximum idle data, then the data is an active signal. Value of standard deviation and maximum idle data can be calculated using equation 1 and 2.

$$SD = \sqrt{\frac{\sum_{i=0}^{N}(X_i - \mu)^2}{N}} \tag{1}$$

Where:
SD = standard deviation
N = sample data
X = raw idle data
μ = average of idle data

$$Max_{\text{idle data}} = X_{\text{idle data}} + SD_{\text{idle data}}) \tag{2}$$

Where:
Max = max value of idle data
X = average of idle data
SD = standard deviation

B. Feature Exraction

Feature extraction needs to be done in order to get the features of input signal each movement [2] [7]. In this research, researchers implement RMS method to obtain signal features each movement. RMS (root mean square) is "squared and then averaged, then squared root) [2]. RMS is carried out to identify the characteristic features of each movement. In this study the characteristics used to identify each movement are the RMS value of each EMG channel. The RMS value of each channel can be calculated using equation 3.

$$\boldsymbol{RMS} = \sqrt{\frac{\sum_{0}^{n} \boldsymbol{Xn^2}}{\boldsymbol{N}}} \tag{3}$$

Where:
RMS = value of RMS (*root mean square*)
Xn = n^{th} data
N = the number of signal

If RMS value of each channel has been found, then the next step is to find the minimum and maximum values of the RMS value. The minimum and maximum values are used to normalize the data to all channels with the range of value between 0 and 1. The normalized data can be calculated using equation 4.

$$\boldsymbol{Dn} = \frac{\boldsymbol{X - dataMin}}{\boldsymbol{dataMax - dataMin}} \quad (4)$$

Where :
Dn = data normalized
X = RMS value
dataMin = smallest data
dataMax = biggest data

Calculation of equations 3 and 4 will produce RMS values that have been normalized for each channel. These data will form a pattern that will be used as input for back propagation. Example of movement pattern is shown in Fig. 2.

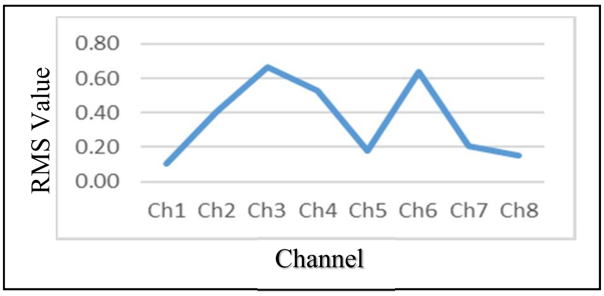

Fig. 2. Example of RMS data pattern that has been normalized

C. *Backpropagation*

Back propagation artificial neural network is one model of the popular network on artificial neural networks. This network model many used to be applied in the resolution of a problem related to the identification, prediction, pattern recognition, classification and so forth [6]. In practice repeatedly, this algorithm will produce a better performance. This means that the "weight of interconnection" ANN getting closer to weights that should be. Another advantage of this back propagation artificial neural networks is its ability to learn (adaptive) and immune to error (Fault Tolerance) with that advantage, the artificial neural networks can create a system that will withstand damage (robust) and consistently worked well. Thus, in this research only using back propagation artificial neural networks method as a method for pattern recognition and classification.

The method used in this research to recognize signal patterns is back propagation. Back propagation is one of a artificial neural network with supervised learning. Back propagation has three layers, namely input layer, hidden layer and output layer. In this research, back propagation method is selected because it has forward and backward learning so it is more accurate to recognize patterns of signals and classify them to be a type of movement. Input from back propagation on this signal is normalized RMS data of each channel. So the network architecture consists of eight input nodes, 24 hidden nodes and 5 output nodes. The resulting output is sent to a microcontroller on the bionic hand robot. It is expected to create network structure which can be used to classify 5 movements. The architectural design for the back propagation of this system is shown in Fig. 3.

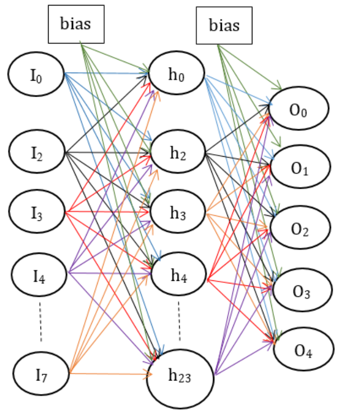

Fig. 3. Structure back propagation network

Learning Forward

Layer 1:

Each input node (xi, i = 1,..., n) receives signals (xi) and deliver the signal to all hidden layer node,

$$O_i^{\ L1} = X_i \quad (5)$$

Layer 2:

$$a_j = \sum_{i=1}^{N} O_i^{\ L1}\, W^{L1-L2}{}_{i,j} \quad (6)$$

$$O_i^{\ L2} = \frac{1}{1 + exp^{-(a_j + bias_j)}} \quad (7)$$

Layer 3:

$$b_k = \sum_{j=1}^{N} O_j^{\ L2}\, W^{L2-L3}{}_{i,j} \quad (8)$$

$$O_k^{\ L3} = \frac{1}{1 + exp^{-(b_k + bias_k)}} \quad (9)$$

Calculations of the average error of learning patterns were performed using the MSE (Mean Square Error) function.

$$Err(MSE) = \frac{1}{2}\left(O^{\ L3} - O_K^D\right)^2 \quad (10)$$

Learning Backward

Error output Layer 2

$$a_j = \partial_2 = \frac{dErr_k}{da_j} = \frac{dErr_k}{db_k}\ x\ \frac{db_k}{dO_j^{L2}}\ x\ \frac{dO_j^{L2}}{da_j} \quad (11)$$

$$Err_j = \frac{dErr_k}{db_k}\ x\ \frac{db_k}{dO_j^{L2}} = \sum_{k=1}^{L} \partial_3 w_{i,j}^{L2-L3} \quad (12)$$

$$a_i = \partial_2 = Err_j O_j^{L2}\left(1 - O_j^{L2}\right) \quad (13)$$

Updates weight L2-L3 (Hidden to Output)

$$\Delta w_{j,k}^{L2-L3} = \eta.\frac{dErr_k}{dw_{j,k}^{L2-L3}} = \eta.\frac{dErr_k}{db_k}.\frac{db_k}{dw_{j,k}^{L2-L3}} = \eta.\partial_3 O_j^{L2} \quad (14)$$

$$w^{L2-L3} = w^{L2-L3} + \Delta w_{j,k}^{L2-L3} \quad (15)$$

Updates weight L1-L2 (Input to Hidden)

$$\Delta w_{i,j}^{L1-L2} = \eta.\frac{dErr_k}{dw_{i,j}^{L1-L2}} = \eta.\frac{dErr_k}{da_j}.\frac{da_j}{dw_{i,j}^{L1-L2}} = \eta.\partial_2 O_i^{L1} \quad (16)$$

$$w^{L1-L2} = w^{L1-L2} + \Delta w_{i,j}^{L1-L2} \quad (17)$$

Learning rate updated with

$$Learning\_rate = \eta(k) = \frac{\eta_0}{1+\frac{k}{k_0}} \quad (18)$$

Information:

X_i : Input signal.
${O_i}^{L1}$: Output layer 1.
a_j : Addition
${W^{L1-L2}}_{i,j}$: Weight between layer 1 and layer 2
${O_i}^{L2}$: Output *layer* 2.
b_k : Addition
${W^{L2-L3}}_{i,j}$: Weight between layer 2 and layer 3
${O_k}^{L3}$: Output *layer* 3.
$Err(MSE)$: Error output layer 3.
O_K^D : Target.
∂_2 : Error output layer 2.
$\Delta w_{j,k}^{L2-L3}$: Delta weight layer 2 and layer 3.
$\Delta w_{i,j}^{L1-L2}$: Delta weight layer 1 and layer 2
η : learning rate.
K_0 : initial time constant
K : constant time.

In this research, the training data used for learning at the back propagation method is still being done with a trials phase just one user by taking 10 times data of each movement. Because only one user, this research has not been conducted validation of a system that is built for example validated with the data set. Then the data used to train the system as much as 50 data for each movement were taken each 10 times the data.

To get the most excellent architectural design, the researchers tested the value of the parameter value by changing the number of hidden layer parameter that must be equated, namely learning rate and error tollerance.

In this research pilloted by changing the parameters of hidden layer, with learning rate by 0,6 and error tollerance is 0,00001. At the time of the training process in a number of hidden layer 8 obtained the number of iterations is small but there is an error that is high enough. At the time the training process on a number of hidden 16 found the number iterations for more but still there is an error is nearly equal to the number of hidden 8. Meanwhile, at the time of the training process on the number of hidden layer 24 obtained the number of iteration is quite a lot compared hidden 8 and 16 but the resulting error value is small.

Therefore, based on the testing that was done on a number of hidden used this system requires a high degree of accuracy so that the researchers chose to use the number 24 because it has a high hidden small error.

TABLE I. ARCHITECTURE DESIGN TESTING

Hidden	Learning Rate	Error Tolerance	Number of Iteration	Error
8	0.6	0.00001	184885	0.000017
16	0.6	0.00001	218852	0.000016
24	0.6	0.00001	262359	0.000011

In this system design, layer one of back propagation network has eight nodes. Each node contains normalized RMS values of each EMG channel. Normalized back propagation input values are in the range of 0 to 1. Value range of 0 and 1 is chosen to make it easier to perform computation on computers. Layer two on back propagation network has eight nodes, obtained from the experiment. Table 1 shows the back propagation input of this system.

TABLE II. INPUT BACK PROPAGATION

No	Node Layer 1	Input
1	Node 1	Normalization RMS Channel 1 EMG
2	Node 2	Normalization RMS Channel 2 EMG
3	Node 3	Normalization RMS Channel 3 EMG
4	Node 4	Normalization RMS Channel 4 EMG
5	Node 5	Normalization RMS Channel 5 EMG
6	Node 6	Normalization RMS Channel 6 EMG
7	Node 7	Normalization RMS Channel 7 EMG
8	Node 8	Normalization RMS Channel 8 EMG

Output of back propagation is used to classify the five movements including clenching, pointing, spreading, wave in and wave out. Table 2 shows the initialization of the target value of the desired output for each movement.

TABLE III. INITIALIZATION TARGET OUTPUT BACK PROPAGATION

No	Movement	Out 1	Out 2	Out 3	Out 4	Out 5
1	clenching	1	0	0	0	0
2	wave in	0	1	0	0	0
3	pointing	0	0	1	0	0
4	wave out	0	0	0	1	0
5	spreading	0	0	0	0	1

From the results of training with the learning rate of 0.00001, is obtained the weight of input to hidden and the weight of hidden to output. The weight values of input to hidden and hidden to output will be used to classify 5 output movement. Table 3 shows the input pattern for each movement.

TABLE IV. INPUT PATTERN EVERY MOVE

Movement	Move the input pattern							
	Ch1	Ch2	Ch3	Ch4	Ch5	Ch6	Ch7	Ch8
clenching	0.43	1	0.33	0.50	0.77	0.92	0.73	0.28
wave in	0.22	0.12	0.33	0.48	0.29	0.45	0.51	0.88
pointing	0.25	0.44	0.41	0.29	0.48	0.66	0.64	0.49
wave out	0.56	0.93	0.79	0.63	0.15	0.04	0.08	0.11
spreading	0.10	0.40	0.67	0.53	0.18	0.64	0.21	0.15

Table 3 shows the feature extraction pattern for each channel to be used as input back propagation. The value of each EMG channel is used as input of back propagation, and then mapped using weight value of input to hidden and hidden to output that have been obtained at the time of training. Mapping results are shown in Table 4.

TABLE V. RESULT MAPPING OF INPUT TO OUTPUT

Movement	Out1	Out2	Out3	Out4	Out5
clenching	0.96	0.00	0.00	0.00	0.00
wave in	0.00	0.99	0.00	0.00	0.00
pointing	0.00	0.00	0.92	0.00	0.00
wave out	0.00	0.00	0.00	0.90	0.29
spreading	0.00	0.02	0.00	0.00	0.99

IV. RESULT

Testing phase of bionic arm robot movement is the end result of the aforementioned steps. At this test, the bionic arm robot is already integrated with a PC that is used to process the signals that have been recognized by back propagation. At this stage, the arm robot receives data that has been processed on the PC and recognized by back propagation as a desired movement pattern.

a. Relaxing Movement

From Fig. 4, it shows a demonstration of relaxing movement. When the user's hand is not moving or in a state of relaxation, the robot will perform relaxing motion.

Fig. 4. Robotic arm for movement relax

b. Clenching Movement

From Fig. 5, it shows a demonstration of clenching movement. When a user's hand is clenching, then the robot will mimic its movement. In this case, when the user's hand is clenching, the robot is also clenching.

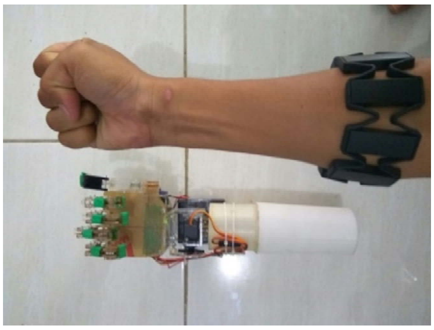

Fig. 5. Robotic arm for movement clenching

c. Pointing Movement

From Fig. 6, it shows a demonstration of pointing movement. When a user's hand is pointing, the robot will duplicate its movement. In this case, when the user's hand is pointing, the robot is also pointing.

Fig. 6. Robotic arm for movement appoint

d. Wave In Movement

From Fig. 7, it shows a demonstration of wave in motion. When a user's hand is doing a wave in, then the robot will also be doing the same movement. In this case, when the user’s hand is doing wave in, the robot is also doing wave in.

Fig. 7. Robotic arm for movement wave in

e. Wave Out Movement

From Fig. 8, it shows a demonstration of wave out motion. When a user's hand is doing a wave out, then the robot will also be doing the same movement. In this case, when the user’s hand is doing wave out, the robot is also doing wave out.

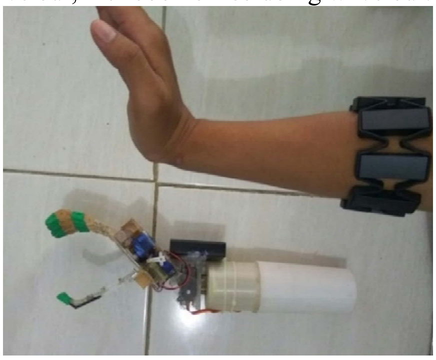

Fig. 8. Robotic arm for movement wave out

f. Spreading Movement

From Fig. 9, it shows a demonstration of spreading movement. When a user's hand is spreading, then the robot will mimic its movement. In this case, when the user's hand spread, then the arm robot will also spread.

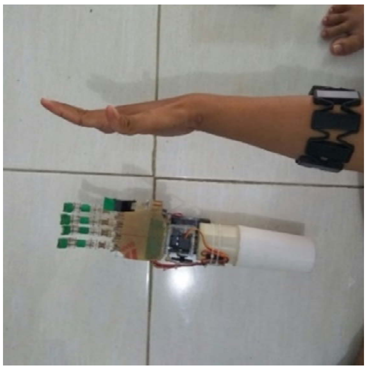

Fig. 9. Robotic arm for movement spreading

From the 20 tests on each movement, the percentage of obtained errors is shown in Table 5.

TABLE VI. RESULT 20 TEST ON EACH MOVEMENT

Movement	Amount Trial	Succeed	Failed	Error (%)
Clenching	20 times	13 times	6 times	35%
Pointing	20 times	15 times	5 times	25%
Spreading	20 times	20 times	0 times	0%
Wave in	20 times	20 times	0 times	0%
Wave out	20 times	15 times	5 times	25%

V. Conclusions

From the results of the RMS of each movement respectively, it is obtained quite different patterns. These patterns distinguish between each movement and will be used as input of back propagation and classification. The test results showed that the accuracy of the pattern recognition of clenching is about 65%, the pattern recognition of pointing is about 75%, the pattern recognition of wave in is about 100%, the pattern recognition of wave out is about 75%, and the pattern recognition of spreading is about 100%. Overall percentage of the obtained error is about 17%.

VI. Future Work

In this research, there are still some weakness. Therefore, for future researchers will do several things:

1. Will validate the data that used to system using a data set.
2. Will use a time window based on getting nicer features.

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References

[1] Setiawan, Cahyo, “Tangan Robot Bionik dengan Kendali Otot Berbasis EMG”, Computer Engineering, Electronic Engineering Polytechnic Institute of Surabaya, Surabaya, Indonesia, 2015.

[2] Malik, Iqbal Maulana, “Sistem Pengenalan Pola Gerak Tangan Untuk Persentase Interaktif Dengan Sensor EMG (Electromyogram)”, Computer Engineering, Electronic Engineering Polytechnic Institute of Surabaya, Surabaya, Indonesia, 2015.

[3] Suresh.M, et al, “Electromyography Analysis for Person Identification”, Kalpataru Institute of Technology, India, 2011.

[4] Nomiyasari, “Perancangan dan Pembuatan Modul ECG dan EMG dalam satu unit PC”, Electronic Engineering, Electronic Engineering Polytechnic Institute of Surabaya,Surabaya, Indonesia, 2011.

[5] B. Peerdeman, D. Boere, H. Witteveen, R.H. in t Veld, H. Hermens, S. Stramigioli, et al., "Myoelectric forearm prostheses: State of the art from a user-centered perspective", *JRRD*, vol. 48, no. 6, pp. 719-738, 2011.

[6] A.H. Al-Timemy, G. Bugmann, J. Escudero and N. Outram, "Classification of finger movements for the dexterous hand prosthesis control with surface electromyography", *IEEE J. Biomed. Health Informatics*, vol. 17, no. 3, pp. 608-618, 2013.

[7] C. Miller, Real-Time Feature Extraction and Classification of Prehensile EMG Signals, 2008