Journal of Critical Reviews

ISSN- 2394-5125 Vol 7, Issue 12, 2020

A MODELING OF EXTENDED KALMAN FILTER TO IMPROVE ACCURACY IN ELBOW JOINT ANGLE ESTIMATION

Triwiyanto[1,*], Bambang Guruh Iranto[1], I Dewa Gede Hari Wisana[1], Her Gumiwang Ariswati[1], Moch. Prastawa Assalim Tetra Putra[1], Iswanto Iswanto[2]

[1]Department of Electromedical Engineering, Poltekkes Kemenkes Surabaya, Indonesia
[2]Department of Electrical Engineering, Universitas Muhammadiyah Yogyakarta, Indonesia
***Corresponding Email: triwiyanto123@gmail.com**

Received: 18.03.2020 ***Revised: 20.04.2020*** ***Accepted: 21.05.2020***

Abstract
The essential problem in the estimation of a human elbow angle position using myoelectric or electromyography (EMG) is that the EMG features have non-linearity characteristics. The non-linearity of the EMG features influences the performance of the estimation. The objective of this paper is to develop an extended Kalman filter based on the time domain feature to predict the position of the elbow using a myoelectric signal. The contribution of this study is that the non-linearity of EMG feature can be linearized effectively on flexion and extension motion. This is achieved by linearizing the EMG feature in extended Kalman filter using first-order Tailor series. The Ag(AgCl) was used to collect the myoelectric activities from biceps muscle. In this study, the sign slope feature (SSC) extracted the EMG signal to get the evidence that is associated with the position of the elbow. The extended Kalman filter (EKF) was chosen to linearize and to approximate the elbow position using EMG features. The performance of the proposed method is 12.81% and 9.65 % for periodic and arbitrary motion, respectively. We have confirmed the success of the presented EKF method to improve the performance of the estimation. Further, the proposed method can be implemented to an assistive exoskeleton for elderly people or stroke patients for a better life.

Keywords: Extended Kalman filter, elbow joint angle estimation, EMG, features non- linear.

DOI: http://dx.doi.org/10.31838/jcr.07.12.156

INTRODUCTION

Recently, the development of human and machine interaction has been progressed intensively. The electromyography (EMG) signal is the most bioelectric signal which is often used to control the machines such as prosthetics, wheelchair, exoskeleton, and teleoperation devices because the position, force, torque of the limb, and muscle fatigue can be predicted using the EMG signal [1]. EMG signal bears random and stochastic properties in nature [2]. In order to estimate the position of the human limb, a linear relationship between the EMG signal (or EMG features) and the joint angle is very important to obtain better accuracy in the estimation. However, the previous study shows that EMG features have non-linear characteristics.

Some attempts have been studied to forecast the position of the upper limb's elbow joint using the EMG signal. A supervised machine learning based on pattern recognition based on back-propagation multi perceptron, support vector machines, and neuro-fuzzy was often used to solve the non-linear characteristics of the myoelectric in the prediction [3]. However, the limitation of the using of those supervised machine learning is required to train the machine for each new input pattern and other weakness is an overfitting phenomenon. Another approach to estimate the joint position is by applying a non-pattern recognition (NPR) based method. The NPR based method is a method to predict the position of the elbow without a machine learning but authors preferred to used feature extraction, filtering techniques and optimization. The advantages of using NPR is that the prediction directly depends on the pre-processing stages. The Kalman filter was the most effective algorithm for estimating the condition of the system and was also used to predict the joint of the limb by previous studies [4] [5]. Kyrylova et al. suggested an upper limb elbow joint assistive system that used a combination of an EMG signal and a motion sensor to monitor the exoskeleton unit [6]. In the study, they used the Kalman filter to predict and correct the error in the estimation. Even though the proposed method resulted in high accuracy in the elbow joint angle estimation but those methods used an additional sensor (motion sensor) to detect the position of the elbow. This sensor could improve or reduce the accuracy, depending on whether the sensor position was correct or not because of the high sensitivity of the sensor.

We have previously researched the efficiency of the Kalman filter to estimate the elbow position using the EMG signal. However, the proposed method was only evaluated using a periodic motion which can be assumed to have a linear response to the EMG features and approached to the linear Kalman filter. A complex or random motion of the elbow was more preferred to be evaluated because it was related to the human motion in daily life. Li et al. developed an assistive device for upper limb exoskeleton based on the EMG signal [7]. The pre-processing stages, which consist of high pass filter, full-wave rectifier, low pass filter, linearly normalization and non-linearly normalization, were performed before the Kalman filter was applied. However, this work was assumed that the EMG feature was in the linear condition after a non-linear normalization. Furthermore, in the elbow joint prediction using the EMG signal based on NPR, a feature extraction played an important role in the performance of the model. In the previous work, we have investigated the 12-time domain feature. Our finding showed that the Sign Slope Change (SSC) has better performance in relation to the human elbow motion [8].

Previous research used a Kalman filter to estimate the elbow position by means of the EMG signal. A various pre-processing stage was applied before the Kalman filtering process. However, the limitation of using a linear Kalman filter is that it requires a state space and state observation in the linear function. The Kalman filter will fail as the estimator when the state is in the non-linear function. In order to solve the problem in the Kalman filter, an extended Kalman filter is proposed to solve the non-linearity of the state. In order to predict the position of the elbow, the EMG signal is required to be extracted to obtain the information associated to the position of the elbow. In this study, the SSC feature was chosen to do a feature extraction process due to the higher performance in the estimation [8]. The linearization to the features was performed by applying the extended Kalman filter (EKF) which is based on a Taylor series [9]–[11]. Therefore, in order to solve the problems mentioned in the previous studies, the paper aims to build an extended Kalman filter model based on the SSC feature to estimate the elbow joint angle using electromyography (EMG) signal for flexion and extension motion. The impact of this study is that the proposed method can be used to linearize a non-linear state (sensor, features, etc.) relevant to the EMG signal. The results of the study are expected to be able to estimate the position of the elbow joint with good performance compared to the conventional linear Kalman filter.

This article is comprised of five sections, section 2 described the materials and method, section 3 presents results and discussion of the study, and finally, section 4 concludes the study and proposes a recommendation.

MATERIALS AND METHOD

Experiment Protocol

A high-quality disposable Ag / AgCl electrodes (Ambu, BlueSensor R, Malaysia) were used to monitor the EMG signal output from the muscles of the biceps while the elbow performed an extension and flexion movement. A linear potentiometer was placed at the joint of the exoskeleton frame to measure the real angle and further, it will be used to calculate the root mean square error (RMSE) values.

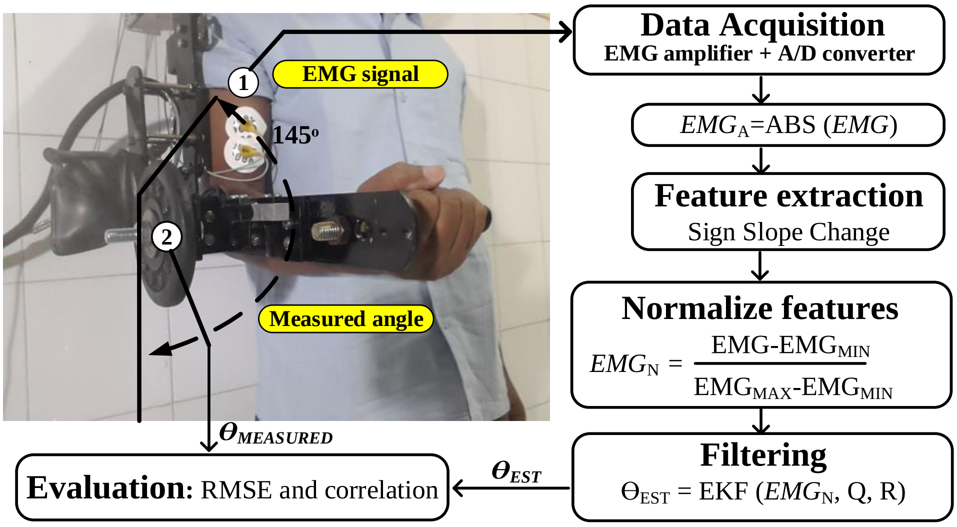

Figure 1. The diagram block of the estimation

A data acquisition unit consists of an EMG amplifier, A/D converter, microcontroller, and personal computer. A sequence of the digital signal processing is performed to obtain the elbow joint angle estimation as shown in Figure 1. In the data collection, the 10 healthy male subjects (20.5±2.3 years and 60.5±4.6 kg) were involved for EMG data acquisition.

Feature Extraction

EMG signal contains a series of amplitude which represents the activities of the muscle. In order to obtain the information related to the motion, feature extraction is needed. Time-domain feature extraction is widely used in the biomedical signal processing due to fast computation and low complexities. Feature extraction is mainly divided into three categories namely, based on energy, complexities, and frequency. The previous study revealed that the time domain features based on frequency have better performance than others. One of the features which showed the best performance is the sign slope change feature (SSC) [Eq. (1)]. The information related to this feature (SSC) can be found on this reference [8], [12].

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

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

where xi shows the i-th signal, SSC is the selected time domain feature, N shows the length of the signal, f(x) is the function to decide the output condition, true or false value, and the threshold voltage is a predefined constant to limit the EMG signal. In this case, the window length is 200 samples.

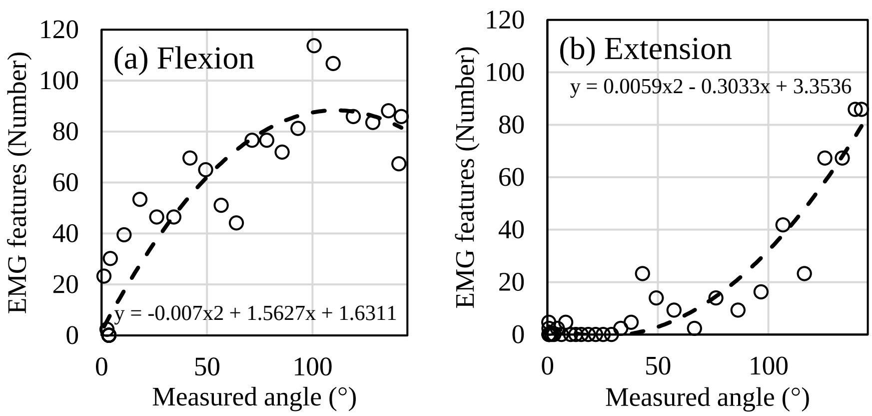

Figure 2. The non-linearity response of the EMG feature (Sign Slope Change feature) for (a) flexion and (b) extension motion.

In the preliminary research, it showed that the response of the EMG feature in the flexion and extension motion was a non-linear function as shown in Figure 2. The non-linearity of the SSC feature can be approached to the second-order polynomial function. The flexion and extension pattern showed difference polynomial function as shown in Eqs. (2) and (3).

$$y_{fn} = -0.007x_n^2 + 1.5627x_n + 1.6311$$

(2)

$$y_{en} = 0.0059x_n^2 + 0.3033x_n + 3.3536$$

(3)

where the yfn, yen indicates the response (output) of the feature when the elbow performed the flexion and extension motion, respectively. The xn indicates the position of the elbow in degree unit. The second order in the xn variable shows that the SSC feature has a non-linear function.

Extended Kalman Filter

The reception of the EMG feature to the position was described in Figure 3. We can assume that the response has a non-linear function. The state and observation equation with an additive white Gaussian noise can be presented as shown in Eqs. (3) and (4).

$$\mathbf{x}_n = \mathbf{A}\mathbf{x}_{n-1} + \mathbf{w}_n$$

(3)

$$\mathbf{y}_n = h_n(\mathbf{x}_n) + \mathbf{v}_n$$

(4)

where A indicates a transformation matrix which related the current state and previous state. In this case, the matrix A can be assumed as a scalar constant and equal to one. The observation state is presented by the non-linear function hn(xn). The parameter of wk and vk are the noise and supposed to be white Gaussian, zero mean and uncorrelated each other with the covariance, respectively.

$$\mathbf{Q} = E\left\{\mathbf{w}_n\mathbf{w}_n^T\right\}$$

(5)

$$\mathbf{R} = E\left\{\mathbf{v}_n\mathbf{v}_n^T\right\}$$

(6)

The non-linear function in observation state can be approached to be a linear function using first-order Taylor series as shown in Eq. (7)

$$h_n(x_n) \cong h_n(\hat{x}_n^-) + H_n(x_n - \hat{x}_n^-)$$

(7)

where

$$H_n = \frac{\partial h_n}{\partial x}\Big|_{\hat{x}_n^-}$$

(8)

is the Jacobian of the observation state and $x_n - \hat{x}_n^-$ is prior estimation error. The Jacobian for both observation state (flexion and extension) from Eqs. (1) and (2) can be written as follows:

$$H_{fn} = \frac{\partial h_n}{\partial x}\Big|_{\hat{x}_n^-} = -0.014x + 1.5627$$

(9)

$$H_{en} = \frac{\partial h_n}{\partial x}\Big|_{\hat{x}_n^-} = 0.012x + 0.3033$$

(10)

where Hfn and Hen are the Jacobian of observation state for flexion and extension motion, respectively. The Kalman filtering process is shown in Figure 3 consists of prediction, gain computation, update estimation, and update error covariance.

The value of $\hat{x}_{k-1}$ and P_{k-1} needs to be defined in the initial state before the Kalman filter is calculated. Algorithm 1 shows the calculation of the extended Kalman filter.

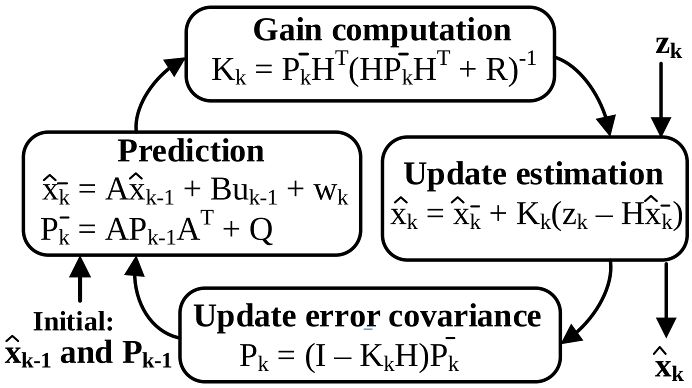

Figure 3. The Kalman filtering process

Algorithm 1: Extended Kalman filtering	
	Init : $\hat{x}_0, P_0$
	Input : z_k, Q, R
	Output: $\hat{x}_k, P_k$
1	for n=1: N do
2	$\hat{x}_k^- = A\hat{x}_{k-1}$
3	$P_k^- = AP_{k-1}A^T + Q$

4	$K_k = P_k^- H^T (H P_k^- H^T + R)$
5	$\hat{x}_k = \hat{x}_k^- + K_k (z_k - H\hat{x}_k^-)$
6	$P_k = (I - K_k H) P_k^-$
7	end

Evaluation

The error of the estimation is computed using root mean square error (RMSE) as shown in Eq. (11). It calculated the error between the measured and estimated angle. Previous studies have used this parameter to validate the estimation results. The correlation coefficient (r) was also calculated in order to attain the association between the measured and predicted.

$$RMSE = \frac{\sum_{i=1}^{n}(x-y)^2}{\sqrt{\sum_{i=1}^{n} x^2}\sqrt{\sum_{i=1}^{n} y^2}} \qquad (11)$$

The correlation coefficient was calculated using Eq. (12).

$$r = \frac{\sum_{i=1}^{n} xy - \frac{(\sum_{i=1}^{n} x)(\sum_{i-1}^{n} y)}{n}}{\sqrt{(\sum_{i=1}^{n} y^2 - \frac{(\sum_{i=1}^{n} y)^2}{n})(\sum_{i=1}^{n} x^2 - \frac{(\sum_{i=1}^{n} x)^2}{n})}} \qquad (12)$$

where RMSE (root mean square error) is the error between the predicted and true value and r (Pearson's correlation coefficient) is the coefficient which related between the predicted and the true value.

RESULTS AND DISCUSSION

The Estimation

When the elbow moved in the direction of the flexion and extension (0 to 150º) then the EMG signal generated amplitude with the range of -1.25 mV to 1.25 mV following the joint angle as shown in Figure 4 (a). The EMG signal was generated randomly by the human body from negative to positive amplitude which the negative part was eliminated by rectifying the EMG signal. After the rectification stage, the EMG signal was processed using the sign slope change (SSC) feature. The advantage of this feature is that we can eliminate a low amplitude which can be considered as noise by adjusting the threshold value in the SSC equation (1). The EMG features were resulted after the feature extraction process, commence tracking the position of the elbow however with some ripples on the estimation. In addition, after applying the extended Kalman filter, we obtained that the approximate angle was closely matched to the elbow joint angle, as shown in Figure 4(4)(b). A representation of the estimation was shown in Figure 4 (b) which is the performance of the RMSE and correlation are 12.65º and 0.92, respectively. On the other type of motion (random motion), the result of this study, the EMG signal, and estimation are shown in Figure 5 (a) and (b), respectively. In this motion, the EMG signal has more complex activities than periodic motion. In this representation (estimation in random motion), the performance of the RMSE and correlation are 15.50º and 0.89, respectively.

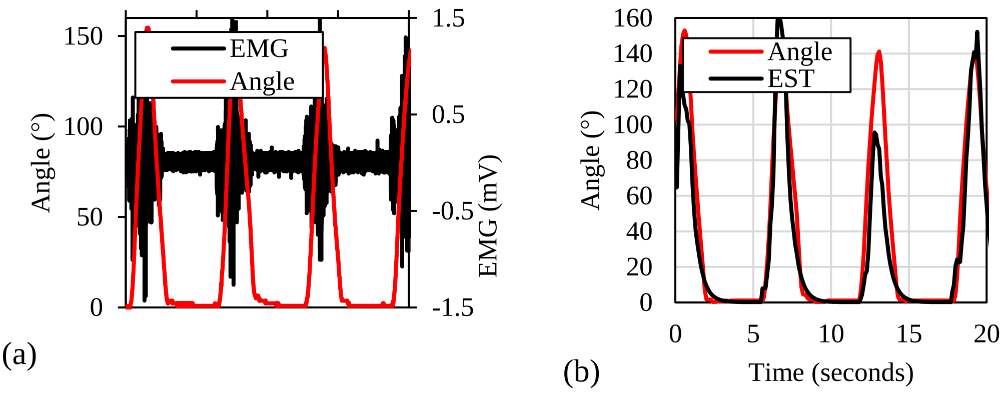

Figure 4. (a) The recorded EMG signal, (b) the predicted angle on periodik motion of flexion and extension using EKF method.

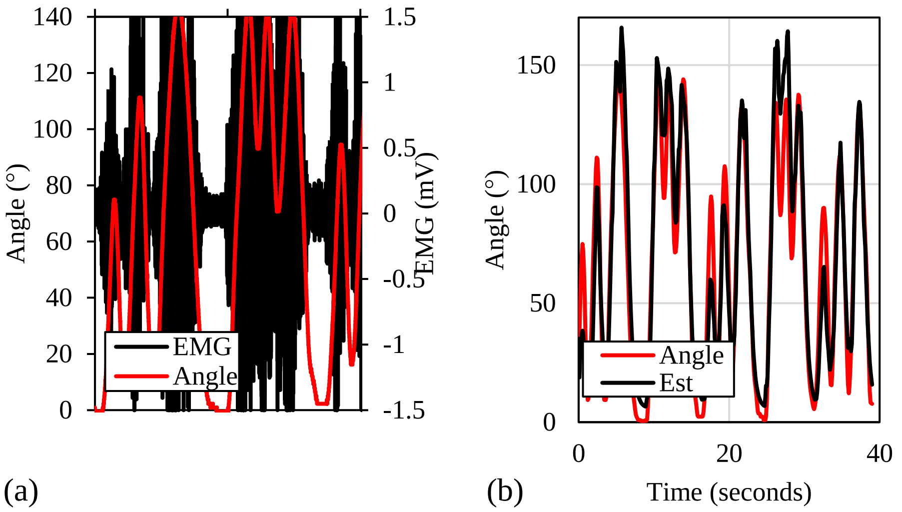

Figure 5. (a) The recorded EMG signal, (b) the predicted angle on random motion of flexion and extension using the EKF method.

A presentation of the prediction using the proposed (EKF) and standard (KF) method is shown in Figure 6(a) and 6(b). An estimation based on EKF and KF was represented by a black solid line and black dash line, respectively. Both of the estimations were able to follow the real angle (red line). However, the estimation based on KF has a larger offset than the EKF. In the estimation of periodic motion, the EKF and KF had an accuracy of 13.25° and 18.29°, respectively. In the random motion, the accuracy was lower than the periodic motion due to the complexities of the EMG features. Even though, the EMG features are more complex in the random motion but the EKF still able to predict the elbow position. A representation of the prediction for a random motion is shown in Figure 6(b). The accuracy of the EKF and KF in the random motion was 13.15° and 15.97º, respectively.

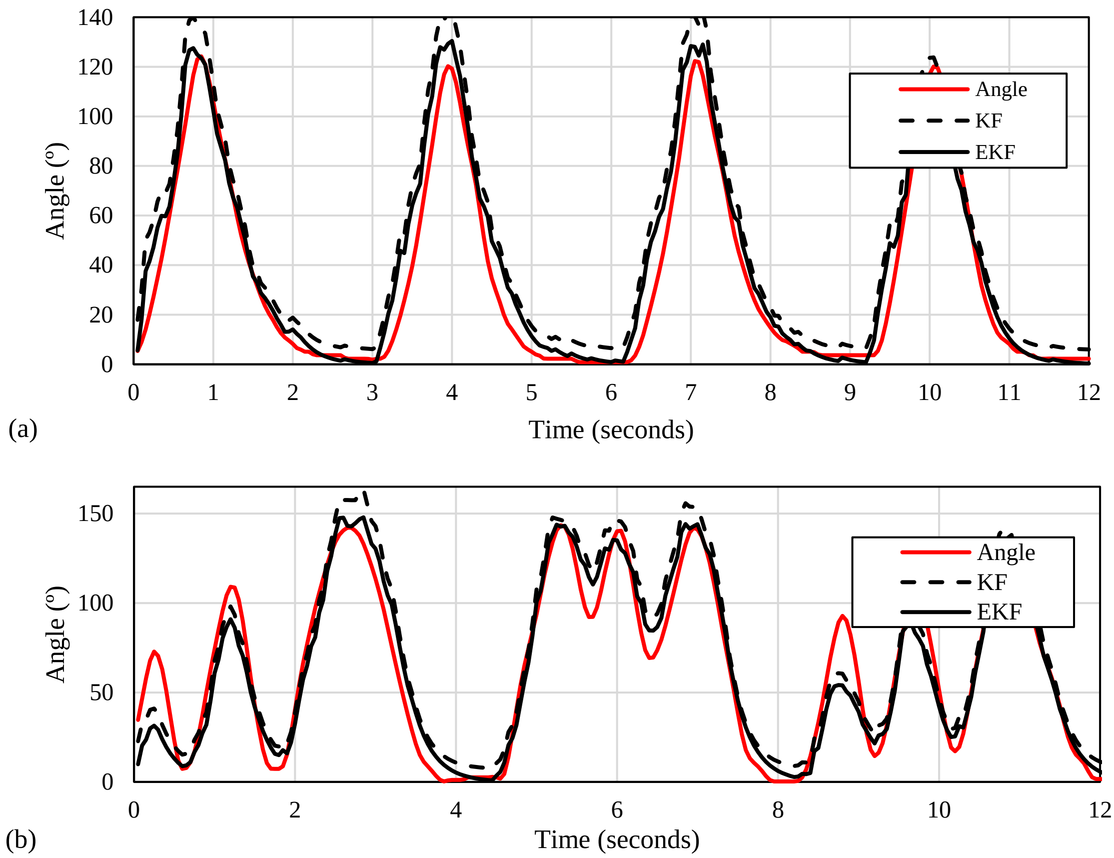

Figure 6. The comparison of the performance of the estimation between extended Kalman filter and Kalman filter for (a) periodic and (b) random motion.

Performance of the Proposed Method

The performance (RMSE and correlation) of the estimation from 10 subjects was pooled, grouped based on EKF and KF methods, and analyzed using descriptive statistics. A boxplot diagram can be used to define the mean, median, minimum, and maximum values of the performance. In the periodic motion, the RMSE boxplot resulted from EKF showed lower error (15.11±1.85) than the KF method (RMSE=17.33º±2.76º) as shown in Figure 7(a). On the other hand, the correlation boxplot resulted from EKF present higher correlation (0.87±0.042) than the KF (0.80±0.076) method as shown in Figure 7(b). In the random motion, the RMSE and correlation based on EKF method were 16.84º ±3.06º and 0.85±0.063, respectively. On the other hand, the performance of the estimation with the linear Kalman filter was 18.64º ±3.28º and 0.80±0.102 for RMSE and correlation, respectively.

Here, superior results (RMSE and correlation) were also found in random motion when we performed the estimation with EKF (Figure 8). A T-test statistical was performed for both of the groups (EKF and KF) to find a significant difference in the performance. Table 1 and Table 2 show that there is a significant difference of performance (p-value<0.05) between EKF and KF for periodic and random motion. The p-values are 0.010 and 0.027 for periodic and random motion, respectively. Thus, the p-value is lower than the alpha (0.05) which is indicated that there was a significant difference of performance between EKF and KF. For all of data, the performance (RMSE) was improved at 12.81% and 9.65% for periodic and random motion, respectively.

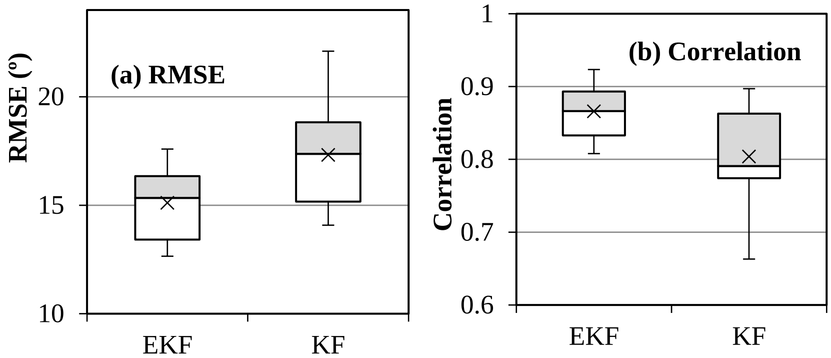

Figure 7. The performance of the estimation based on extended Kalman filter and Kalman filter for periodic motion. (a) in RMSE and (b) in Correlation.

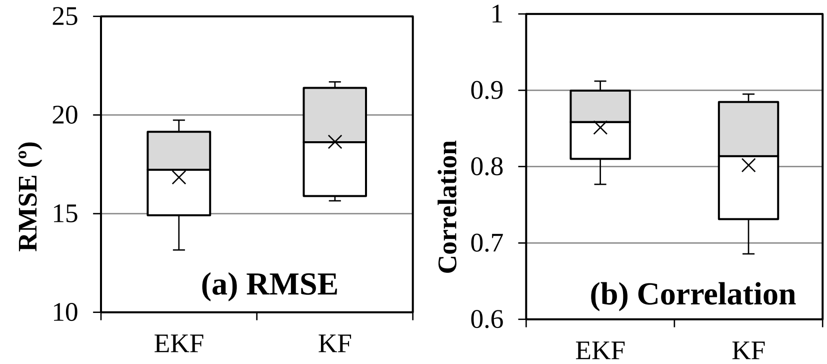

Figure 8. The performance of the estimation based on extended Kalman filter and Kalman filter for random motion. (a) in RMSE and (b) in Correlation.

Table 1. The average value of the prediction (RMSE) in degree (º) unit based on extended Kalman filter and Kalman filter. The statistics T-test is performed with significant of 0.05.

Parameter	Periodic motion		Random motion	
	EKF	KF	EKF	KF
Average RMSE	15.11±1.85	17.33±2.76	16.84±3.06	18.64±3.28
p-value	0.010		0.027	

Table 2. The average value of the prediction (RMSE) in degree (º) unit based on extended Kalman filter and Kalman filter. The statistics T-test is performed with significant of 0.05.

Parameter	Periodic motion		Random motion	
	EKF	KF	EKF	KF
Average Corr.	0.87±0.042	0.80±0.076	0.85±0.063	0.80±0.102
p-value	0.00174		0.043	

In this study, we found that the performance of the estimation, in the random motion, was lower than periodic motion because the waveform of the EMG signal was more complex in the random motion. Another method which is based on non-pattern recognition (NPR) was developed by Pang et.al [13]. They used Hill-muscle based model to predict the position of the elbow joint. The performance of the estimation was 6.53º±3.2 º, 22.0º±6.6º and 22.4º±5.0º for single, periodic continue and random motion, respectively. Here, we also found that in complex motion, the performance was lower than the others. Thongpanja et.al. investigated the relationship between the elbow joint angle and EMG feature in the frequency domain [14]. They found a linear relationship between the elbow joint angle and MDF (median frequency), with a coefficient of correlation of 0.86. As a comparison, another related study also proposed an elbow position based on a supervised back-propagation artificial neural network (ANN) [15]. In this analysis, the performance was 10.7, 9.67, and 12.42 for a periodic motion of 2 s, 4 s and 8 s, respectively. A drawback of using the pattern recognition based method is that the model needed to be re-train for each new subject.

The quality of the EMG signal can be influenced by many parameters such as the instrumentation amplifier, electrodeposition, sweat, and muscle fatigue [16]. The previous study has proved that localized muscle fatigue could affect EMG characteristics. In the fatigue condition, the amplitude is higher than in the non-fatigue condition and the frequency is shifted to the lower frequency [17] [18] [19]. A fusing method which considers muscle fatigue is required in future work in order to maintain the accuracy of the estimate. In the related works, this proposed method, a linearizing the feature using EKF, can be used to solve a non-linear problem in a mechanical sensor for medical devices or industrial.

CONCLUSION

The results of this paper have shown the effectiveness of the extended Kalman filter in linearizing the non-linear response of the EMG function and estimate the elbow joint position. The main finding of this study is that the position can be predicted using the myoelectric signal which only from one group of muscle. The limitation of this work is that the proposed method is only tested for elbow joint angle prediction. In future work, the method could be implemented to the human and machine interaction to support human life.

REFERENCES

1. Triwiyanto, O. Wahyunggoro, H. A. Nugroho, and Herianto, “String actuated upper limb exoskeleton based on surface electromyography control,” *Proc. - 2016 6th Int. Annu. Eng. Semin. Ina. 2016*, pp. 176–181, 2017.
2. C. J. De Luca, “The use of surface electromyography in biomechanics,” *J. Appl. Biomech.*, vol. 13, no. July 1993, pp. 1–38, 1997.
3. T. D. Lalitharatne, K. Teramoto, Y. Hayashi, T. Nanayakkara, and K. Kiguchi, “Evaluation of Fuzzy-Neuro Modifiers for Compensation of the Effects of Muscle Fatigue on EMG-Based Control to be Used in Upper-Limb Power-Assist Exoskeletons,” *J. Adv. Mech. Des. Syst. Manuf.*, vol. 7, no. 4, pp. 736–751, 2013.
4. 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, 2017.
5. X. Feiyun, Y. Gao, W. Shengxin, and J. Zhao, “Prediction of joint angle by combining multiple linear regression with autoregressive (AR) model and Kalman filter,” in *2015 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, 2015, pp. 1139–1144.
6. A. Kyrylova, T. Desplenter, A. Escoto, S. Chinchalkar, and a L. Trejos, “Simplified EMG-driven Model for Active-Assisted Therapy *,” *IROS 2014 Work. Rehabil. Assist. Robot. Bridg. Gap Between Clin. Robot.*, p. 6, 2014.
7. Z. Li, B. Wang, F. Sun, C. Yang, Q. Xie, and W. Zhang, “SEMG-based joint force control for an upper-limb power-assist exoskeleton robot,” *IEEE J. Biomed. Heal. Informatics*, vol. 18, no. 3, pp. 1043–1050, 2014.
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, pp. 448–458, 2017.
9. H. Tanizaki and R. S. Mariano, “Nonlinear filters based on taylor series expansions ∗,” *Commun. Stat. - Theory Methods*, vol. 25, no. 6, pp. 1261–1282, Jan. 1996.
10. V. A. Bavdekar, A. P. Deshpande, and S. C. Patwardhan, “Identification of process and measurement noise covariance for state and parameter estimation using extended Kalman filter,” *J. Process Control*, vol. 21, no. 4, pp. 585–601, 2011.
11. Y. S. Shmaliy, S. Zhao, and C. K. Ahn, “Unbiased FIR Filtering : An Iterative Alternative to Kalman Filtering Ignoring Noise and Initial Conditions,” *Control Systems Magazine*, no. October, pp. 70–89, 2017.
12. A. Phinyomark, P. Phukpattaranont, and C. Limsakul, “Feature reduction and selection for EMG signal classification,” *Expert Syst. Appl.*, vol. 39, no. 8, pp. 7420–7431, 2012.
13. M. Pang, S. Guo, Q. Huang, H. Ishihara, and H. Hirata, “Electromyography-based quantitative representation method for upper-limb elbow joint angle in sagittal plane,” *Journal of Medical and Biological Engineering*, vol. 35, no. 2. pp. 165–177, 2015.
14. S. Thongpanja, A. Phinyomark, C. Limsakul, and P. Phukpattaranont, “Application of Mean and Median Frequency Methods for Identification of Human Joint Angles Using EMG Signal,” in *Information Science and Application*, Springer Berlin Heidelberg, 2015, pp. 689–696.
15. 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.
16. C. J. De Luca, S.-S. Chang, S. H. Roy, J. C. Kline, and S. H. Nawab, “Decomposition of surface EMG signals from cyclic dynamic contractions,” *J. Neurophysiol.*, vol. 113, no. 6, pp. 1941–1951, 2015.
17. T. Triwiyanto, W. Oyas, A. N. Hanung, and H. Herianto, “Adaptive threshold to compensate the effect of muscle fatigue on elbow-joint angle estimation based on electromyography,” *J. Mech. Eng. Sci.*, vol. 12, no. 3, pp. 3786–3796, 2018.
18. 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 *Proceedings of 2016 8th International Conference on Information Technology and Electrical Engineering: Empowering Technology for Better Future, ICITEE 2016*, 2017.
19. T. Triwiyanto, O. Wahyunggoro, H. A. Nugroho, and H. 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, pp. 424–434, 2017.