International Journal of Applied Engineering Research
ISSN 0973-4562 Volume 9, Number 10 (2014) pp. 1289-1301

http://www.ripublication.com

Comparative Study of EMG based Joint Torque Estimation ANN Models for Arm Rehabilitation Device

M. H. Jali[1, a], M. F. Sulaima[1, b], T. A. Izzuddin[1, c], W. M. Bukhari[1, d] and M. F. Baharom[1, e]

[1]Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka
Hang Tuah Jaya, 76100 Malacca, Malaysia
[a]mohd.hafiz@utem.edu.my, [b]fani@utem.edu.my, [c]tarmizi@utem.edu.my,
[d]bukhari@utem.edu.my, [e]mohamad.faizal@utem.edu.my

Abstract

Rehabilitation device is used as an exoskeleton for people who had failure of their limb. Arm rehabilitation device may help the rehab program whom suffered with arm disability. The device used to facilitate the tasks of the program should improve the electrical activity in the motor unit 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. In order 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 compare the performance of the joint torque estimation model from 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 comparison between two ANN models is made to observe the performance difference between these models. The experimental results show that ANN model with double input nodes has a better performance result in term of Mean Squared Error (MSE) and Regression (R) which is crucially important to represent EMG-torque relationship for arm rehabilitation device control.

Keywords - Electromyography, Artificial Neural Network, Arm Rehabilitation Device, Joint Torque Estimation, Exoskeleton

1. 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 technique of measuring electrical activity that produced from the muscles during rest or contractions known as electromyography (EMG). The electric signal generates from the brain and sends to the muscles via motor neuron. The EMG may detect the dysfunctional of the muscles or failure in signal transmission from nerve to muscle. The failure of sending the electrical signal from the brain requires electrical stimulation from the external source to muscles. Electrodes are used for signal detection of electrical activity in muscles. The study of this electrical activity is important for combination of electromyogram and rehabilitation device.

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 is used 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 [5]. The joint torque is estimated from EMG signals using Artificial Neural Network [6]. The 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]. There are several work that has applied BPNN for modeling the muscle activity of ankle to joint torque relationship. It is done by approximating the force from the EMG signal under static conditions [7]. The network is evaluated based on the best linear regression between the actual joint torque and the estimated joint torque [4].

2. Methods

Figure 1 shows a block diagram of our research 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.

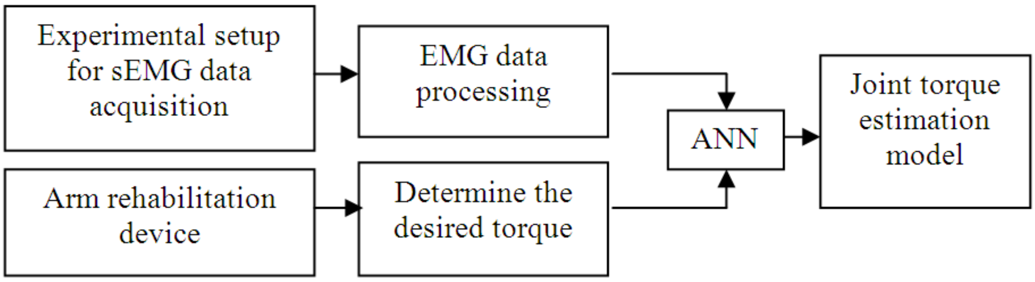


Figure 1. Research methods

2.1 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 in Figure 2(b) for 5 times. 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 analysing 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° (arm in rest position), up to 120°(arm is fully flexion). Data was collected from two subjects by 5 repetitions of each flexion movements [8].

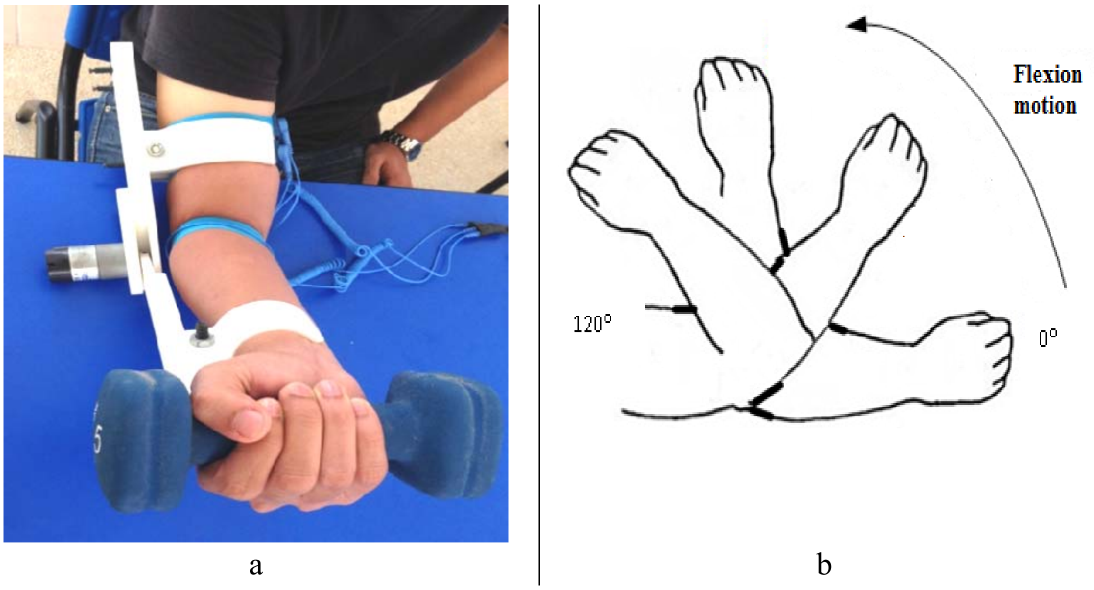
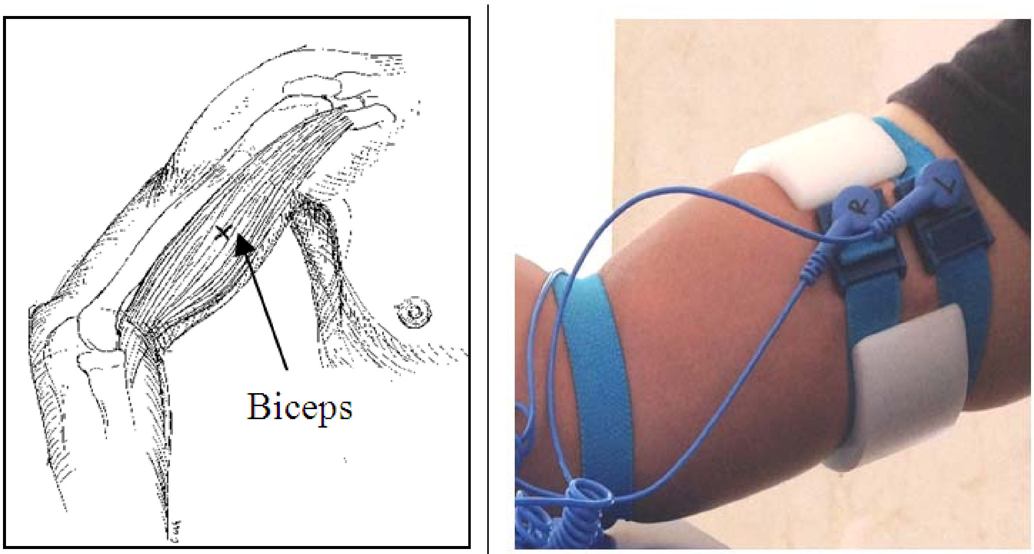


Figure 2. Subject is set-up with arm rehabilitation assistive device for experiment (a), Simulation of subject's to lift up the dumbbell 2.268kg of weight (b).

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.



a b

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

2.2 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^{th} order Butterworth type low-pass filter with cut off frequency 10Hz and the smooth signal is illustrate in Figure 5(d) [8][9].

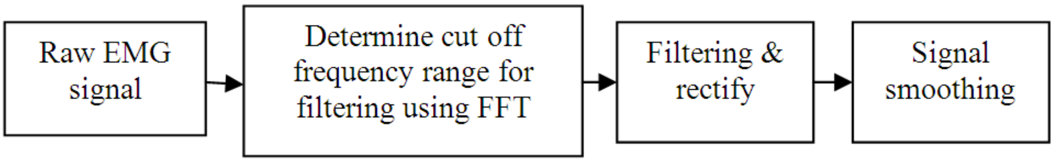


Figure 4. EMG data processing

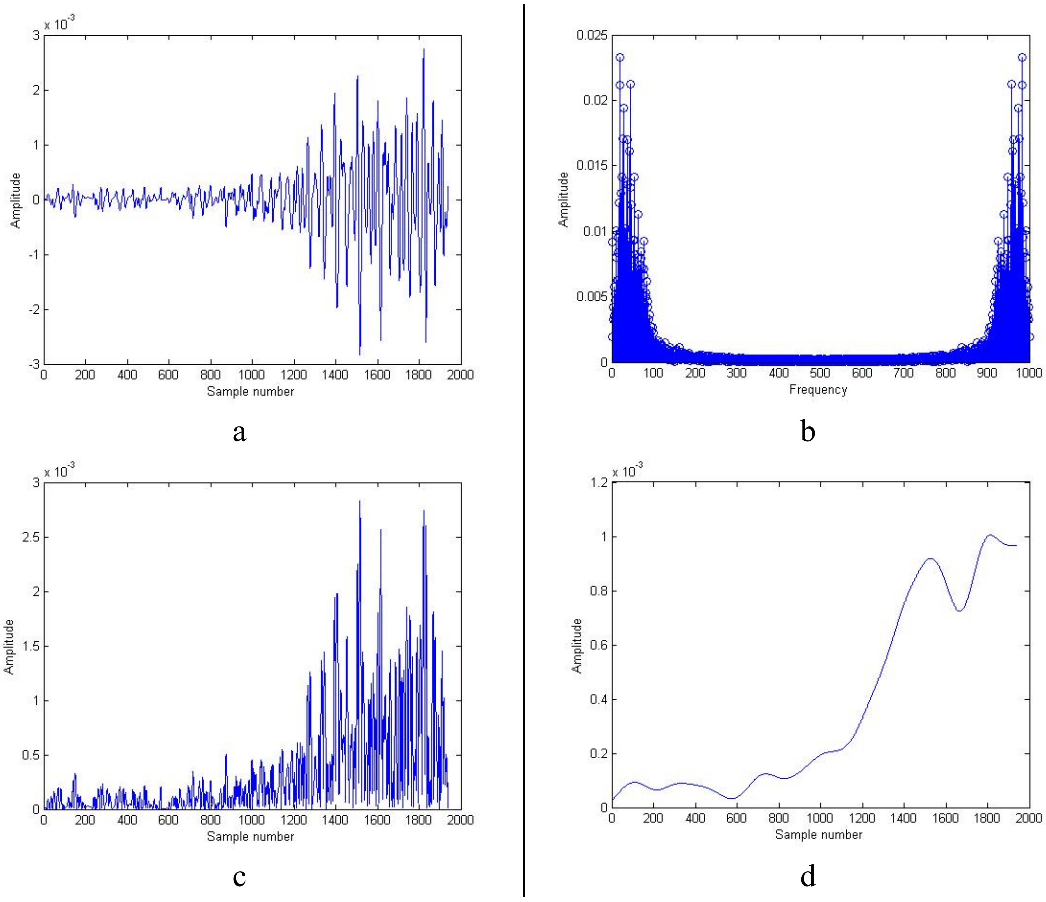


Figure 5. Raw EMG signal (a), Power Spectral Density (b), Rectified signal (c), Smooth signal (d)

2.3 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. The data is collected throughout the angle from 0^0 to 120^0 angle with increment of 0.0619^0 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: -

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

Where r_{load} is distance from the elbow 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 θ 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.

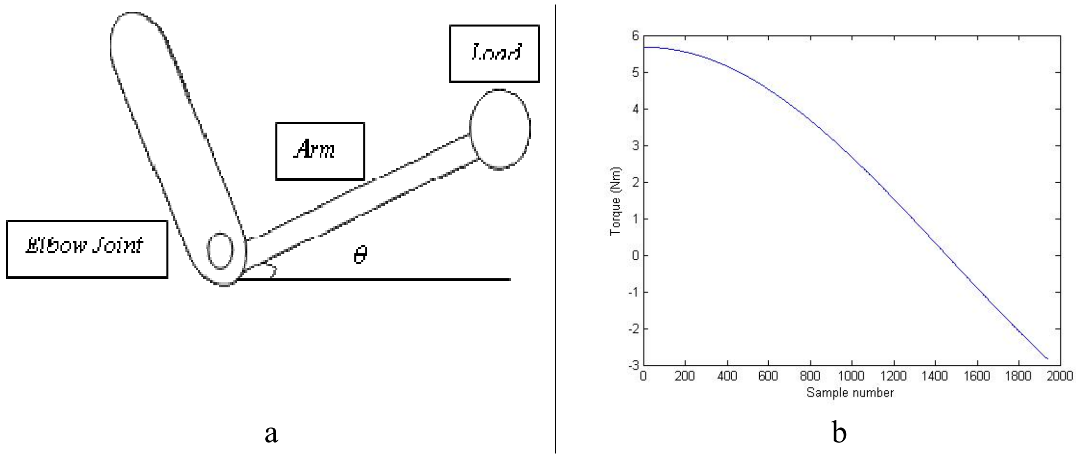


Figure 6. Arm rehabilitation device position (a), Desired torque characteristic (b)

2.4 Artificial Neural Network (ANN) Model

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 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 [10]

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 [11]. 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 [8]. 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 [12].

A Lavenberg-Marquardt training back propagation algorithm is implemented for this work to model the EMG to torque signal. Two ANN models is considered to compare the performance of each model. ANN model 1 consist of input layer with single node which is denoted as b that represent EMG signal from biceps while ANN model 2 has additional node at the input layer which denoted as t that represent the movement time which act as a training data. The output layer has only one node which is denoted as τ that represents the desired torque act as a target data. Table I describe the difference between the models and the network structure of each model is shown in Figure 7[4]. The network was trained using 1839 sets of EMG data for arm flexion motion from 0^0 angles to 120^0 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 [10]. MATLAB software is used to construct the BPNN network. The network requires data for learning and testing in order to determine the weights each node uses. The training has been done by dividing the input data of 70% for training, 15% for validation and 15% for testing [9]. The network will be trained until the following condition fulfilled before it stop [10]: -

- reach maximum number of epochs
- gradient performance became less than the minimum gradient
- validation performance increased more than the maximum fail times since the last decreased one

Table 1. ANN model description

ANN model	Model 1	Model 2
No. of input node	1	2
Node 1	EMG data, b	EMG data, b
Node 2	Movement time, t	-
Hidden neurons	10	10
Output node	Desired torque, τ	Desired torque, τ

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 [10].

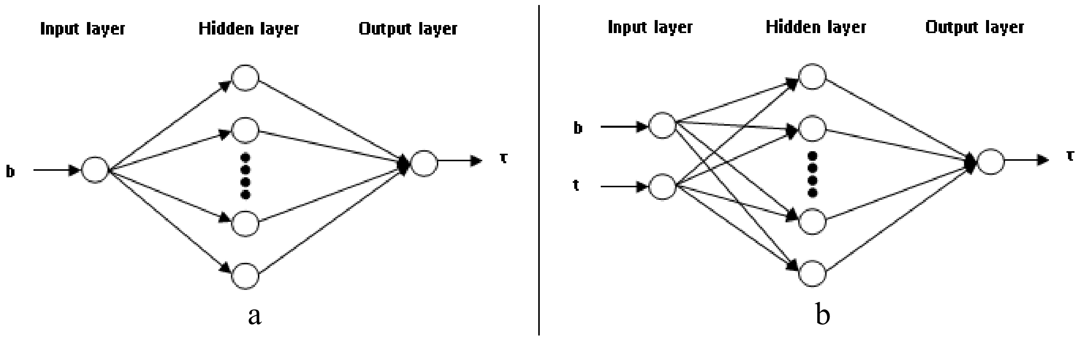
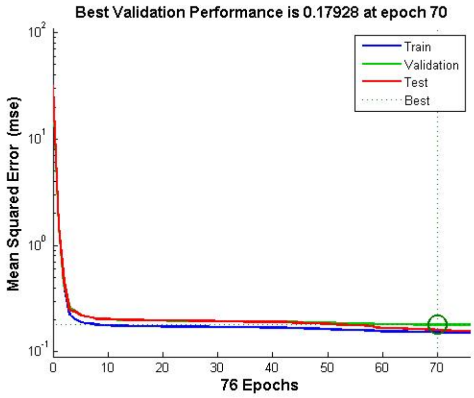


Figure 7. (a) Model 1, (b) Model 2

3. Experimental Results & Discussion

In order to optimize the network performance, different number of hidden neurons is simulated for several times until achieved the satisfactory results [10].The network is trained using Lavemberg-Marquardt algorithm and the performance of the network is measured using MSE and R. The best validation performance of Model 1 is 0.17928 at epoch 70 as shown in Figure 8(a) while 2.6521e-10 at epoch 1000 for Model 2 in Figure 8(b). Thus it is clear that Model 2 provide better result in term of MSE compare to Model 1. However the stop epoch of Model 2 is higher than Model 1.

Both results show that the MSE has decreased rapidly along the epochs during training. The regression for Model 1 is 0.989 while 1.000 for Model 2. Figure 9(b) shows that Model 2 produces better curve fitness for training, test and validation data around compare to Model 1 as shown in Figure 9(a) [9][13].



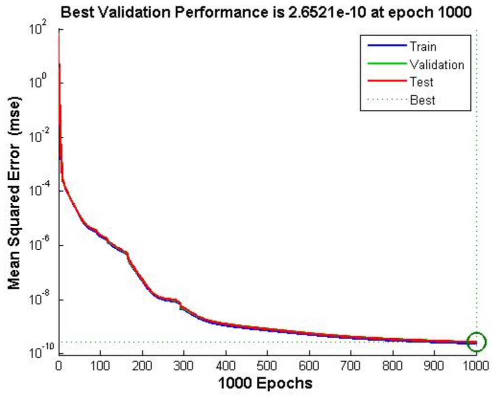
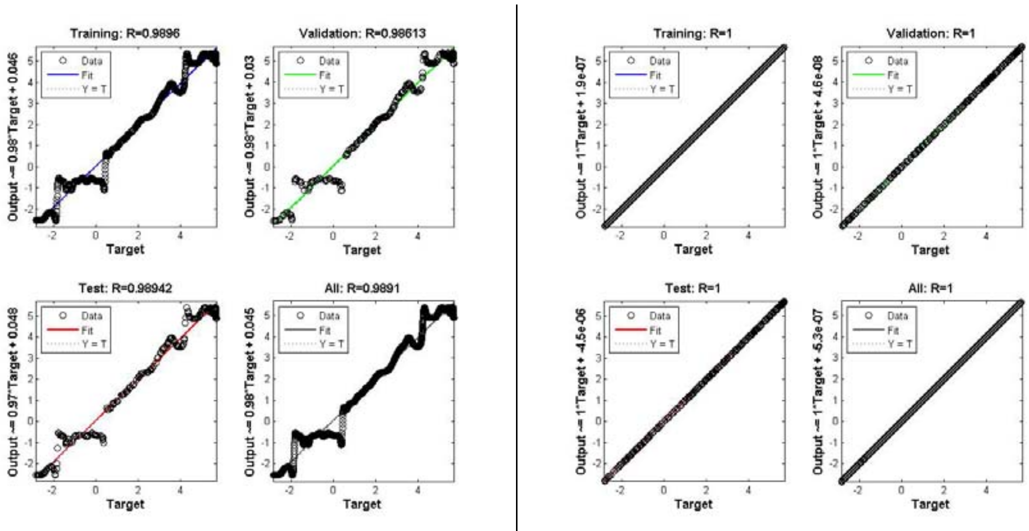


Figure 8. (a) Best validation performance Model 1, (b) Best validation performance Model 2

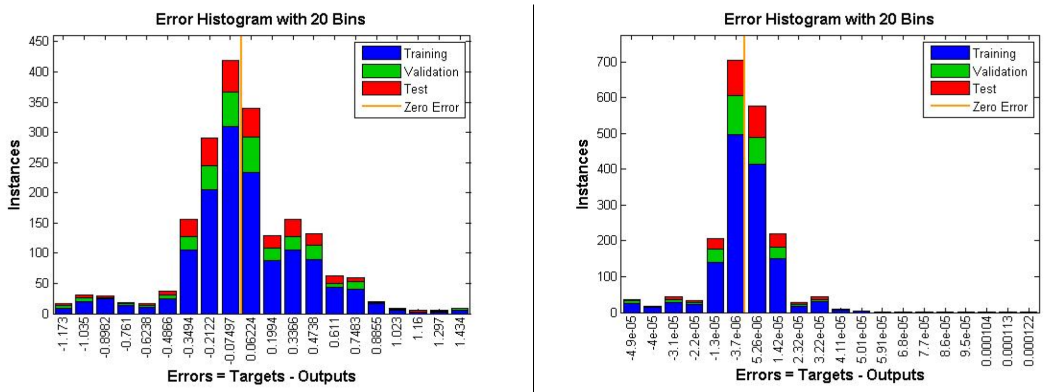
Error sizes are well distributed if most error approaching zero values that make the trained model performs better. Figure 10(a) shows that Model 1 has maximum instance around 450 of MSE distributed around the zero line of the error histogram while Figure 10(b) shows that Model 2 has maximum instance around 700 of MSE distributed around zero line [13].

This histogram could be interpreted with error fluctuation diagram along the zero values as shown in Figure 11(a). It described that Model 1 exhibit a large value of fluctuation from the zero values compared to Model 2. Fig. 11(b) shows a comparison between prediction output from the trained network and target torque for Model 1 and Model 2. The prediction output for Model 2 has absolutely spectacular agreement with the target output compare to Model 1that has only fairly good agreement with the characteristics with the target data [4]. Table 2 summarize the performance result of both model.



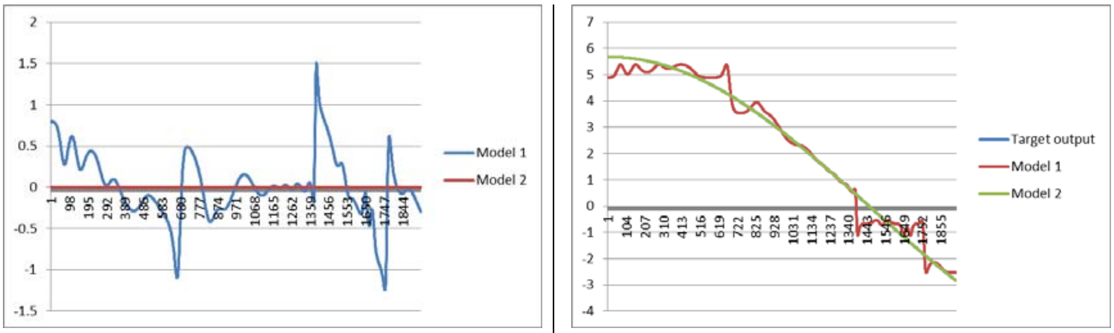
a b

Figure 9. (a) Regression of the trained Model 1, (b) Regression of the trained Model 2



a b

Figure 10. (a) Error histogram of the trained Model 1, (b) Error histogram of the trained Model



a b

Figure.11 (a) Error fluctuation along zero line, (b) Target vs trained network output

Table 2. Summary of the result

BPNN Structure	Model 1	Model 2
Stop Epochs	70	1000
Regression	0.9891	1
MSE	0.17928	2.6521e-10
Time Elapsed (Seconds)	0.04	1.00

Conclusions

Based on the result, it can be concluded that the ANN Model 2 has better performance in term of MSE and R compare to ANN Model 1. Model 2 has a super low MSE value as well as perfect result for R. However the stop epochs and time elapsed for Model 2 is worse than Model 1. The computational time for Model 2 consume a longer time which is 1.00 seconds compare to Model 1 that required only 0.04 seconds. Therefore there is tradeoff between these models. In order to improve the Model 2 stop epochs and time elapsed, evolution neural network training algorithm such as genetic algorithm and particle swarm optimization can be implemented to produce a good mean squared error and regression performance result while reducing the computational time. Model 2 is considering a good performance as it shows that this ANN 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.

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.

References

[1] S. D. C. G. C. Louise Ada.: Strengthening Interventions Increase Strength and Improve Activity After Stroke: A Systematic Review. Australian Journal of Physiotherapy, vol. 52, pp. 241-248, 2006.
[2] B. B.: Adult Hemiplegia: Evaluation and treatment..Oxford, Butterworth-Heinemann., 1990.
[3] J. Muthuswamy.: Biomedical Signal Analysis in Standard Handbook Of Biomedical Engineering And Design. Mc-Graw Hill, 2004, pp. 18.1 - 18.30.
[4] Li Dapeng, Zhang Yaxiong.: Artificial Neural Network Prediction of Angle Based on Surface Electromyography. International Conference on Control, Automation and Systems Engineering (CASE).pp. 1-3, 2011.
[5] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin.: Techniques of EMG Signal Analysis: Detection, Processing, Classification and Applications. Biological Procedures Online, vol. 8, pp. 11-35, 2006.
[6] Morita, S. Kondo, T. Ito, K.: Estimation of Forearm Movement from EMG Signal and Application to Prosthetic Hand Control, IEEE International Conference on Robotics and Automation(ICRA).vol.4.pp.3692-36972. 2001.
[7] Kent, L.M. Siegler, S. Guez, A. ; Freedman, W..: Modelling Of Muscle EMG To Torque By The Neural Network Model Of Backpropagation . IEEE International Conference of the Engineering in Medicine and Biology Society, Proceedings of the Twelfth Annual. Pp 1477-1478.1990.
[8] Favieiro, G.W. Balbinot, A. Barreto, M.M.G.: Decoding Arm Movements by Myoeletric Signals and Artificial Neural Networks. Conference of Biosignals and Biorobotics(BRC). pp 1-6. 2011.
[9] Naeem, U.J. Abdullah, A.A. ; Caihua Xiong.: Estimating human arm's muscle force using Artificial Neural Network . IEEE International Symposium on Medical Measurements and Applications Proceedings (MeMeA), pp 1-6.2012
[10] Ahsan, M.R. ; Ibrahimy, M.I. ; Khalifa, O.O. EMG Motion Pattern Classification through Design and Optimization of Neural Network. International Conference on Biomedical Engineering (ICoBE), pp 175-179.2012
[11] B. Hudgins, P. Parker, and R. Scott.: A new strategy for multifunction myoelectric control. IEEE Trans. Biomed. Eng., vol. 40, no. 1, pp. 82– 94, Jan. 1993.
[12] Mars, P, Chen JR, Nambiar, R Learning Algorithms.: Theory and applications in signal processing, control and communications. CRC 1996.
[13] Supeni, E. E. and Epaarachchi, J. A. and Islam, M. M. and Lau, K. T. (2013) Development of artificial neural network model in predicting performance of the smart wind turbine blade. In: 3rd Malaysian Postgraduate Conference (MPC 2013), 4-5 Jul 2013, Sydney, Australia.