Upper Limb Elbow Joint Angle Estimation Based on Electromyography Using Artificial Neural Network

Triwiyanto, Oyas Wahyunggoro, Hanung Adi Nugroho
Department of Electrical Engineering & Information Technology,
Universitas Gadjah Mada
Yogyakarta, Indonesia
triwiyanto123@gmail.com

Herianto
Department of Mechanical & Industrial Engineering
Universitas Gadjah Mada
Yogyakarta, Indonesia

***Abstract*—This paper proposed a time delay artificial neural network (TDANN) to estimate elbow joint angle based on electromyography (EMG) signal. One channel EMG signal was recorded from biceps using disposable surface electrode while the upper limb elbow joint performed a flexion and extension motion randomly. The EMG signal was extracted using Wilson amplitude feature with windows length of 100 sample points. In order to identify the EMG features, the TDANN was constructed as follows: input, hidden, and an output layer consists of 5 time-delays of input nodes, 15 hidden nodes, and 1 output node, respectively. The proposed method reveals that by using single channel EMG from biceps, it is able to estimate the elbow joint angle. The performance of the elbow joint angle estimation in the random motion is 18.87°±3.46° and 0.80±0.09 for RMSE and Pearson's correlation coefficient, respectively.**

Keywords*— *EMG; Wilson amplitude; TDANN; elbow joint angle estimation.

I. Introduction

Electromyography (EMG) signal is used a lot in many fields including biomechanical such as the exoskeleton, a prosthetic arm and teleoperation [1]–[3]. EMG signal can be related to the human motion. Some studies estimated angle, force and torque of the human limb from the EMG signal [4]–[8]. In order to represent the position and kinematic parameters, the EMG signal passed through the feature extraction process. The feature extraction process can be conducted into time, frequency and time-frequency domain. The time domain features extraction was more preferred to be used than others domain. This is due to less computation load that needed to extract the features.

In order to recognize the EMG features as an elbow joint angle, force or torque, some researchers optimized the features by using filtering techniques such as low pass filter [9] and Kalman filter [10] to obtain a better performance in estimation. In order to obtain the best performance of estimation using filtering technique, however, it needs a tuning process and calibration stage. Another method developed by some previous studies was by using machine learning based such as an artificial neural network (ANN) [11], neuro-fuzzy [12] and support vector machine (SVM) [13] to estimate the elbow joint angle by training the pattern which is related to the EMG features. Tang extracted the EMG signal from four muscles (biceps, triceps, brachioradialis, and anconeus) to obtain the features [11]. EMG to elbow joint angle model was developed by using the ANN with back propagation method. Li developed a model to predict the knee joint angle using SVM [13]. Seven muscles from lower limb (vastus rectus muscle (VR), vastus lateralis muscle (VL), semitendinosus muscle (SM), biceps muscle of thigh (BM), tibialis anterior muscle (TA), extensor pollicis longus (EP), and gastrocnemius muscle (GM)) were used to estimate the knee joint angle. Oskoei developed an SVM to classify five hand motions by collecting the EMG signal from three muscles (biarticulate wrist flexor, triarticulate, and biarticulate wrist extensor muscles) [14].

Even though good performance was obtained in the previous studies, however, mostly previous studies used four muscles or more to estimate the joint angle of the limb. In real condition, it is preferred to use fewer electrodes due to the effectiveness of the measurement and processing time. In addition, the previous study commonly evaluated the model with regular or periodic motion. In fact, in the real life, a model should be able to estimate and recognize the EMG signal when the elbow performing a random motion. Therefore, in this study, a model was proposed to estimate the elbow joint angle based on EMG signal using only one muscle group from biceps and trained the artificial neural network (ANN) to recognize the elbow joint angle with random motion. Specific purpose of this study is to evaluate the performance of the model using root mean square error (RMSE) and Pearson's correlation coefficients parameters. In this study, the model was developed by using ANN with backpropagation algorithm. In this study, the ANN was configured as time delay artificial neural network (TDANN). This paper was organized as follows. In section II, the matterials and method are presented which include the time domain feature, and the ANN. In section III, the results of this study including the performance (root mean square error and Pearson's correlation coefficients) of the elbow joint angle estimation, and discussion are presented. In section IV, the summaries and some recommendations from this study are concluded.

978-1-5386-5094-3/18/$31.00 ©2018 IEEE

II. Materials and Method

A. Data Acquisition

Fig. 1 presents a block diagram of the data acquisition, time domain feature extraction, structure of the artificial neural network, and evaluation of the model. Single channel surface EMG was recorded from biceps muscle using disposable surface electrode (Ag/AgCl, size: 57 x 48 mm, Ambu, Blue Sensor R, Malaysia). A single surface electrode was also located on bony part of the elbow which was used as a common ground reference. The EMG signal was amplified with the gain of 1,000x to 2,000x. In accordance with the characteristic of the EMG signal, the EMG signal was filtered to eliminate the unwanted signal using bandpass filter with the frequency cut-off at 20 Hz and 500 Hz. A 50 Hz notch filter was also used to eliminate the power line interferences. A 12-bit A/D converter with a sampling frequency of 2,000 Hz was used to record the EMG signal. This sampling frequency is in accordance with Nyquist requirement [15]. Four healthy male participants were involved in this study. Before the subjects performed the experimental procedures, subjects read and agree with the informed consent forms which had been approved by the ethics committee. Each subject performed an elbow motion randomly (aperiodic motion) from extension to flexion between 0° and 140° for about 1 minutes as shown in Fig. 2.

B. Time Domain Feature

The recorded EMG signal was digitally rectified using an absolute function to obtain a real positive value of the EMG

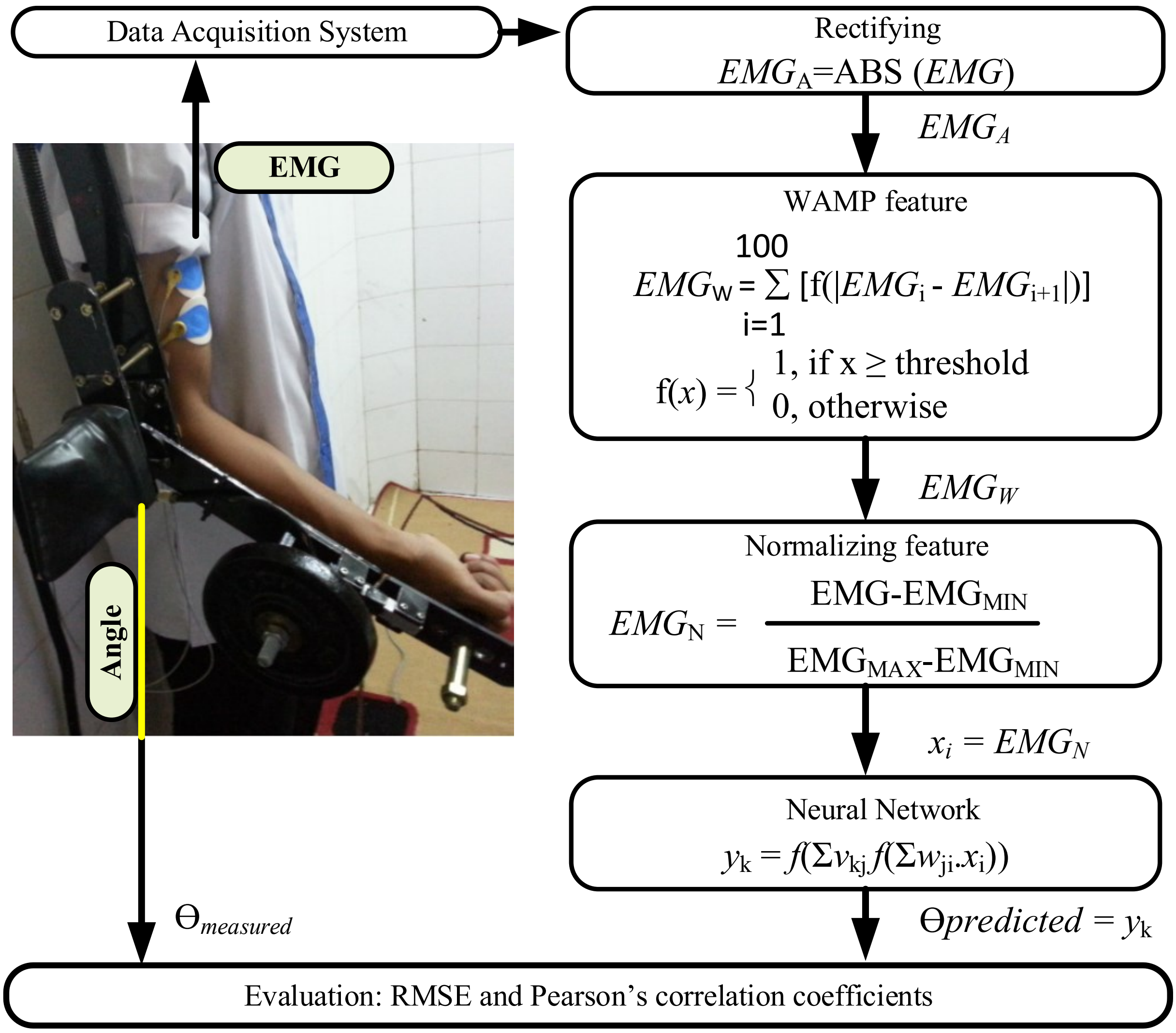

Fig. 1. The diagram block of data acquisition, digital signal processing and artificial neural network for elbow joint angle estimation based on EMG signal.

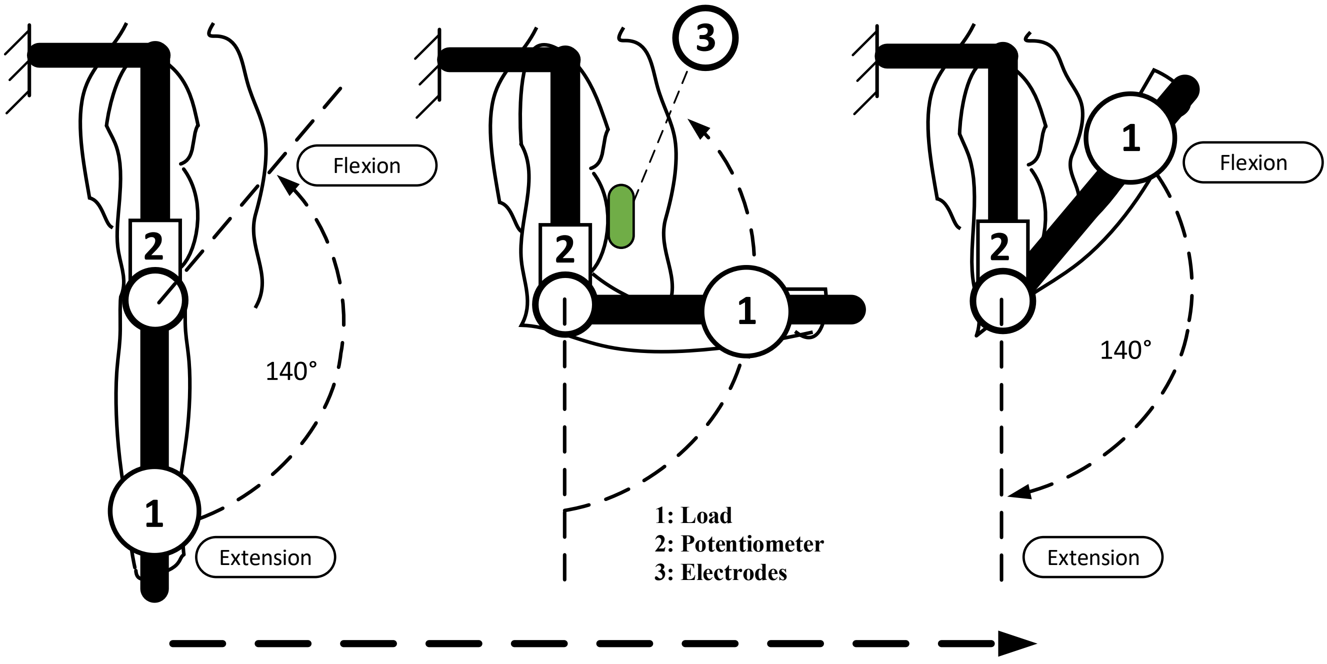

Fig. 2. The ROM (range of motion) of the elbow joint angle in the experiment protocol. The motion was started from extension to flexion and return to extension position.

signal. After performing a full wave rectifying, the EMG signal was extracted for each segment which is limited in the time slot. The EMG signal was segmented using disjoint segmentation for every 100 points of the data. This windows length was recommended by the previous study [16]. Furthermore, each segment of the EMG signal was extracted using time domain feature. In the previous study [17], the 12-time domain features had been evaluated and the results showed that Wilson amplitude (WAMP) feature has a better performance to estimate the elbow joint angle than the others feature. The WAMP feature is expressed as follows [17]:

$$WAMP = \sum_{i=1}^{N-1} [f(|x_i - x_{i+1}|)] \tag{1}$$

with $f(x)$ is written as follows:

$$f(x) = \begin{cases} 1, if \rightarrow x \geq threshold \\ 0, otherwise \end{cases} \tag{2}$$

where x_i is the EMG signal and *threshold* is a level of voltage to limit the EMG signal to be counted. The EMG signal was extracted with window length of 100 samples. This window length had been investigated in the previous study [16]. The normalization of the EMG feature was performed so that the features can be used as an input of the ANN.

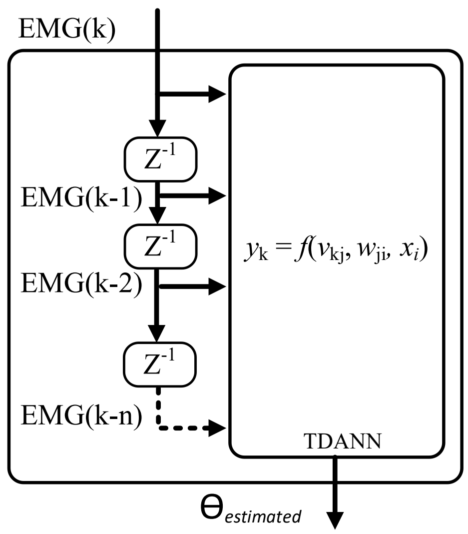

Fig. 3. The architecture of the time delays artificial neural network (TDANN).

C. Artificial Neural Network

The elbow joint angle estimation was performed by using artificial neural network with back propagation algorithm. In this case, the input of the network is a time series, therefore the

ANN is configured as a time delay artificial neural network (TDANN) (Fig.3). The network consisted of input, hidden, and output layer and each layer consisted of number of nodes. Hidden weight (w_{ji}) was used to connect input layer and hidden layer and output weight (v_{kj}) which was used to relate the hidden layer and the output layer. The equation which related to input (x_i) and output (y_i) was written in a equation (3) as follows:

$$y_k = f(\textstyle\sum_{j=1}^{n} v_{kj} \cdot f(\sum_{i}^{m} w_{ji} \cdot x_i)) \tag{3}$$

with sigmoid function is written as follows (4):

$$f(z) = \frac{1}{1+e^{-z}} \tag{4}$$

The back-propagation algorithm is used to train the network by taking the differences between output [y_k(t)] and target or desired [d_k(t)] as shown in equations (5).

$$E = \tfrac{1}{2}\textstyle\sum_{k=1}^{l}[(d_k(t) - y_k(t)]^2 \tag{5}$$

The TDANN was developed using MATLAB (R2014a, Math Works, Inc., USA). In this study, the number of time delay (TD) in the input layer was 5 nodes. If the sampling period of the EMG signal is 0.5 milliseconds, then the number of total delay for 5 nodes of TD is 2.5 milliseconds. After performing the experiment, the number of hidden node was chosen as many as 15 nodes. The number of output node is 1 node which represented the elbow joint angle estimation. The number of subject involved in this study was 4 and 100,000 samples of EMG signal was recorded for each subject so that the number of the sample used to train and test the TDANN is 400,000. The first 320,000 data were used to train the TDANN and the rest of the data was used to test the TDANN.

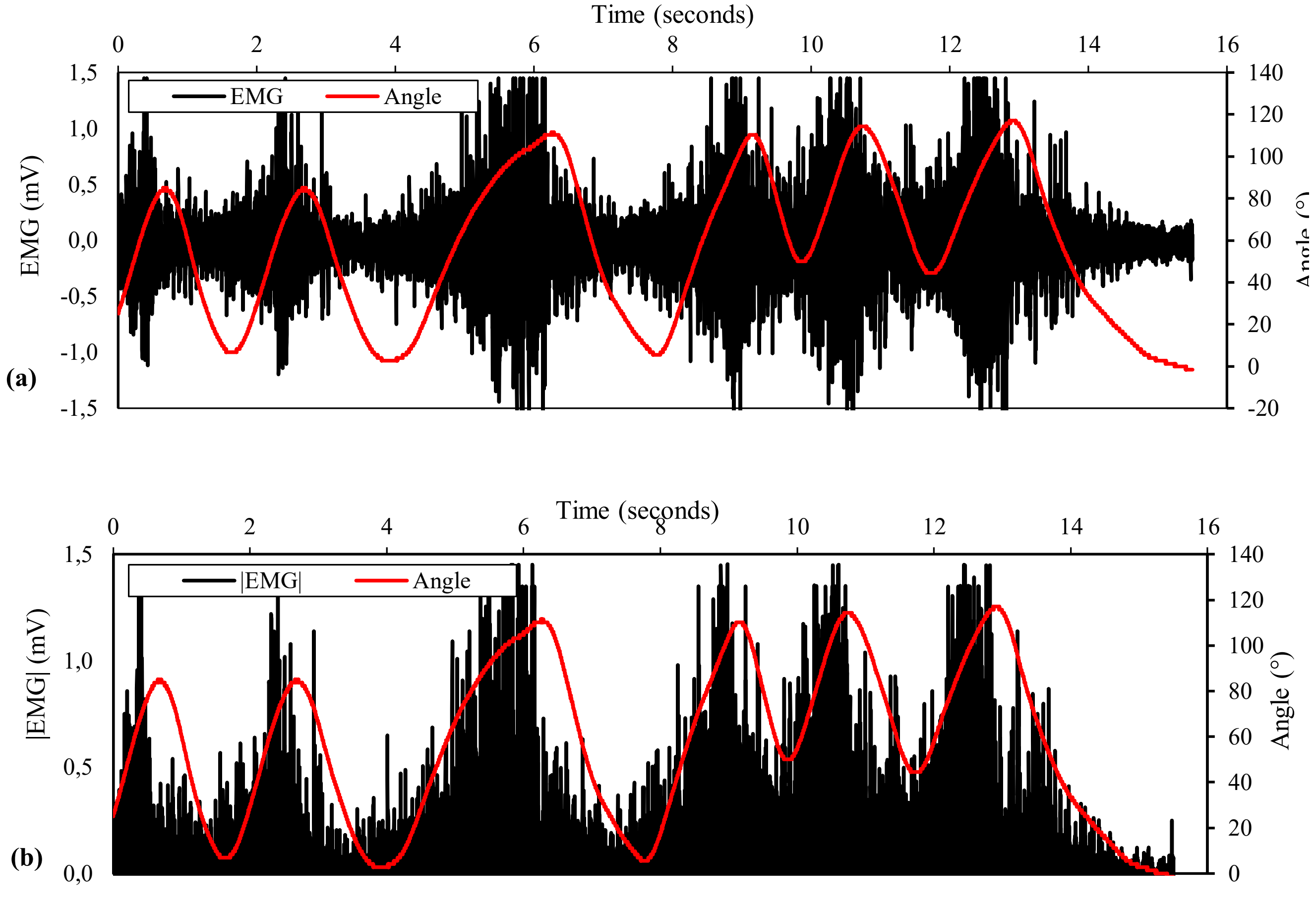

Fig. 4. (a) The raw EMG signal from biceps when the elbow performed a flexion and extension motion. (b) The rectified EMG signals. The black line indicates the EMG signal and the red line shows the measured angle.

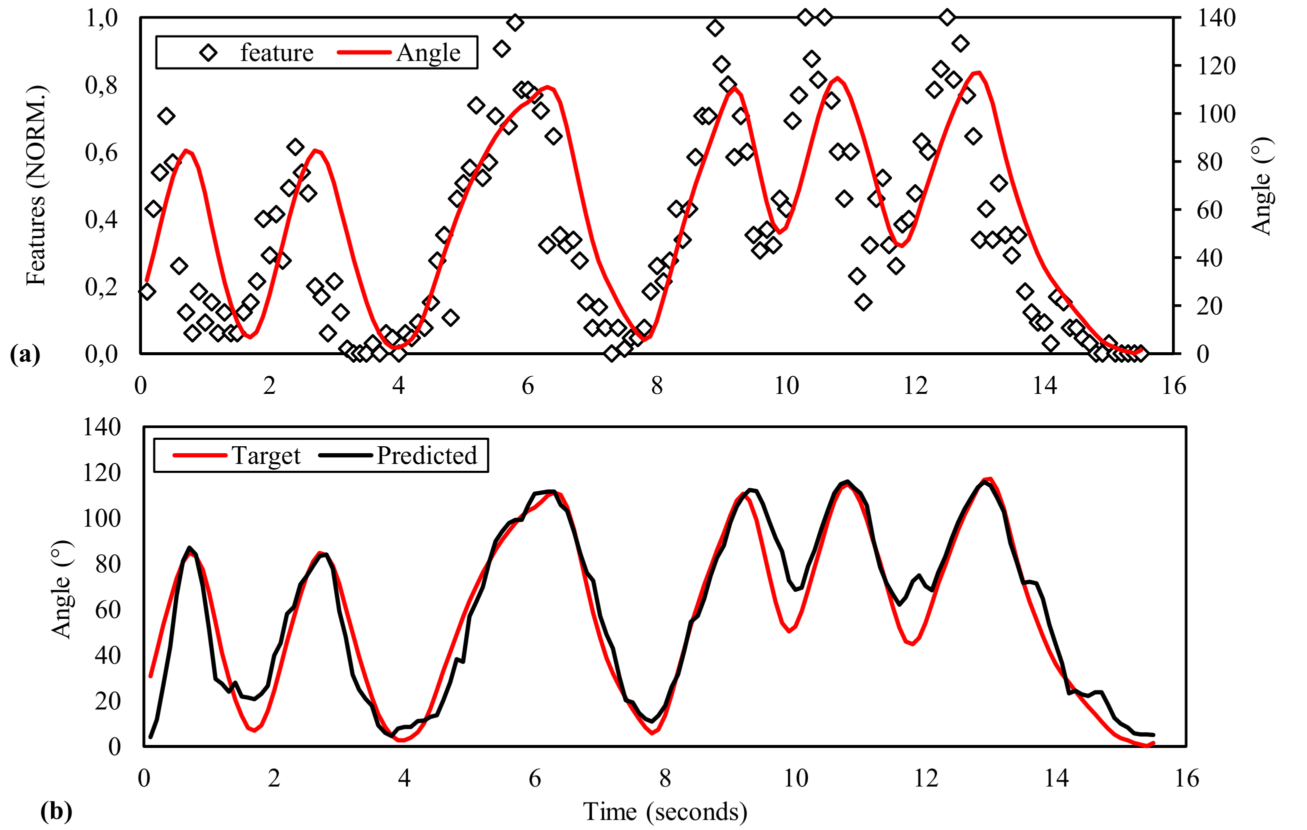

Fig. 5. (a) the little rectangle shows the EMG features which is extracted using WAMP feature, and (b) the estimated elbow joint angle from TDANN after the training process.

III. Results and Discussion

The proposed method has demonstrated the effectiveness of the model to estimate the elbow joint angle using EMG signal from single muscle (biceps). Fig. 4 shows the response of the EMG signal when the elbow performed a flexion and extension in a random motion. The EMG signal displays varies amplitude in accordance with the position of the elbow. After the rectifying process [Fig. 4(b)], the EMG signal was extracted, normalized and then used as the input of the ANN. The EMG features, as shown in Fig. 5(a), almost followed the elbow joint angle but with some noises. After the training process, the TDANN is able to estimate the elbow joint angle smoothly [Fig. 5(b)].

In the testing step, the performance (RMSE and Pearson's correlation coefficients) of the elbow joint angle estimation was varied (Fig. 6), because the characteristic of the EMG signal was also varied for each subject. RMSE represented the performance of the model when compared between output TDANN and desired target (measured angle) so that the RMSE values closed to zero is the better performance. The Pearson's correlation coefficient represents the relation between the

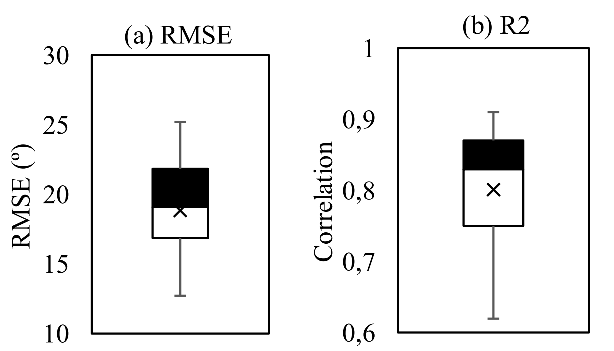

Fig. 6. The performance of the TDANN in estimating the elbow joint angle at the testing steps. The RMSE value in the (a) RMSE and (b) Pearson's correlation coefficient.

TABLE I. The mean and standard deviation of the performance (RMSE and correlation) of the elbow joint angle estimation from TDANN).

Performance	RMSE (°)	Correlation
Mean	18.87	0.80
Standard Deviation	3.46	0.09
Median	19.09	0.83
Minimum	12.73	0.62
Maximum	25.21	0.91

output of TDANN and measured angle, therefore, the values closed to one is better.

Table 1 shows the summary of descriptive statistics of the testing process for all subjects. The mean and standard deviation of the RMSE and Correlation are 18.87°±3.46° and 0.80±0.09, respectively.

In this study, the performance of the proposed method was compared to the others related studies. In the previous study which used Kalman filtering technique [10], the RMSE value ranged between 9.41°±2.53° and 15.07°±2.14° (for four subjects). However, those studies, the evaluation was only conducted in periodic motion. Pau evaluated the performance of the estimation for periodic and random motion, the RMSE values were 22.0°±6.6° and 22.4°±5.0°, respectively [18]. In the data acquisition process, this study was only conducted in the non-fatigue condition. Previous studies had revealed that the muscle fatigue affected the parameters (amplitude and frequency) of the EMG signal [19] [20]. In the next study, the muscle fatigue was needed to be considered, in order to obtain a better performance against the time variance in the EMG signal

IV. Conclussion

This paper revealed that the TDANN model was able to estimate the elbow joint angle based on EMG signal for random motion. This study suggested that the elbow joint angle can be estimated only using biceps. The performance of the estimation was varied since the EMG characteristics for each subject was also varied. In the next study, some parameters need to be investigated such as the structure of the TDANN, a number of subjects and muscle fatigue to obtain the better performance.

References

[1] M. Halaki and K. a Ginn, "Normalization of EMG Signals: To Normalize or Not to Normalize and What to Normalize to?," *Comput. Intell. Electromyogr. Anal. - A Perspect. Curr. Appl. Futur. Challenges*, pp. 175–194, 2012.

[2] K. Nishihara and T. Isho, "Location of Electrodes in Surface EMG," in *EMG Methods for Evaluating Muscle and Nerve Function*, InTech, 2012, pp. 17–30.

[3] A. Merlo and I. Campanini, "Technical Aspects of Surface Electromyography for Clinicians," *Open Rehabil. J.*, vol. 3, pp. 98–109, 2010.

[4] M. Asghari Oskoei and H. Hu, "Myoelectric control systems-A survey," *Biomed. Signal Process. Control*, vol. 2, no. 4, pp. 275–294, 2007.

[5] R. Singh and S. Chatterji, "Trends and Challenges in EMG based Control Scheme of Exoskeleton Robots-A Review," *Int. J. Sci. Eng. …*, vol. 3, no. 8, 2012.

[6] C. W. Antuvan, M. Ison, and P. Artemiadis, "Embedded human control of robots using myoelectric interfaces," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 4, pp. 820–827, 2014.

[7] A. Fougner, O. Stavdahl, P. J. Kyberd, Y. G. Losier, and P. a. Parker, "Control of upper limb prostheses: Terminology and proportional myoelectric controla review," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 20, no. 5, pp. 663–677, 2012.

[8] X. Zhang *et al.*, "On design and implementation of neural-machine interface for artificial legs," *IEEE Trans. Ind. Informatics*, vol. 8, no. 2, pp. 418–429, 2012.

[9] G. Jang, J. Kim, Y. Choi, and J. Yim, "Human shoulder motion extraction using EMG signals," *Int. J. Precis. Eng. Manuf.*, vol. 15, no. 10, pp. 2185–2192, 2014.

[10] T. Triwiyanto, O. Wahyunggoro, H. A. Nugroho, and H. Herianto, "Evaluating the performance of Kalman filter on elbow joint angle prediction based on electromyography," *Int. J. Precis. Eng. Manuf.*, vol. 18, no. 12, pp. 1739–1748, Dec. 2017.

[11] Z. Tang, K. Zhang, S. Sun, Z. Gao, L. Zhang, and Z. Yang, "An Upper-Limb Power-Assist Exoskeleton Using Proportional Myoelectric Control," *Sensors*, vol. 14, no. 4, pp. 6677–6694, Apr. 2014.

[12] K. Kiguchi and Y. Hayashi, "EMG-Based Control of a Lower-Limb Power-Assist Robot," in *Intelligent Assistive Robots, Springer Tracts in Advanced Robotics 106*, Springer, 2015, pp. 371–383.

[13] Q. Li, Y. Song, Z. Hou, and B. Zhu, "sEMG based joint angle estimation of lower limbs using LS-SVM," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 8226 LNCS, no. PART 1, pp. 292–300, 2013.

[14] M. a. Oskoei and H. H. H. Hu, "Support Vector Machine-Based Classification Scheme for Myoelectric Control Applied to Upper Limb," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 8, pp. 1956–1965, 2008.

[15] Li Tan & Jean Jiang, *Digital Signal Processing: Fundamental and Applications*, vol. 70, no. 3. 2008.

[16] Triwiyanto, O. Wahyunggoro, H. A. Nugroho, and Herianto, "Effect of window length on performance of the elbow-joint angle prediction based on electromyography," *J. Phys. Conf. Ser.*, vol. 853, no. 1, 2017.

[17] Triwiyanto, O. Wahyunggoro, H. A. Nugroho, and Herianto, "An investigation into time domain features of surface electromyography to estimate the elbow joint angle," *Adv. Electr. Electron. Eng.*, vol. 15, no. 3, 2017.

[18] J. W. L. Pau, S. S. Q. Xie, and A. J. Pullan, "Neuromuscular interfacing: Establishing an EMG-driven model for the human elbow joint," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 9, pp. 2586–2593, 2012.

[19] T. Triwiyanto, O. Wahyunggoro, H. A. Nugroho, and H. Herianto, "DWT Analysis of sEMG for Muscle Fatigue Assessment of Dynamic Motion Flexion-Extension of Elbow Joint," in *2016 8th International Conference on Information Technology and Electrical Engineering (ICITEE)*, 2016, pp. 1–6.

[20] Triwiyanto, O. Wahyunggoro, H. Adi Nugroho, and Herianto, "Continuous wavelet transform analysis of surface electromyography for muscle fatigue assessment on the elbow joint motion," *Adv. Electr. Electron. Eng.*, vol. 15, no. 3, 2017.