



## JOINT TORQUE ESTIMATION MODEL OF SEMG SIGNAL FOR ARM REHABILITATION DEVICE USING ARTIFICIAL NEURAL NETWORK TECHNIQUES

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### ABSTRACT

Rehabilitation device is used as an exoskeleton for peoples who had failure of their limb. Arm rehabilitation device may help the rehab program to who suffered with arm disability. The device is used to facilitate the tasks of the program and minimize the mental effort of the user. Electromyography (EMG) is the techniques to analyze the presence of electrical activity in musculoskeletal systems. The electrical activity in muscles of disable person is failed to contract the muscle for movements. To minimize the used of mental forced for disable patients, the rehabilitation device can be utilize by analyzing the surface EMG signal of normal people that can be implemented to the device. The objective of this work is to model the muscle EMG signal to torque for a motor control of the arm rehabilitation device using Artificial Neural Network (ANN) technique. The EMG signal is collected from Biceps Brachii muscles to estimate the elbow joint torque. A two layer feed-forward network is trained using Back Propagation Neural Network (BPNN) to model the EMG signal to torque value. The performance result of the network is measured based on the Mean Squared Error (MSE) of the training data and Regression (R) between the target outputs and the network outputs. The experimental results show that ANN can well represent EMG-torque relationship for arm rehabilitation device control.

**Keywords:** electromyography, torque, artificial neural network.

### INTRODUCTION

Human support system is endoskeleton. Endoskeleton plays a role as a framework of the body which is bone. Our daily movements are fully depends on the functionality of our complex systems in the body. The disability one or more of the systems in our body will reduce our physical movements. The assistive device is a need for rehab as an exoskeleton. The functionality of the rehabilitation device has to smooth as the physical movement of normal human.

The rehabilitation programs provide the suitable program for conducting the nerve and stimulate the muscles. People who have temporary physical disability have the chances to recover. Nowadays, rehabilitation program are using exoskeleton device in their tasks. The functionality of exoskeleton depends on muscle contraction. Electromyogram studies help to facilitate the effectiveness of the rehabilitation device by analysing the signal transmitted from the muscle.

The rehabilitation device is a tool that used to help the movements for daily life activities of the patients who suffer from the failure of muscle contractions, due to the failure of the muscles contractions the movements is limited. The ability of the patients to do the tasks in the rehabilitation programs need to be measured. The rehabilitation programs have to assure whether the tasks will cause effective or bring harm to the patients [1].

Historically, the rehabilitation tasks have been avoided due to a belief that it would increase spasticity [2]. In this research, the analysis of the data will be focusing on upper limb muscles contraction consisting of biceps muscles only. The experiment is limited to the certain of upper limb movements that use in training. EMG is a

division of bio signal; the bio signal analysis is the most complex analysis. Thus, the signal analysis is a complicated process that has to be through many phases of analysis [3].

EMG signal function as a control signal for the arm rehabilitation device. A system needs a model to estimate relationship between EMG and torque [4]. EMG signal based control could increase the social acceptance of the disabled and aged people by improving their quality of life. The joint torque is estimated from EMG signals using Artificial Neural Network [5, 6]. The Back Propagation Neural Network (BPNN) is used to find a solution for EMG-joint torque mapping. The EMG signal of the biceps brachii muscle act as the input of the ANN model whiles the desired torque act as the ideal output of the model. Hence the EMG signals considered the 'intent' of the system while the joint torque is the 'controlled' variable for the arm rehabilitation device [7]. The network is evaluated based on the best linear regression between the actual joint torque and the estimated joint torque [4]. The experiment results shows that the model can well represent the relationship between EMG signals and elbow joint torque by producing MSE of 0.13807 and average regression of 0.999.

This paper is organized as follows. Section 1 explains brief introduction about this research work. Section 2 describes all the related works of this study. Section 3 demonstrates the method implemented for this work that covered the experimental setup, EMG data processing, desired torque determination and ANN technique. Section 4 presents the experimental results as well as the discussion of each result obtained. Finally the paper ends with conclusion and recommendations.



## RELATED WORKS

There have been several studies that have applied ANN for modeling the muscle activity to joint relationship. Author [7] proposed the ANN model to measure the ankle EMG-joint torque relationship at a full range of torque under isometric, supine conditions by inserting EMG signal from 6 muscle sites into the model as in the input, while the measured torque is entered into the model as the ideal output. The learning process occur approximately 16000 iterations resulting error that is less than 6 percent.

More recent study has been conducted by author [4] to predict the elbow joint angle based on EMG signals using ANN. The three layer BPNN was constructed by using the RMS of the raw EMG signal from biceps and triceps. The result from 40 group EMG signals when subjects do bowing and extending elbow joint action reveal that the prediction output from the trained network was very close with the target angle. According to author [6], it is quite difficult to know the elbow shoulder joint torque on the natural condition. The learning method which is based on the feedback error learning schema is proposed by modifying the ANN with the torque error which calculated from the desired angle and measured angle.

Studies of muscle force models have been carried out by author [8]. The model was estimated based on a rectified smoothed EMG signal using the BPANN method to predict the muscle force. The proposed model can efficiently extract muscle force features from (EMG) signals in a fast and easy method. The results showed that the regression of the ANN model exceeded 99%. However among all the previous studies related to EMG based ANN model been conducted, none of them really emphasize on the data processing phase which involve EMG data processing and desired torque determination. Therefore this paper will explain in detail this phase.

## METHODS

Figure-1 shows a block diagram of our research methodology that consists of two major phases. First phase

is EMG data processing and desired torque determination. Second phase is the ANN construction and testing. The data collection from the first phase is used to validate and teach the ANN algorithm in second phase.

## Experimental setup

Implementation of arm rehabilitation device based on movement is recorded from the EMG signal of healthy subjects. From the human anatomy studies, different angle movements of upper limb with elbow as the reference is depends on relation of agonist and antagonist. In this study is focusing on the behaviour of biceps muscle as agonist and the triceps as the antagonist respectively. Muscle that involved in this movement is biceps and triceps, however in this study to understand the electrical activity during muscle contraction, the biceps is the only muscle that taking into account. The movements' ranges in between position of arm flexion until arm fully extend.

The environment is in a room with low lighting especially the fluorescent light, any electromagnetic devices is away from the experiment equipment and the environment is in silent room. Then, the experimental is set up with the subject sit on the chair while the hand is on the Table. The subject has to complete the task of lift up the dumbbell with 2.268 kg of weight as shown in Figure-2(b). Normally, the appearance of EMG signal is chaos and noisy depends on the type of electrodes also the noise factor. To simplify the difference of amplitude response for the motion, the dumbbell is functioned to amplify the amplitude in analyzing the electrical activity during rest and contract. The rehabilitation devices (white in color on Figure-2(a)) helps to keep the position of the elbow joint and the wrist joint in line. Mostly, the EMG signal is obtained after several trials of the movements. These movements are specified from angle of  $0^\circ$  (arm in rest position), up to  $120^\circ$  (arm is fully flexion). Data was collected from two subjects by 5 repetitions of each flexion movements [9].

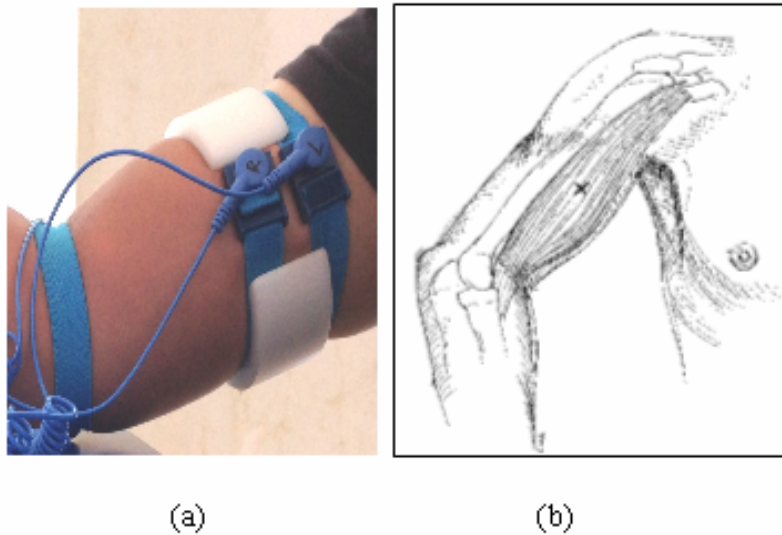


**Figure-2.** Subject is set-up with arm rehabilitation assistive device for experiment (a). Simulation of subject's to lift up the dumbbell 5 pounds of weight (b).



Prior of data collection process, the skin needs a preparation. The preparation of skin is ruled by the Surface Electromyography for the Non-Invasive Assessment of Muscles (SENIAM) procedure for non-invasive methods. The subject's skin has to be shaved by using small electrical shaver and cleaned with sterile alcohol swabs saturated with 70% Isopropyl Alcohol. This step is to be taken for minimizing the noise and to have a good contact with the electrodes of the skin by decreasing the impedance of the skin. The skin has to be clean from any contamination of body oil, body salt, hair and the dead cells. The preparation of skin can be done by wiping the

alcohol swab into the area of skin that electrode placement to be applied. The placements of the electrode have to be at the belly of the muscles not in the tendon or motor unit. This ensured the detecting surface intersects most of the same muscle on subject as in Figure-3(a) at the biceps brachii, and as a result, an improved superimposed signal is observed. Reference electrode has to be at the bone as the ground, for this experiment it placed at elbow joint as shown in Figure-3(b). These electrodes are connected to the combination of hardware Olimex EKG-EMG-PA and Arduino Mega for data collection.

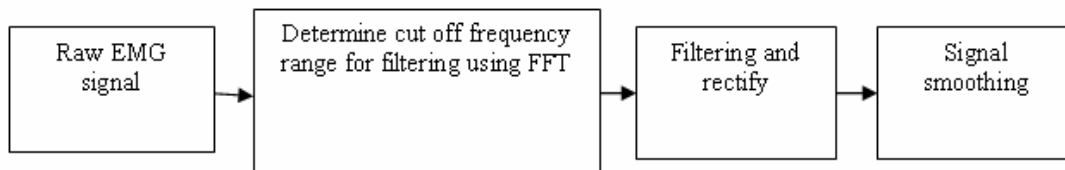


**Figure-3.** The biceps brachii muscles for electrode positions (a), the electrode placements on subject skin (b).

### EMG data processing

Figure-4 shows the EMG data processing block diagram. After obtained satisfactory EMG signal as shown in Figure-5(a), Fast Fourier Transform (FFT) is performed to the signal to analyses the frequency content of the signal. The EMG signal is break into its frequency component and it is presented as function of probability of their occurrence. In order to observe the variation of signal in different frequency components, the FFT signal is represented by Power Spectral Density (PSD). From the PSD we can describes how the signal energy or power is

distributed across frequency. Figure-5(b) shows that most of the power is in the range of below 10Hz, therefore the EMG signal should be filtered in the range of above 10Hz as a cut off frequency for low pass filtered. After decide the cut off frequency for filtering, the DC offset of the EMG signal is removed and is rectified to obtain its absolute value as shown in Figure-5(c). Finally, the signal was smoothed and normalized passing it through a 5<sup>th</sup> order Butterworth type low-pass filter with cut off frequency 10Hz and the smooth signal is illustrate in Figure-5(d) [8, 9].



**Figure-4.** EMG data processing.

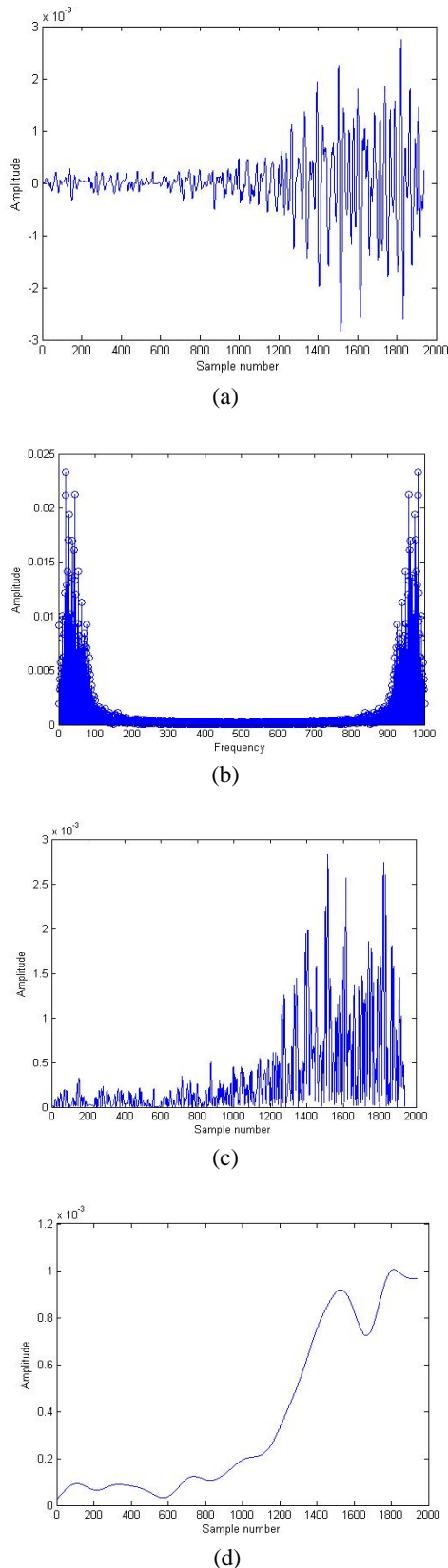


Figure-5. Raw EMG signal (a), Power spectral density (b), Rectified signal(c), Smooth signal (d).

**Desired torque**

Desired torque of the elbow joint is used as target data for our ANN techniques as well as act as output signal for muscle [10]. The data is collected throughout the angle from  $0^{\circ}$  to  $120^{\circ}$  angle with increment of  $0.0619^{\circ}$  each step to align with the sample number of EMG signal. Figure-6(a) shows the arm rehabilitation device position for torque calculation. The desired torque for elbow joint is determined by applying standard torque equation:

$$\tau = (r_{load} F_{load} + a_{arm} F_{arm}) \cos \theta \tag{1}$$

Where  $r_{load}$  distance from the elbow is joint to the load,  $F_{load}$  is force due to load,  $F_{arm}$  is the force due to the mass of the lever arm and  $r_{arm}$  is evenly distributed distance of mass of arm distance which is half of  $r_{load}$ . The angle  $\theta$  between  $r$  and  $F$  is drawn from the same origin. A applied load is 5 pounds (2.268kg) dumbbell and the distance from the elbow joint is 0.25m while the mass of the lever arm is 0.1kg. Figure-6(b) shows the desired torque characteristic for the elbow joint.

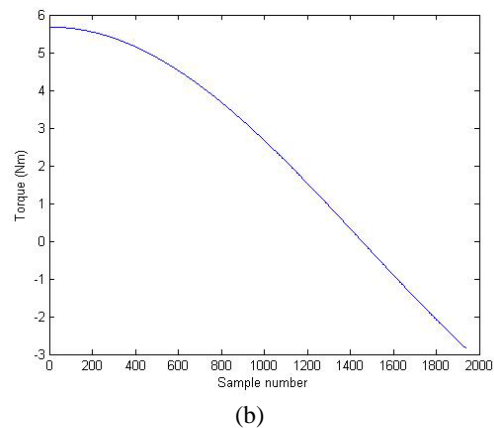
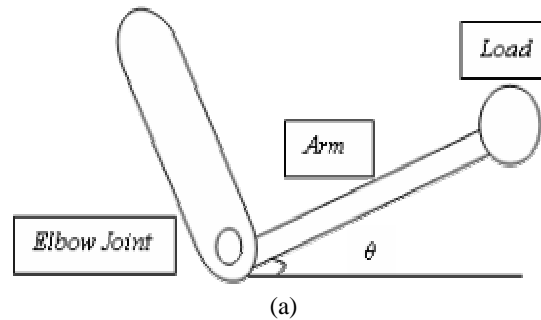


Figure-6. Arm rehabilitation device position (a), desired torque characteristic (b).

**Artificial Neural Network (ANN) Techniques**

ANN is a computing paradigm that is loosely modeled after cortical structures of the brain. It consists of interconnected processing elements called nodes or neuron



that work together to produce an output function. It is capable to map a data set of numeric inputs with a set of numeric outputs. It is also the most widely applied training network which has input layer, hidden layer and output layer. The neurons on each layer need to be considered carefully to produce high accuracy network. The number of hidden neurons could affect the performance of the network. The network performance not always been improved if the hidden layer and its neurons is increased [4]. Therefore the number of hidden neurons is tested to achieve the optimized network. However there is constraint in determining the number of neurons. If the numbers of hidden neurons is too large, the network requires more memory and the network become more complicated while if the number of hidden neurons is too small, the network would face difficulty to adjust the weigh properly and could cause over fitting which is problem where the network cannot be generalized with slightly different inputs [11].

The input signal is propagated forward through network layer using back propagation algorithm. An array of predetermined input is compared with the desired output response to compute the value of error function. This error is propagated back through the network in opposite direction of synaptic connections. This will adjust the synaptic weight so that the actual response value of the network moved closer to the desired response [12]. BPNN has two-layer feed-forward network with hidden neurons and linear output neurons. The function used in the hidden layer of network is sigmoid function that generates values in range of -1 to 1 [9]. There are layers of hidden processing units in between the input and output neurons. For each epoch of data presented to the neural network, the weights (connections between the neurons) and biases are updated in the connections to the output, and the learned error between the predicted and expected output, the deltas, is propagated back through the network [13].

A Lavenberg-Marquardt training back propagation algorithm is implemented for this work to model the EMG to torque signal. This algorithm is chosen due to the facts that it outperforms simple gradient descent and other conjugate gradient methods in a wide variety problem such as convergence problems. Single input EMG signal that act as a training data while single output which is the desired torque act as a target data. The network is optimized for 20 hidden neurons as shown in Figure-7[4]. The network was trained using 1839 sets of EMG data for arm flexion motion from 00 angles to 1200 angle. It also has output data which is torque of correspondent arm motion. The training process was iteratively adjusted to minimize the error and increased the rate of network performance [11]. The training has been done by dividing the input data of 70% for training, 15% for validation and 15% for testing [8].

The performance evaluation of the network is based on the Mean Squared Error (MSE) of the training data and Regression (R) between the target outputs and the network outputs as well as the characteristics of the training, validation, and testing errors. The network is

considered has the best performance if it has lowest MSE and highest R while exhibit similar error characteristics among the training, validation and testing. However even if the MSE shows very good result but the validation and testing vary greatly during the training process, the network structure is still considered unsatisfactory because the network is not generalized. Therefore further tuning and training need to be conducted in order to improve the network performance [11].

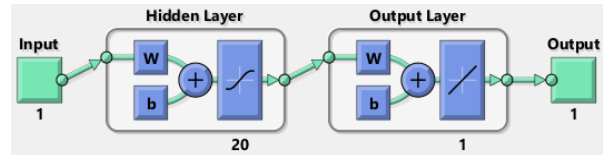


Figure-7. BPNN model

## EXPERIMENTAL RESULTS

In order to optimize the network performance, different number of hidden neurons is simulated for several times until achieved the satisfactory results [11]. The network is trained using Lavenberg-Marquardt algorithm and the performance of the network is measured using MSE and R. The best validation performance of the network is 0.13807 at epoch 46 as shown in Figure-8. It is an acceptable result since the test set error and the validations set error have similar behavior. It shows that the MSE has decreased rapidly along the epochs during training. The regression also produces a good curve fitness for training, test and validation data around 0.999 which give an optimal value for our model as shown in Figure-9 [8, 14].

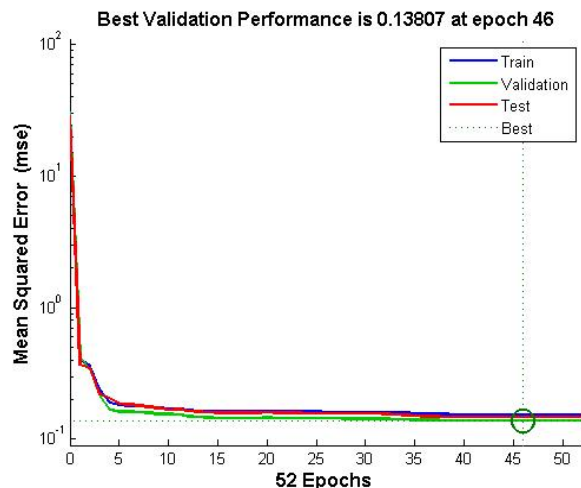


Figure-8. Best validation performance.

Error sizes are well distributed since most error approaching zero values that make the trained model perform better as shown in Figure-10(a). The network has maximum instance around 450 of MSE distributed around the zero line of the error histogram [14]. Figure-10(b) shows a comparison between prediction output from the



trained network and target torque. The prediction output has fairly good agreement with the characteristics of the target data.

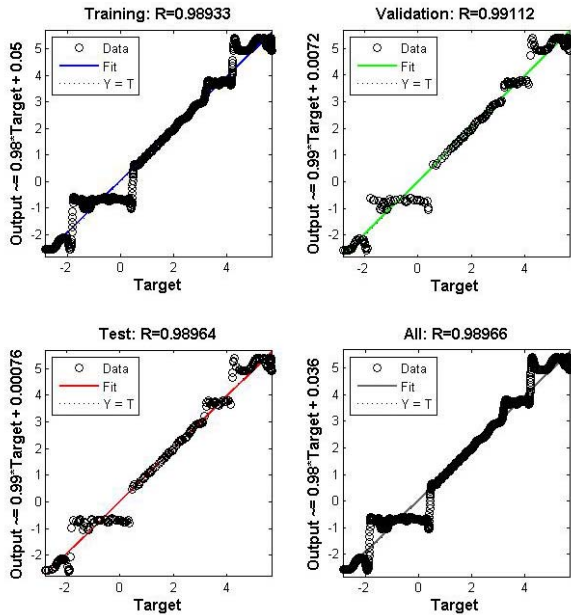


Figure-9. Regression of the trained model.

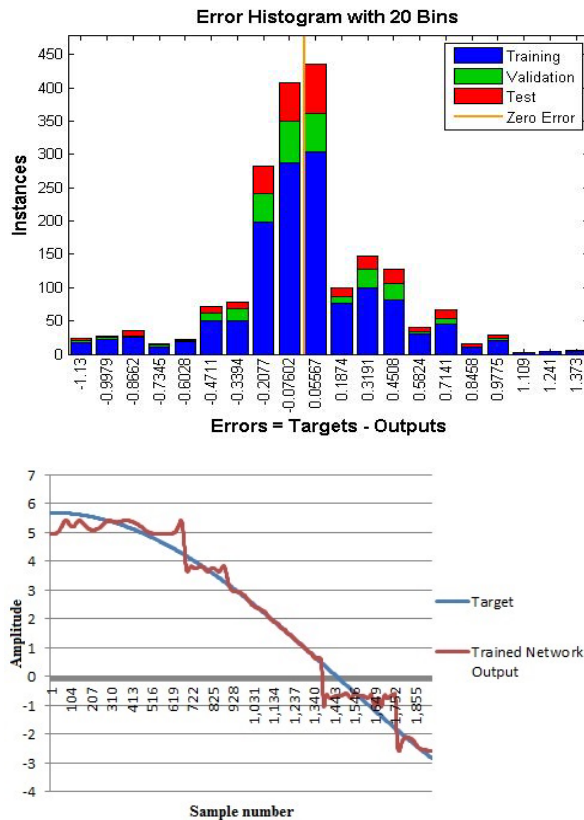


Figure-10. Error histogram of the trained model (a), Target vs trained network output (b).

**CONCLUSIONS**

Based on the result, it can be concluded that the ANN model with 20 hidden neurons produce MSE of 0.13807 and average regression of 0.999. It is consider a good performance as it shows that this neural network model can well represent the relationship between EMG signals and elbow joint torque. Hence this model can be used for motor torque control of the arm rehabilitation devices. The model can be further improved by applying other artificial intelligence training algorithm such as genetic algorithm and particle swarm optimization to produce better mean squared error and regression performance result.

**ACKNOWLEDGEMENTS**

The authors would like to thanks Universiti Teknikal Malaysia Melaka (UTeM) and Ministry of Education, Malaysia for the financial supports given through Research Grant.

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