Adaptive threshold to compensate the effect of muscle fatigue on elbow-joint angle estimation based on electromyography

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ABSTRACT

Muscle fatigue is a major problem in the study based on electromyography (EMG) signal. When the muscle in the fatigue condition, the power of the EMG signal increases significantly. This phenomenon can be a problem in the elbow-joint angle estimation. The purpose of this study is to develop a method in order to compensate the effect of the muscle fatigue on the elbow-joint angle estimation based on time domain features using EMG signal. The EMG signal was collected from biceps while the subjects performed a fatiguing motion of flexion and extension. The EMG was extracted using four time-domain features, namely zero crossing (ZC), sign slope change (SSC), Wilson amplitude (WAMP) and myopulse percentage rate (MYOP). The yielded features were filtered using second order Butterworth low pass filter. In the proposed method, to compensate the effect of the muscle fatigue, the RMS of the EMG signal was calculated for every cycle and used it as a threshold value of the features. The results show that the proposed method is able to compensate the effect of muscle fatigue with a consistent root mean square error (RMSE). The improvement of the performance ranges between 17.41% and 37.9% (for all adaptive features).

Keywords: Electromyography; feature extraction; elbow-joint angle estimation; muscle fatigue; low pass filter.

INTRODUCTION

Recently, electromyography (EMG) [1, 2] is used a lot in the human-machine interaction such as virtual reality, prosthetic devices, exoskeleton and teleoperation [3-6]. Joint-angle estimation is essential in the development of the human-machine interaction to estimate the position of the limb or to learn the human motion [7, 8]. The following are the examples of the estimation of an elbow-joint angle using a machine learning method. Tang used an artificial neural network (ANN) [9] with the back-propagation algorithm to estimate the elbow-joint angle from the EMG features [10]. Lee proposed a method to estimate knee joint angle using least square support vector machine (LS-SVM) [11]. Previous researchers were also used Hill-based muscle model to estimate the elbow-joint angle [13]. Pau used Genetic Algorithm (GA) to optimize the estimate, however, the GA is a high time consuming to perform an optimization [12]. Kiguchi used a neuro-fuzzy algorithm to estimate the force from EMG to control an upper limb exoskeleton [14]. However, the problem in elbow joint

angle estimation which involves machine learning based methods is that the method requires a learning stage to recognize the EMG pattern. Previous studies also developed a non-machine learning-based method to estimate the elbow-joint angle and force using EMG signal [15-18]. However, the problem and limitation are that the previous studies have not considered the effect of the muscle fatigue to the performance of the estimation.

When a human performs a repetitive and intense motion, the muscle fatigue might occur. This muscle fatigue can be categorized as physiological fatigue or localized muscle fatigue which refers to the failure of the muscle to sustain the force [19]. Muscle fatigue could be detected accurately based on invasive methods such as blood test and examination of the body tissue. However, those methods are not in accordance with the experiment which has to be observed continuously. Previous studies were preferred to use a non-invasive method for detecting the muscle fatigue using EMG signal [19, 20]. Since the muscle fatigue caused the frequency and amplitude of the EMG signal to change [21-23], a new method has to be introduced to compensate the effect of muscle fatigue so that the estimation can be maintained. Na proposed a method to estimate the elbow joint force using muscle twitch model [24]. He found that the method can compensate the effect of muscle fatigue in the force estimation. Thilina developed a method to compensate the effect of muscle fatigue on the elbow joint angle estimation which is used to control upper limb exoskeleton [25]. In the study, he used the mean power frequency (MPF) to detect muscle fatigue and to adjust the weight of the neuro-fuzzy. The MPF was obtained after the EMG signal was transformed into a frequency domain using fast Fourier transform (FFT). Therefore, the feature such as MPF which based on frequency domain needs a high computation time to process.

In addition to the features based on the frequency domain, the time domain features are the most popular used to extract the EMG signal into some information, related to the elbow-joint angle [3, 10, 26]. Time domain features are divided into three categories, namely based on energy, complexities, and frequency [27]. In the time domain features based on frequency, we can get the frequency content of the EMG signal without any transformation such as FFT. These features are sign slope change (SSC), zero crossing (ZC), Wilson amplitude (WAMP) and myopulse percentage rate (MYOP). The result of these features is determined by the amplitude of the EMG signal and a threshold parameter. Due to the effect of muscle fatigue, the amplitude of EMG signal increases significantly [24]. In this case, the changes of the EMG signal can be detected by using root mean square (RMS) feature and further, it is used to modify the threshold parameter of the SSC, ZC, WAMP, and MYOP features.

According to the problems, the purpose of the study is to develop a method to compensate the effect of the muscle fatigue on the elbow-joint angle estimation based on EMG signal. The proposed method consists of time domain features extraction, low pass filter, and an adaptive threshold. The specific objectives of this study are: (1) to evaluate the performance of the elbow-joint angle estimation for both the standard method and the proposed method using standard parameter of root mean square error (RMSE), (2) to perform a statistical analysis in order to find the significant difference of performance between the proposed and the standard method using pair samples T-test.

METHODS AND MATERIALS

Data Collecting

The experiment protocol of this study had been approved by Ethics Committee of Health Polytechnic of Surabaya, Ministry of Health, Indonesia (No: 035/S/KEPK/V/2017). Ten healthy male subjects were involved in this study. First of all, the subjects read and filled the form of consents to understand the experimental protocols. Generally, in the flexion and extension motion, the muscle groups affected the EMG signal are biceps and triceps [29]. The previous study has revealed that biceps are more active to generate EMG signal than that from triceps [30]. Therefore,

in this study, the EMG signal was only recorded from biceps muscles using a pair of disposable electrode (Ag/AgCl, size: 57 x 48 mm, Ambu, Blue Sensor R, Malaysia) and one common electrode as the common ground. The placement of the electrodes was in accordance to SENIAM [31]. In order to assess the muscle fatigue, the subjects were in the standing position and held an exoskeleton frame (Figure 1) with a two-kg of load.
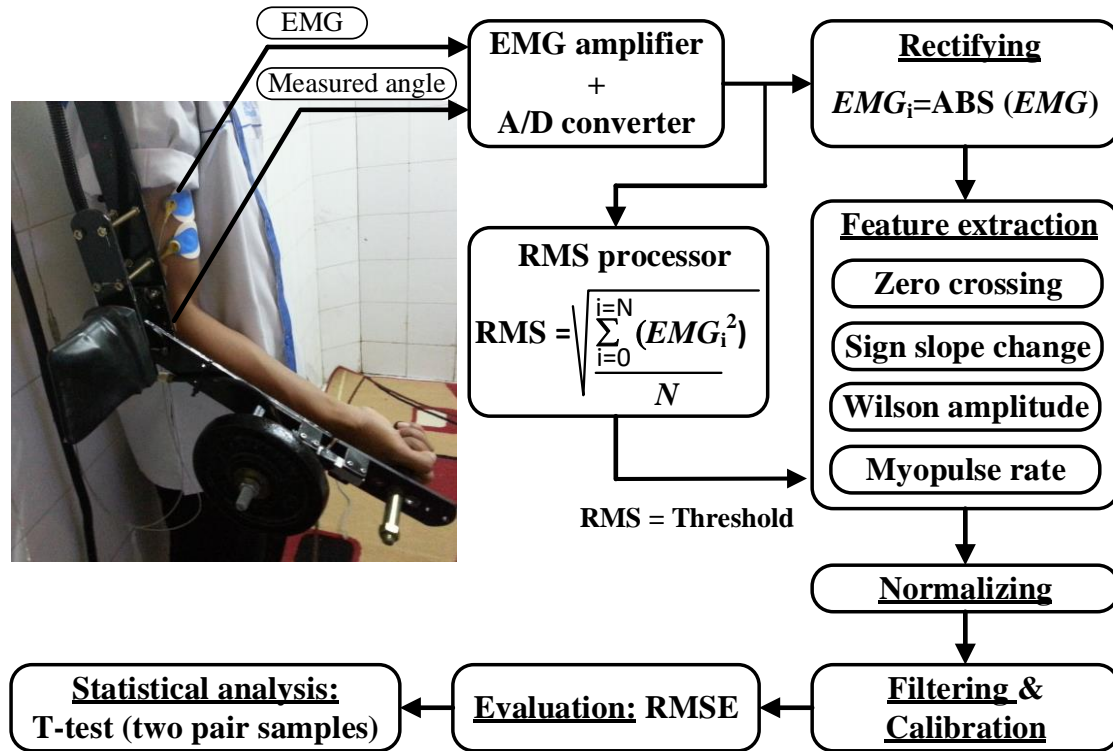

Figure 1. The experiment protocol of the data collection.

The exoskeleton frame is used to synchronize the elbow joint motion (flexion and extension) (Figure 1). In this work, in the initial time of the data collection, the subjects were assumed in the non-fatigue condition. Before the data collection is performed, subjects suggested not to do any heavy activity as stated in the form of consents of experiment protocols. The subjects were asked to move the elbow from extension to flexion motion repetitively within the range of 0˚ to 140˚, The subjects had to maintain the motion (flexion and extension) from non-fatigue to fatigue condition in fifteen minutes or the subjects can stop the motion if they experienced a discomfort condition in the biceps. In this study, the standard protocol used to assess muscle fatigue followed the procedures which had been performed by previous studies [32, 33]. The EMG signal was amplified using an amplifier with a bandpass filter of 20 to 500 Hz and notch filter of 50 Hz. The EMG signal was sampled with a sampling frequency of 1000 Hz, this is according to the Nyquist rule [34]. The real angle of the elbow-joint was measured using a linear potentiometer and filtered using a low pass filter. The EMG and elbow-joint angle were recorded using data acquisition system and standard computer (Intel Core i3-3217U CPU at 1.80GHz, 8 GB of RAM, Windows 8).

Data Processing, Evaluation, and Statistical Analysis
The EMG data processing was consisted of rectifying, time-domain features extraction, features normalization, filtering, calibration, evaluation and statistical analysis (Figure 1). The EMG data along with the measured angle were processed from non-fatigue to fatigue condition up to 15 minutes. The EMG signal was extracted using four standard time-domain features and four

modified features. The features were selected which have a threshold parameter. The EMG signal was segmented and extracted with a window length (WL) of 100 milliseconds. These features are zero crossing (ZC), sign slope change (SSC), Wilson amplitude (WAMP) and myopulse percentage rate (MYOP) as written in Table 1 [16, 27]. Commonly the threshold-values of these features were set by a real constant value [35-37]. Over a long period of contraction in dynamic motion (flexion and extension), the muscle fatigue would appear and the power of EMG also increased significantly as mention in the previous studies [23, 26, 27]. In order the features able to adapt to the fatigue condition, the threshold values needed to be adjusted adaptively so that the output of the estimation could be maintained as in the non-fatigue condition. In this study, the threshold value was calculated based on the root mean square (RMS) of the EMG signal. This RMS feature is commonly used by previous studies to detect muscle fatigue using EMG signal [38]. In order the threshold parameter could adapt to the EMG signal continuously, the average of RMS value was calculated based on each cycles of motion.

Table 1. Time domain feature extraction based on frequency [27]

No	Features	No	Features
1.	Zero crossing: $ZC = \sum_{i=1}^{N-1}[f(x_i \times x_{i+1}) \cap \mid x_i - x_{i+1} \mid \geq threshold$ $f(x) = \begin{cases} 1, if \to x \geq threshold \\ 0, otherwise \end{cases}$	3.	Wilson amplitude $WAMP = \sum_{i=1}^{N-1}[f(\mid x_i - x_{i+1} \mid)]$ $f(x) = \begin{cases} 1, if \to x \geq threshold \\ 0, otherwise \end{cases}$
2.	Sign slope change: $SSC = \sum_{i=1}^{N-1}[f[(x_i - x_{i-1}) \times (x_i - x_{i+1})]]$ $f(x) = \begin{cases} 1, if \to x \geq threshold \\ 0, otherwise \end{cases}$	4.	Myopulse percentage rate $MYOP = \frac{1}{N}\sum_{i=1}^{N}[f(x_i)]$ $f(x) = \begin{cases} 1, if \to x \geq threshold \\ 0, otherwise \end{cases}$

where N indicates the number of the sample point, x_i indicates the EMG signal, *threshold* indicates the level of amplitude that limited the signal to be processed. Figure 2 shows the EMG signal, measured angle, calculating the threshold from RMS, and feature extraction process using zero crossing feature with an adaptive threshold.

In the proposed method, the threshold of the features (Figure 2) was calculated using the root mean square (RMS). Since the RMS can represent the power of the EMG signal, it can be used to detect the effect of muscle fatigue on the EMG signal [38, 44-48]. The RMS value was calculated based on each cycle of motion and then the value was used in the next feature extraction process as an adaptive threshold. The RMS values were calculated according to the Eq. (1) as follow:

$$Th[m] = RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{1}$$

where N is the number of samples (or window length in milliseconds) and x_i is the EMG sample at discrete-time index i (in mV), and $Th[m]$ is the adaptive threshold for the mth cycles. The threshold parameter of the ZC, SSC, WAMP, and MYOP features (Table 1) can be substituted with Eq. (1).
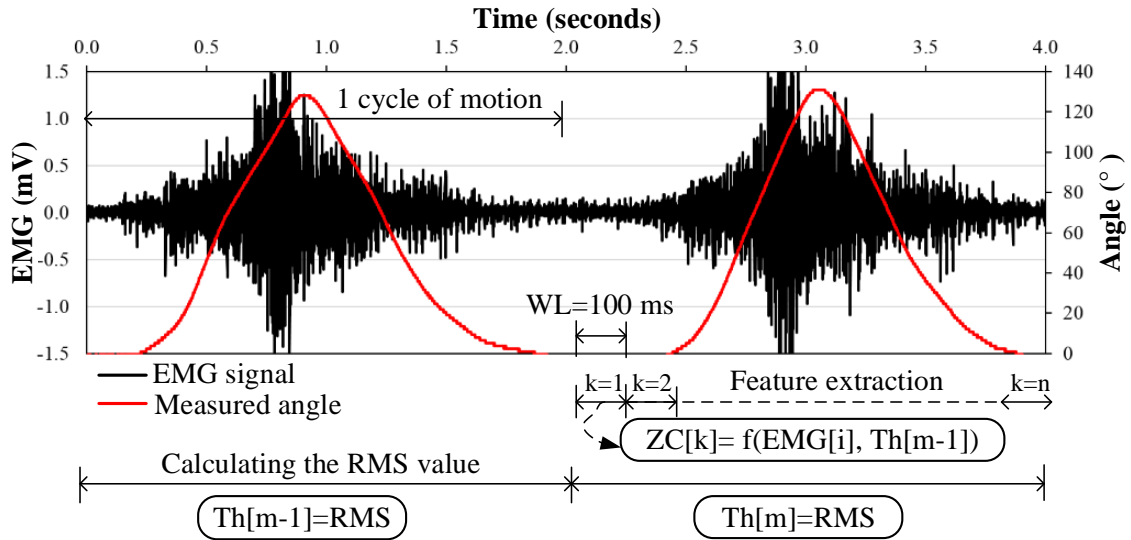
Figure 2. The representation of the ZC feature with an adaptive threshold. The EMG signal is extracted for each window length (WL) or segmented window.

Equation (2) represented a new ZC feature with an adaptive threshold after modifying the threshold parameter.

$$ZC[k] = \sum_{i=1}^{N-1} [f(x_i \times x_{i+1}) \cap | x_i - x_{i+1} | \geq Th[m-1]$$

$$f(x) = \begin{cases} 1, if \rightarrow x \geq Th[m-1] \\ \\ 0, otherwise \end{cases}$$

(2)

where $ZC[k]$ is the feature for the-k segment (window), x_i is the EMG sample at discrete-time index i, and $Th[m]$ is the adaptive threshold which generated from the RMS of the EMG signal. Since each feature resulted has a different range value, the features need to be normalized. After the normalization process, the low pass filter was applied in order to reduce the noises. In this study, the filtering process used the second order Butterworth low pass filter. The filter was designed using infinite impulse response (IIR) as shown in the Eq. (3) [34].

$$y[n] = b_0 x[n] + b_1 x[n-1] + .. + b_P x[n-P] - a_1 y[n-1] - a_2 y[n-2] - .. - a_Q y[n-P]$$ (3)

where $x[n]$ denotes the nth input sample, $y[n]$ denotes n^{th} output sample, b_0, b_1, b_M, a_1, a_2, a_N are the filter coefficients, and $P=Q$ is the filter order. Previous studies used this filtering technique to smooth the estimation [17, 42]. In this study, the coefficients of low pass filter, the feature extraction, and low pass filtering was performed using MATLAB (Student version, Math Works, Inc., USA). The low pass filter was designed with a cutoff frequency of 80 Hz. The calibration was performed to return the unit of the estimation in degree unit. The calibration process is conducted by multiplying the estimated angle (the output of the filtering process) with the maximum value of the range of motion (in this case is 140°). The performance of the proposed and standar method was evaluated using the root mean square error (RMSE) as a standard measurement of the elbow joint angle estimation [10, 12, 13]. The detail of the comparison between the proposed and standard method is shown in Figure 3.
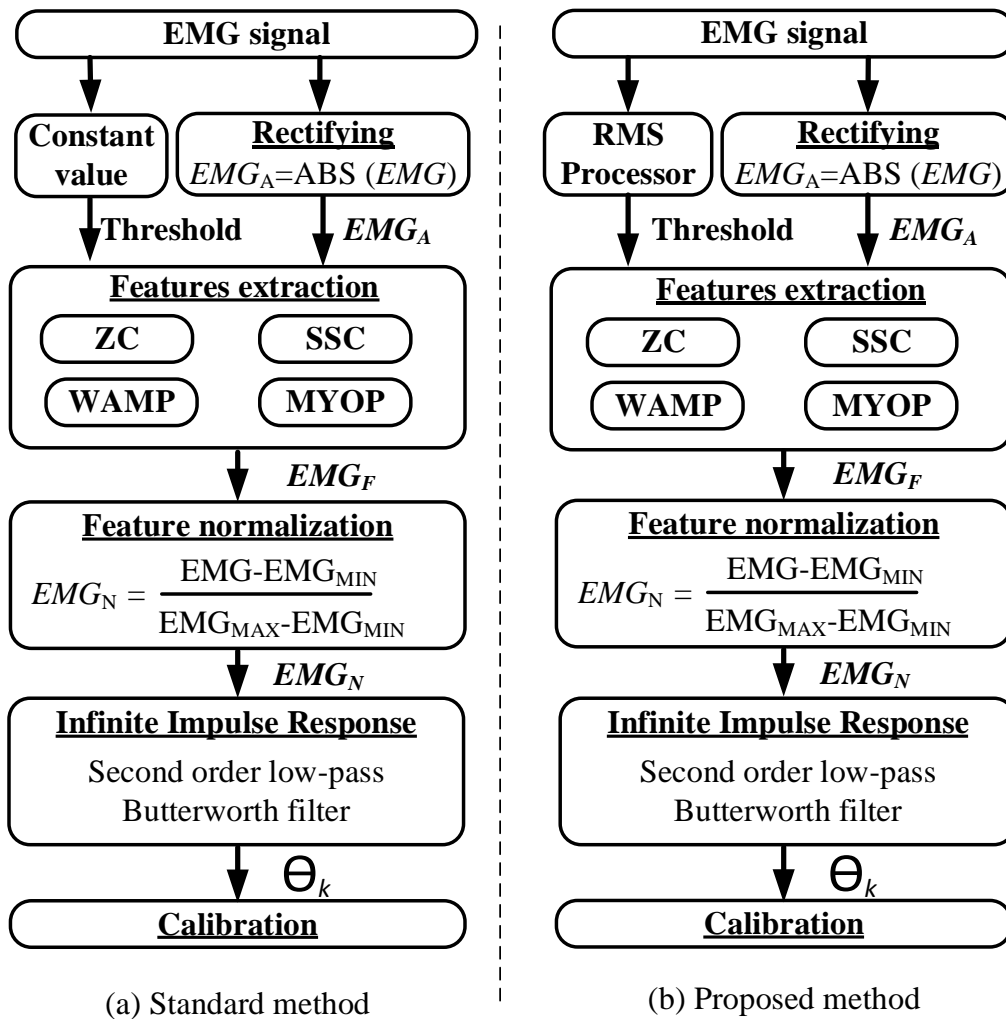
Figure 3. The comparison of method to estimate the elbow-joint angle between (a) standard method and (b) proposed method.

In the standard method as shown in Figure 3(a), the threshold was defined in the first section before the pre-processing with a certain real value. In the proposed method as shown in Figure 3(b), the threshold was calculated before in the pre-processing section. The adaptive threshold was calculated based on the RMS value in each cycle of motion in the elbow flexion and extension so that the feature able to adapt in the non-fatigue and fatigue condition.

The performance of the proposed and standard methods was analyzed using two pair samples T-test with the alpha value is 0.05. The p-value can indicate whether the RMSE values are significant (p-value<0.05) or insignificant difference (p-value>0.05)

RESULTS AND DISCUSSION

The adaptive threshold that we developed in the proposed method could compensate the effect of the muscles fatigue. Based on evaluation of the performance of the elbow joint angle estimation, we found that the proposed method has better performance than the standard method. Statistical analysis showed that there was a significant improvement of the RMSE between the proposed and standard method (p-value<0.05). The representation of the elbow joint angle estimation (from feature SSC) resulted from the standard and proposed method is shown in Figure 4.
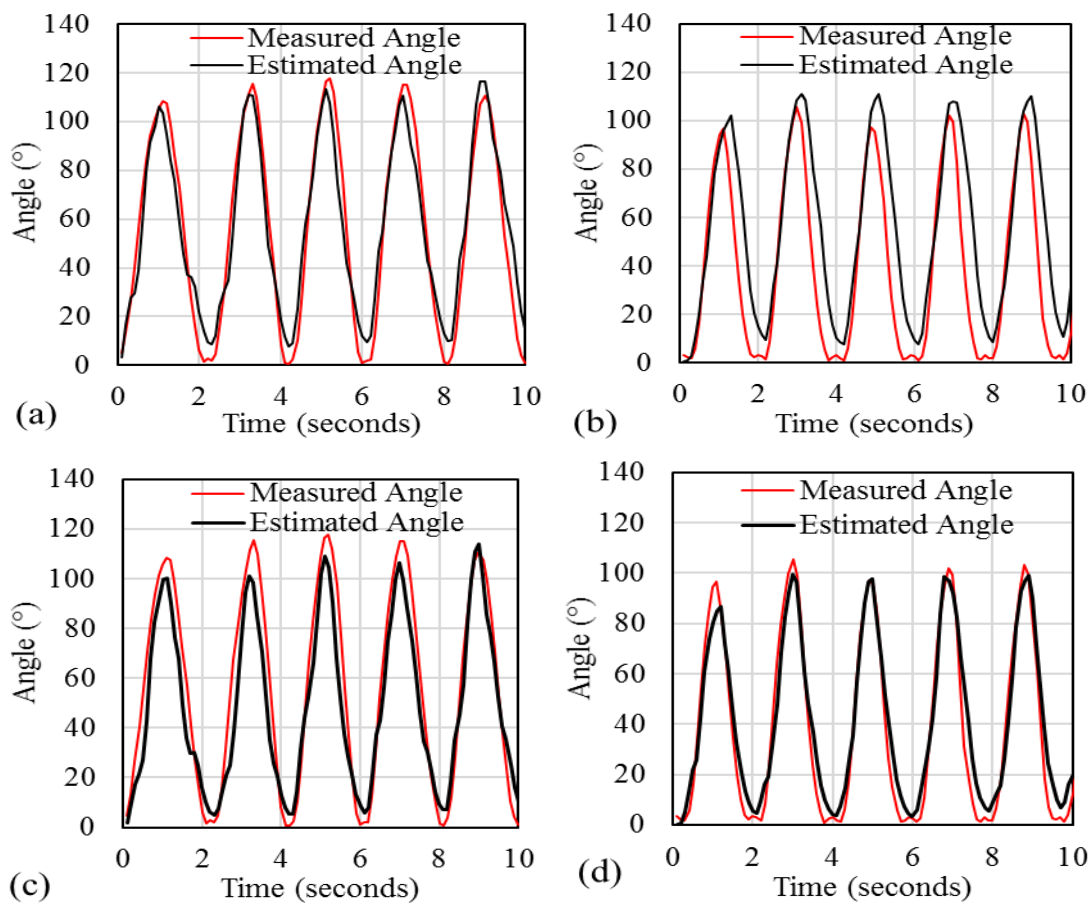
Figure 4. The representation of the estimated angles from modified SSC feature. The estimated angles which resulted from the standard method for (a) non-fatigue and (b) fatigue condition. The estimated angles which resulted from the proposed method for (c) non-fatigue and (d) fatigue condition (from subject C).

In the standard and proposed method (Figure 4), the estimated angles are able to follow the measured angle but with various performance. The RMSE values of the estimated angle as shown in Figure 4 (a), (b), (c), and (d) are 17.61˚, 26.28˚, 13.96˚, and 16.27˚, respectively. When the muscle is in the fatigue condition, the estimated angle tends to shift from the measured angle and its values are relatively higher than the measured angle as shown in Figure 4 (b). However, the proposed method was able to compensate the effect of muscle fatigue. It was shown that the estimated and measured angle was almost coincided [Figure 4(d)]. Furthermore, the RMSE values obtained from non-fatigue to fatigue condition from all subjects were pooled to perform a descriptive statistic. The RMSE values were grouped based on the standard and proposed method for each feature. The statistic descriptive was conducted in order to obtain the mean and standard deviation of the RMSE for all subjects. Figure 5 shows the boxplot diagram of the RMSE for comparison between standard and proposed method (all features). In the standard method [Figure 5(a)], the variability of the RMSE values is wider for all features if it is compared to the proposed method [Figure 5(b)]. This indicated that the proposed method was able to reduce the variability of the RMSE values [Figure 5(b)]. The comparison of the boxplot among the features was found that features SSC has better performance if it is compared to the other features both for the standard and proposed method.
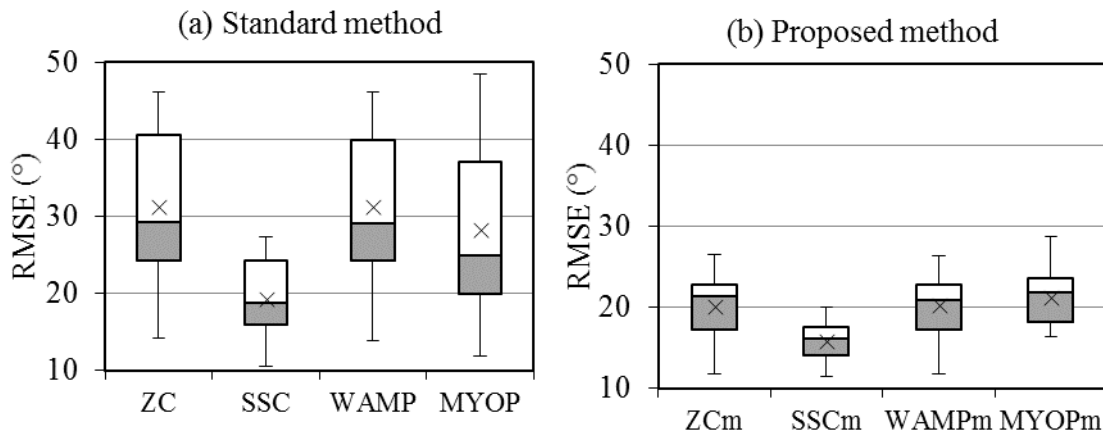
Figure 5. The comparison of RMSE between (a) the standard method and (b) proposed method for all features. The RMSE values is evaluated from non-fatigue to fatigue condition. The m-index indicates the modified feature of ZC, SSC, WAMP, and MYOP (for all subjects). The cross sign in the box indicates the mean values.

The summary of statistics descriptive (mean and standard deviation) of the RMSE values is shown in Table 2. The significant difference of RMSE between proposed and standard method was examined using two paired sample T-test. The alpha value was chosen as 0.05 (95% confidence). The p-value indicated whether there is a significant difference of RMSE or not. When the p-value is less than 0.05, it indicated that there is a significant difference of RMSE and on the contrary. Table 2 shows that there is a significant difference of RMSE between the standard and proposed method for all features (ZC, SSC, WAMP, and MYOP) which the p-values are <0.001). Furthermore, Table 2 shows that the proposed method (all features) can maintain the performance with a small standard deviation which ranged between 2.39˚ and 3.76˚. In the standard method, the standard deviation ranged between 5.19˚ and 11.39˚ for all features. In this study, it is found that the SSC feature has the best performance to estimate the elbow joint angle using EMG signal with muscle fatigue compensation and the estimation is conducted only using single muscle group from biceps muscle.

Table 2. The summary of RMSE (mean±standard deviation) and p-value for standard and proposed method (α=0.05). The RMSE value is calculated from non-fatigue to fatigue condition for all subjects.

Features	Standard method	Proposed method	p-value
ZC	32.36°± 9.60°	20.26°± 3.76°	< 0.001
SSC	19.29°± 5.19°	15.93°± 2.39°	< 0.001
WAMP	31.39°± 9.70°	20.28°± 3.73°	< 0.001
MYOP	28.34°± 11.39°	21.35°± 3.64°	< 0.001

In order to justify the proposed method, the results of this study are compared to the other related studies. Tang proposed an elbow-joint angle estimation based on backpropagation artificial neural network method using EMG signal [10]. He obtained that the RMSE values ranged between 9.67˚ and 12.42˚. However, the experiment is only conducted on one subject and the EMG signal is collected from four muscles, namely: biceps, triceps, brachioradialis, and anconeus. Pau investigated the elbow-joint angle estimation using Hill-based muscle model and optimized the estimate results using a Genetic algorithm [12]. The EMG was extracted from two muscles (biceps and triceps). He found that the RMSE (mean±SD.) for multi-cycle of motion was 22.00˚±6.6°. However, all of those previous methods did not consider to compensate the effect of the muscle fatigue. Thilina developed a neuro-fuzzy modifier to compensate the effect of muscle fatigue using

mean power frequency [25]. He found that the error of estimated elbow joint angle was between 5° and 15°. Na proposed an elbow joint force with muscle fatigue compensation using EMG signal based on twitch muscle model. The %RMSE (mean±SD.) for the dynamic motion was 15,6±24,7 [24]. Although significant results are found in this study, however, this work is only dealing with an elbow flexion and extension motion. A new method should be proposed if it is used to estimate other motion (such as pronation and supination) and more degree of freedom so that the proposed method can be applied in real life. Considering that EMG signal is influenced by muscle fatigue, K-Means clustering [43] approach can be used to classify fatigue levels.

CONCLUSIONS

In this study, elbow joint angle estimation under non-fatigue and fatigue condition using EMG signal is evaluated with an adaptive threshold in order to compensate the effect of muscle fatigue. The adaptive threshold is obtained by extracting the EMG signal using RMS feature. The major contribution of this work is that the proposed method is performed with high performance and consistent results in the non-fatigue and fatigue condition. The performance comparison between standard and proposed method shows that there is a significant difference of RMSE (p-value<0.05). Based on performance evaluation of all features, the modified SSC feature result in better performance than the others. The major difference to estimated the elbow joint angle in this work compared to the others is that the proposed method only uses single muscle (bicep). In the future work, the proposed method can be used in the control algorithm for development of exoskeleton and prosthetic devices so that the system able to estimate the elbow joint angle accurately and to compensate the effect of muscle fatigue using EMG signal.

ACKNOWLEDGEMENTS

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