Time Delay Neural Network to Estimate the Elbow Joint Angle Based on Electromyography

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***Abstract*—Elbow joint angle estimation is essential in the field of biomechanical engineering especially for an apparatus based on myoelectric control. The purpose of this study is to develop a model of electromyography (EMG) signal to elbow joint angle estimation using time delay neural network (TDANN). The EMG signals were recorded only from biceps muscle from ten healthy male subjects. In order to obtain the features, the EMG signal is extracted for every 100 samples using sign slope change (SSC) features. The EMG features are used as the training data, in order the TDANN able to recognize the elbow joint angle. The results of this study reveal that the performance of the estimation is better if it is compared to the other studies. The RMSE values for the continuous and random motion are 14.97°±5.17° and 18.69°± 2.76°, respectively. The Pearson correlation coefficients are 0.87± 0.0087 and 0.78±0.11 for continuous and random motion, respectively. The results have confirmed the usefulness of the proposed method to estimate the elbow joint angle.**

Keywords— EMG; sign slope change; TDANN; elbow joint angle estimation.

I. Introduction

Recently, electromyography (EMG) has been used widely to study the characteristic of EMG to human motion and myoelectric based control [1], [2]. EMG signal is a bioelectricity which is generated from a group of muscles when the muscles conduct a voluntary contraction. The EMG signal can represent the position, force, and torque. Furthermore, the information carried by the EMG signal can be used as a control signal. In order to control the devices based on EMG signal, first of all, a study needs to be conducted to estimate the parameters (position, force, and torque) from the EMG signal. The prediction of the upper limb elbow joint angle was investigated extensively by some previous researchers. Some studies applied a non-pattern recognition based which directly to estimate an elbow joint from the EMG features proportionally. In the elbow joint angle estimation, the previous study used Kalman filter to eliminate the noise in the EMG features [3]. Even though the study obtained a good performance in estimation but the evaluation is performed only for continuous motion. The modeling of the muscle based on Hill-base was studied by Pau [4]. In the study, the performance of the estimation was improved by using a Genetic algorithm. Even though the performance was good in the single cycle motion, however, the performance decreased when the motion was in continuous and random. Other studies presented a pattern recognition based using a machine learning to estimate the elbow joint angle. Li presented a support vector machine to predict the position of the knee joint by extracting the EMG signal using mean absolute value (MAV) feature [5]. In the study, seven muscle groups from one subject were acquired to estimate the knee joint angle. However, to obtain the variance of the estimation among the subjects, more subjects were required in the study. An artificial neural network (ANN) with backpropagation algorithm was also a common method which is proposed in the machine learning based. Tang developed an upper limb exoskeleton by estimating the elbow joint angle using RMS features of the EMG signal [6]. Four muscle groups were used in the study. However, the performance of the estimation was only conducted for continuous motion.

In the EMG data acquisition, previous studies used four to seven muscle groups to estimate the joint (knee and elbow) angle. However, using less muscle groups to estimate the elbow joint angle are more preferred. This is because the more muscle group is the more time computation. Therefore, in this study, a new proposed method was needed to be presented to estimate an elbow joint angle which only use a single muscle group from biceps. In this study, the number of subjects was also considered. This is to reveal the characteristics of the EMG signal for different subjects when the subject performs a flexion and extension motion. Furthermore, in addition to evaluate the proposed method in the continuous motion, a random motion was also evaluated. This is due to the random motions which are close to the real human activities. In order to apply the proposed method, an artificial neural network was configured as a time delay artificial neural network (TDANN). The specific aims of this study are: (a) to evaluate the performance of the estimation using root mean square error (RMSE) and Pearson's correlation

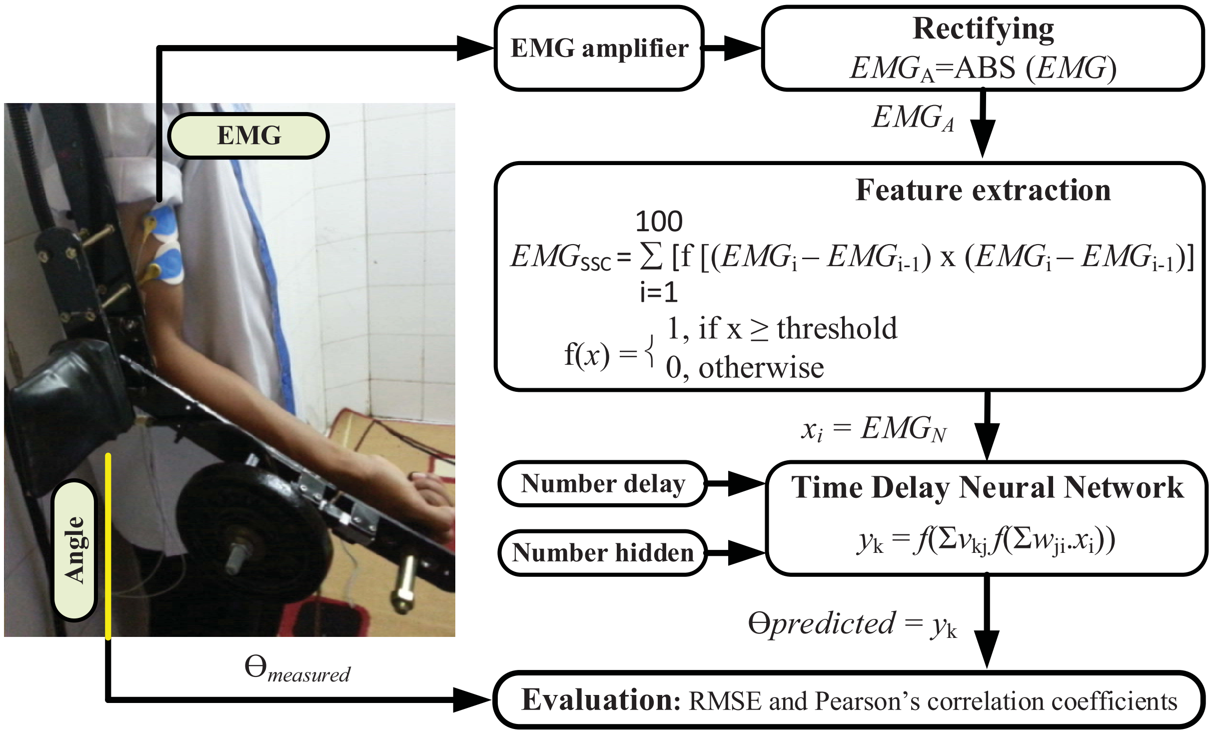

Fig. 1. The diagram block of the proposed method to estimate the elbow joint angle based on EMG signal

coefficients in the continuous and random motion, (b) to evaluate the linear regression of the proposed method between the measured angle and the estimated angle, (c) to test the significant difference of the RMSE between the continuous motion and the random motion using T-test. This paper is structured as follows: Section II presents the experiment protocol, diagram block of the study, time domain features extraction and the configuration of the time delay neural network. Section III shows the result of the study and comparison to the others studies. Section IV concludes the result of the study and shows some recommendations and limitations.

II. Materials and Methods

A. Subjects

Ten healthy male subjects who have no previous injury at the elbow were selected in this study. The homogeneous of the subject was also considered in this study of which the subject meets the criteria as follows: 20-25 years old and 60-80 kg. Before performing the experiment protocols, the subjects were given a consent form to read and sign. The experiment protocol of this study has been approved by Ethic Committee of Health Polytechnic of Surabaya, Indonesia (No: 035/S/KEPK/V/2017).

B. The Experiment Protocols

The EMG signals were recorded from biceps using two electrodes disposable (Ag/AgCl, size: 57 x 48 mm, Ambu, Bluesensor R, Malaysia) and one electrode as common reference was placed on the bony part of the elbow. The placement of the electrodes was in accordance with SENIAM rules [7]. The electrodes were connected to a bio-amplifier with adjustable gain according to each subject. A 12-bit A/D converter was used to convert the analog signal into digital data. The sampling rate for the data acquisition was 2,000 Hz which is in accordance with Nyquist's rule. The Borland Delphi (Version 7.0, Borland Software Corporation, Scotts Valley, California, USA) programming was used to acquire and record the EMG data for further data analysis. In the recording of the EMG signal, the elbow performed a flexion and extension motion of which the range of motion (ROM) is 140 degrees. A linear potentiometer (WX110-203, Bonens, China) was used to measure the real elbow joint angle. In order to synchronize the flexion and extension motion, an exoskeleton frame was used. As shown in Fig. 1, the exoskeleton consisted of two aluminum bars, a holder, load, and potentiometer sensor. The exoskeleton was installed at the wall.

In the experimental protocols shown in Fig. 2, the subjects were instructed to perform the flexion and extension motion for two types of motion which are continuous and random motion. In the continuous motion, the motion was set at 2 second periods. To synchronize the periodic motion, a metronome application was used. In the random motion, the period was undetermined. The pattern of motion was shown in Fig. 3. As shown in Fig. 1, the EMG signal processing was conducted offline which consisted of some process including feature extraction and pattern recognition using artificial neural network (ANN). The recorded of the EMG signal was extracted using Sign Slope Change (SSC) feature. Then, the EMG features were recognized by the artificial neural network which had been trained before the testing step. The model was used to convert EMG pattern

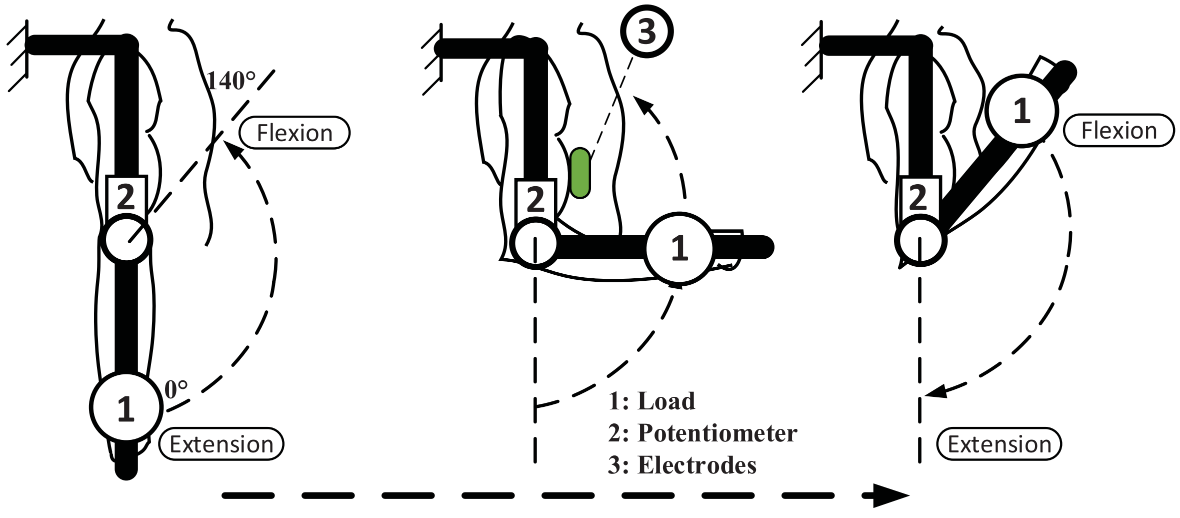

Fig. 2. The position of the elbow joint in flexion and extension motion

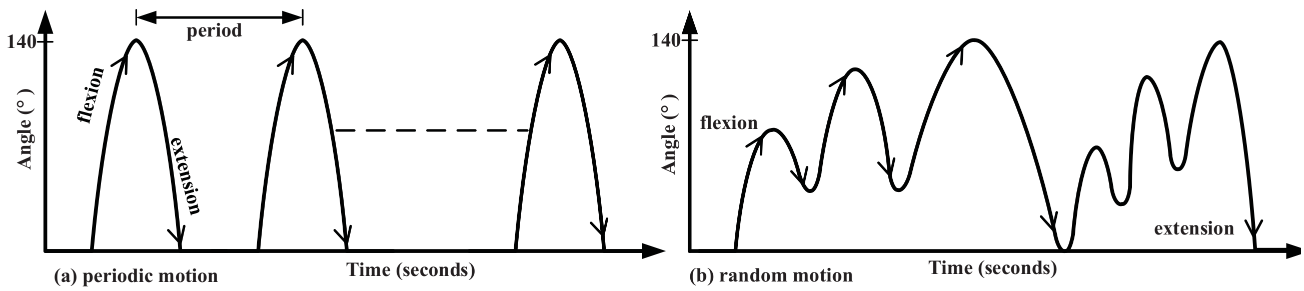

Fig. 3. (a) continuous motion, (b) random motion of the elbow joint.

into the elbow joint angle. The evaluation of the model was performed by using root mean square error (RMSE) and Pearson's correlation coefficients.

C. Time Domain Features

The time domain features are extensively used by previous studies to extract the EMG and to reveal the characteristics of the EMG signal. The previous study has investigated the relation between the EMG signal and elbow joint angle [8] and the Sign slope change (SSC) features have better performance if it is compared to the other features.

$$SSC = \sum_{i=1}^{N-1}[f[(x_i - x_{i-1}) \times (x_i - x_{i+1})]]$$

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

where x_i is the ith sample of the EMG signal and threshold is a constant value.

The SSC features are the number of times the slope of the signal changes its sign within a window of length N. It is formulated in Eq. (1) [9]. The EMG signals were extracted for every 100 samples to obtain the features that related to the elbow

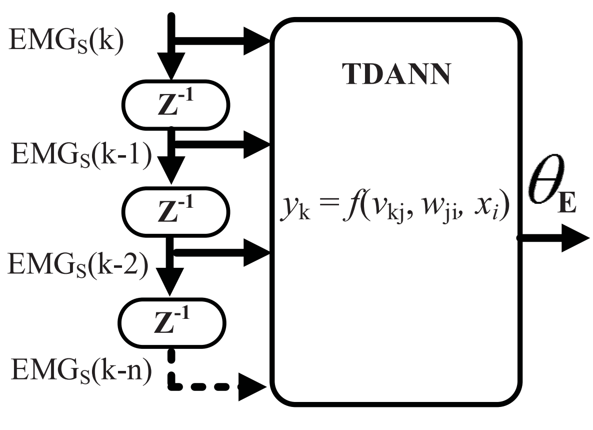

Fig. 4. The structure of the time delay neural network with input SSC

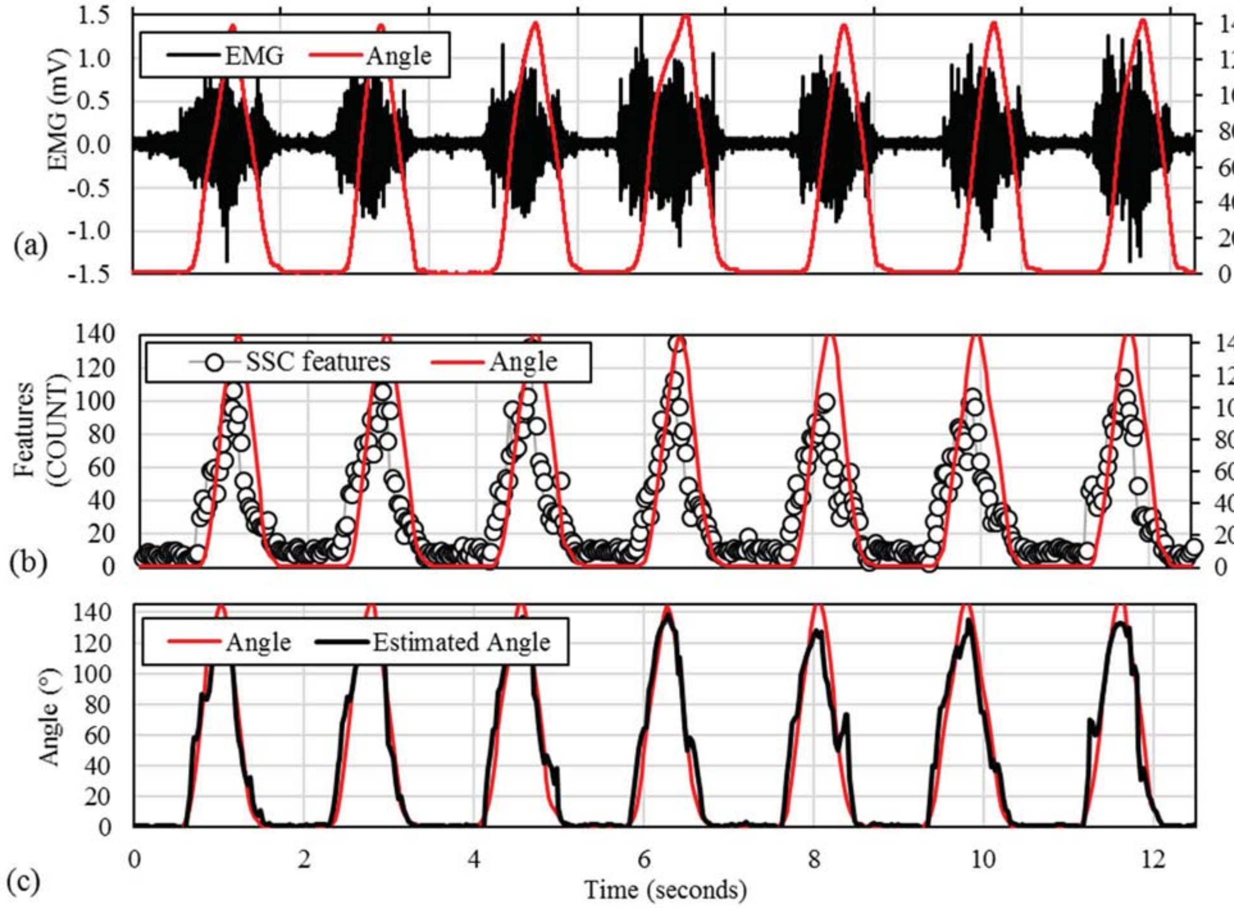

Fig. 5. (a) The EMG signal (b) The SSSC features, and (c) the estimated of the elbow joint angle in continuous motion (period=2s)

joint angle. The threshold constant was determined manually at 0.1 mV in the programming application.

D. Time Delay Neural Network

The model of EMG to elbow joint angle was implemented using the artificial neural network (ANN) with back propagation method (Fig. 4). As the input of the ANN is a time series data then the architecture of the ANN was configured as time delay artificial neural network (TDANN). In this study, the number of time delay was 5. The number of the hidden nodes was determined by experiment. The number of the output node is 1 as the estimated angle of the elbow joint.

$$y_k = f(\textstyle\sum_{j=1}^{n} v_{kj} \,.\, f(\sum_{i}^{m} w_{ji} . x_i)) \tag{2}$$

where y_k is the output of TDANN, v_{kj} is the hidden weight which is related between the hidden node and an output node, w_{ji} is input weight which is related between the input node and hidden node and x_i is the input of the TDANN. The sigmoid function used in Eq. (3) is written as follows:

$$f(z) = \frac{1}{1+e^{-z}} \tag{3}$$

The back-propagation algorithm is used to train the network by taking the differences between the output [y_k(t)] and the target or desired [d_k(t)] as shown in equations (4).

$$E = \tfrac{1}{2}\textstyle\sum_{k=1}^{l}[(d_k(t) - y_k(t)]^2 \tag{4}$$

In order to evaluate the robustness of the model against the various EMG characteristics, the training and testing for TDANN were applied with two schemes. In the first scheme, 70% and 30% data samples each obtained from 10 subjects were used as training and testing, respectively. In the second scheme, 100 % data from 7 subjects were used as training data and 100% data from the other 5 subjects were used as the testing data.

In this study, the digital signal processing of the EMG signal and machine learning of the TDANN was implemented offline using a personal computer (Intel Core i5-4308 CPU @ 2.80GHz, 8 GB of RAM, Windows 8)

III. Results and Discussion

A. Elbow Joint Angle Estimation

The proposed method has demonstrated the elbow joint angle estimation based on EMG signal with a good performance. In the continuous motion, the EMG signals were varied to the

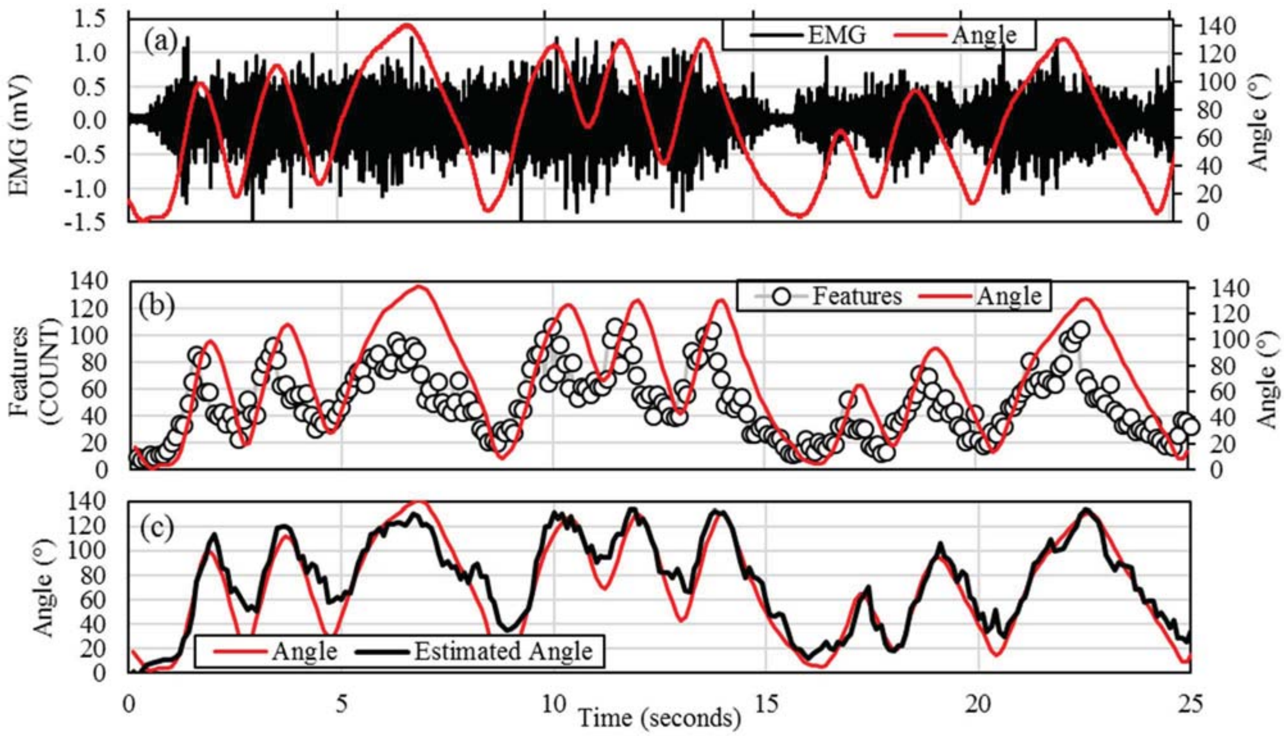

Fig. 6. (a) The EMG signal (b) The SSSC features, and (c) the estimated of the elbow joint angle in random motion

elbow joint angle but with a regular pattern as shown in the Fig. 5(a). Fig. 5(b) shows the EMG features using sign slope change (SSC). In this figure, the features almost follow the track of the elbow joint but with some noises.

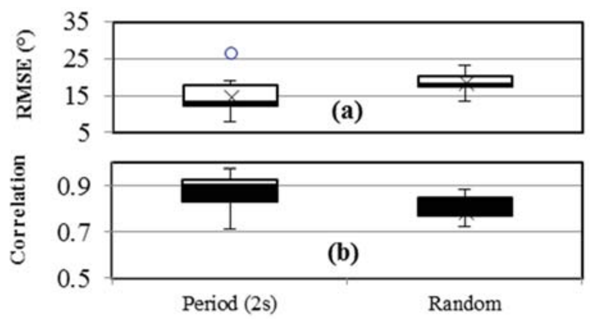

Fig. 7. The boxplot of (a) RMSE and (b) Pearson's correlation coefficient in according to scheme I (see section II.D).

TABLE I. THE SUMMARY OF THE RMSE AND PEARSON'S CORRELATION COEFFICIENTS FOR BOTH TYPE OF MOTION (CONTINUOUS AND RANDOM MOTION). THE PERFORMANCE IS OBTAINED FROM SCHEME I.

Parameters	Continuous (T=2s)		Random	
	RMSE (°)	Correlation	RMSE (°)	Correlation
Mean	14.97	0.87	18.69	0.78
SD.	5.15	0.087	2.76	0.11
Median	13.18	0.90	18.21	0.83
Min.	7.79	0.71	13.43	0.48
Max.	26.70	0.97	23.07	0.83

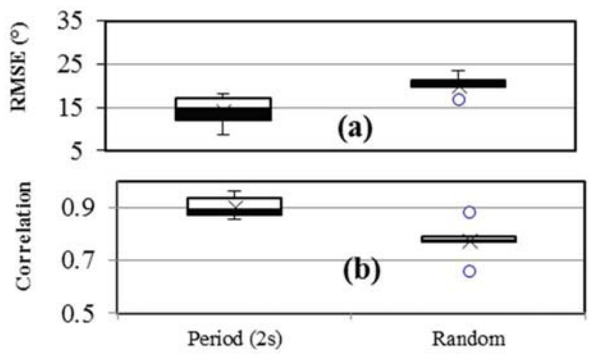

Fig. 8. The boxplot of (a) RMSE and (b) Pearson's correlation coefficient in according to scheme II (see section II.D).

TABLE II. THE SUMMARY OF THE RMSE AND PEARSON'S CORRELATION COEFFICIENTS FOR BOTH TYPE OF MOTION (CONTINUOUS AND RANDOM MOTION). THE PERFORMANCE IS OBTAINED FROM SCHEME II.

Parameters	Continuous (T=2s)		Random	
	RMSE (°)	Correlation	RMSE (°)	Correlation
Mean	14.18	0.90	20.33	0.77
SD.	3.80	0.043	2.36	0.079
Median	14.86	0.89	20.54	0.77
Min.	8.78	0.85	16.88	0.66
Max.	18.19	0.95	23.32	0.88

After the training process, the TDANN is able to estimate the elbow joint angle from the features. For a typical estimation in continuous motion as shown in Fig. 5(c), the RMSE and Pearson's correlation coefficient are 16.92° and 0.88, respectively. A typical estimation for random motion are shown

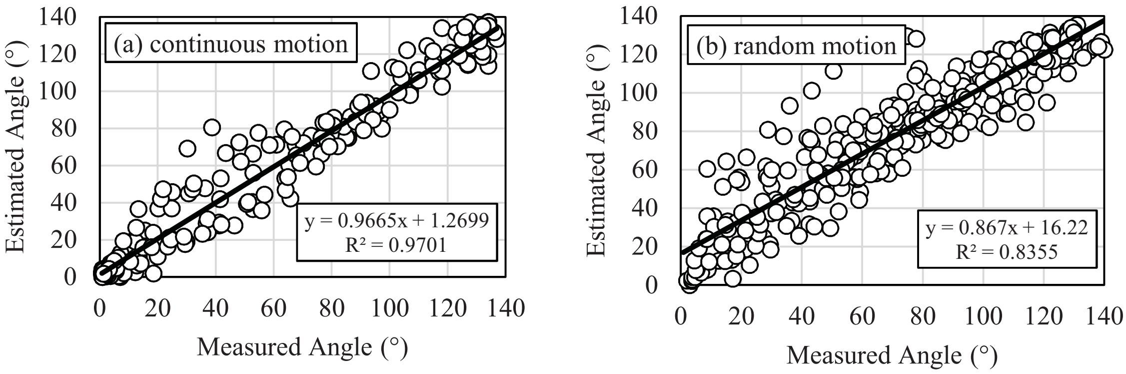

Fig. 9. The line regression of the proposed method in continuous and random motion

in Fig. 6 (c) with the RMSE and Pearson's correlation coefficient are 14.3° and 0.87, respectively.

B. The Performance of Estimation

In order to investigate the robustness of the model to the various subjects, the training and testing of the TDANN was performed in two schemes as mentioned in the section II.D. The variance of the performance was shown in Fig. 7 and Fig. 8 both for continuous and random motion. Table 1 summarized the RMSE and Pearson's correlation coefficients for the scheme I both for continuous and random motion. Table 2 shows the RMSE and Pearson's correlation coefficients for the scheme II. Statistical analysis showed that there was no significant difference of RMSE and correlation (p-value >0.05) between scheme I and II both for continuous and random motion. The performance of the proposed method can be compared to the other studies (Table III).

TABLE III. THE PERFORMANCE OF THE ELBOW JOINT ANGLE ESTIMATION FROM OTHERS STUDIES

Author	Methods	RMSE (°)
Tang [6]	ANN	Single motion: Period 2s: 10,7º Period 4s: 9,67º Period 8s: 12,42º
Pau [4]	Hill-base	Continuous motion: 22º±6.6º, Random motion: 22.4º±5.0º
Triwiyanto [3]	Kalman filter	Continuous motion: Period 6s:12.95º ±1.99º Period 8s: 11.86º ±1.86º Period 12s: 12.96º ±1.60º

C. The Regression

The regression of the proposed method was also evaluated to investigate the linearity between the estimated and the measured angle (Fig. 9). The study was revealed that the regression parameters from continuous motion (R^2=0.97 and slope=0.96) were better than that from the random motion (R^2=0.84 and slope=0.87). This difference was due to the randomness of the features when the evaluation was performed in the random motion. In addition to the EMG signal, mechanical sensor such accelerometer, gyroscope, and inertial measurement unit are usually used to detect the position of the EMG signal.

IV. CONCLUSION

The study has revealed the usefulness of the proposed model to estimate the elbow joint angle based on EMG signal using TDANN. The EMG signal was only recorded from bicep muscle groups. The proposed model was evaluated for continuous motion and random motion. The results show that the performance of the proposed model for the continuous and random motion is better if it is compared to the others studies. However, an additional algorithm needed to be proposed to compensate the effect of the muscle fatigue.

REFERENCES

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

[2] 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.

[3] 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.

[4] 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.

[5] 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.

[6] 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.

[7] H.J. Hermens and B Freriks, "SENIAM Project," *The SENIAM project*, 2017. [Online]. Available: http://www.seniam.org/. [Accessed: 16-Jun-2017].

[8] 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.

[9] R. H. Chowdhury, M. B. I. Reaz, M. A. B. M. Ali, A. a a Bakar, K. Chellappan, and T. G. Chang, "Surface electromyography signal processing and classification techniques.," *Sensors (Basel).*, vol. 13, no. 9, pp. 12431–12466, 2013.