Estimation of Elbow Joint Angle Based on Electromyography Using the Sign-Slope Change Feature and Kalman Filtering

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Abstract. Electromyography (EMG) has widely used in the field of biomedical engineering as a control signal for prosthetic devices and exoskeleton robotic. High accuracy in the prediction of the limb joint is very important to determine the effectiveness of the system. In this study, we propose a new algorithm to improve the elbow joint angle prediction based on electromyography using Sign Slope Change (SSC) feature extraction and Kalman filter (SSC-KF). The EMG signals acquired from the biceps were extracted using SSC feature to get the estimation of the elbow joint angle. The accuracy of the prediction of the elbow joint angle was improved by using Kalman filter. In this study, the SSC-KF algorithm can predict the elbow joint angle with high accuracy. The Pearson’s correlation coefficients (mean±S.D.) were 0.95±0.02, 0.96±0.01, and 0.96±0.015 for the motion period of 12 seconds, 8 seconds, and 6 seconds, respectively. Root Mean Square Errors (mean±S.D.) were 10.37±1.72º, 9.89±1.11º, and 9.99±2.2º, for the motion periods of 12 seconds, 8 seconds, and 6 seconds respectively. This SSC-KF algorithm can predict the elbow joint prediction by using a single lead electrode from biceps muscle.

1. Introduction
A good accuracy in the estimation of the limb joint angle for myoelectric control-based devices is very important because it determines the effectiveness of the devices. Recently, a myoelectric control has been used widely in many areas such as a prosthetic device, an assistive or rehabilitative exoskeleton and a teleoperation machine [1]. Previous studies implemented the estimation algorithm by improving the method such as feature extraction, classifier, and pre-processing data. EMG is a signal that is generated when there is an activity in the muscles. The EMG gives much information, including the limb joint angle [2]. The information on the limb joint angle can be found by realizing a feature extraction on the EMG signal. Feature extraction can be realized in the time, frequency or wavelet domain. The time-domain features are still good features to extract the signal because it is less of complexities and there is no transformation stage. Feature extraction is a pre-processing stage in the implementation of the limb joint estimation algorithm. Previous studies [3], [4] have used time domain feature extraction such as Root Mean Square (RMS), Integral of Absolute Value (IAV), Mean Average (MAV), Waveform Length (WL) and Sign Slope Change (SSC) to develop the limb joint angle estimation.
Some previous studies used a pattern recognition (PR) method, such as Artificial Neural Network [4], and Support Vector Machine (SVM) [5], as a classifier to predict the limb joint angle. Even though high accuracy in the estimation of the joint angle is obtained significantly, but the PR method needs a learning step to train the network for every different subject.

The Kalman filter is commonly used as an estimator for a noisy output from the motion sensor, such as an accelerometer or gyroscope sensor. Some previous studies [6], [7] combined Kalman filter with other methods such as SVM, LDA, and Hill-Based to improve the accuracy of the estimation. Improving the accuracy of the elbow joint estimation based on EMG is still a challenging issue. The success of the estimation depends on the selection of the feature extraction. The objective of this study is to develop a new algorithm to predict an EMG-based elbow joint angle by combining zero crossing feature extraction and Kalman filter. Kalman filter is used to improve the estimation by filtering the output of the feature extraction iteratively. By combining the sign slope change feature and Kalman filter (SSC-KF), we have a non-pattern recognition algorithm that can predict the elbow joint angle according to human intention.

2. Materials and Methods

2.1. Experimental protocol
Healthy male subjects were selected with no previous injury on the elbow. In this research, the exoskeleton was used to synchronize the movement of the elbow joint. The exoskeleton was constructed by two aluminum beams as shown in the Figure. 1. In the exoskeleton joint, we attached a potentiometer to detect the desired elbow joint angle. Prior to the EMG recording process, the subject was trained to move the elbow, flexion and extension direction in the range of 0° to 145° return to 0°. To synchronize the elbow movement, a Windows-based metronome application (TempPerfect version 4.08) was used. In this research, the period of the elbow flexion and extension was adjusted in 12, 8, and 6 seconds period. We collected the EMG signal from biceps muscle using two disposable Ag/AgCl electrodes. The two-channel A/D converters was composed of one channel to collect EMG signal and one channel to collect angle from the elbow joint. The sampling frequency used in the data acquisition process was 1,000 Hz, this is already qualified the Nyquist rules.

2.2. Data Processing
The EMG signal was recorded during the elbow moving in flexion and extension direction. Each segment of the EMG signal was extracted using SSC feature extraction (Figure 1). SSC is a feature that detects how many the signals change the slope and exceed the pre-defined threshold value. The featured SSC was written as follows [8]:

![Figure 1. The block diagram of the proposed method.](image-url)
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\[ SSC = \sum_{i=1}^{N-1} [f[(x_i - x_{i-1}) \times (x_i - x_{i+1})]] \]
\[ f(x) = \begin{cases} 1, & \text{if } x \geq \text{threshold} \\ 0, & \text{otherwise} \end{cases} \]

where \( x_i \) is the \( i \)-th EMG signal, \( N \) is the number of the sample point in each segment and threshold is the level of amplitude that limit the EMG signal. The width of the window sampling is 200 samples as recommended in the previous study [9].

Kalman disseminated a method on the problem of noise by using an adaptive filter approach towards the correction of the error in the system [10] [Figure 2(a)]. In this work, Kalman Filter (KF) was applied as a smoothing function on the output of the feature extraction. The Q and R parameter was tuned by experiment which resulted the best performance. Assume the \( x_k \) is the result of estimation of Kalman Filter and \( z_k \) is the result of the feature extraction. The Kalman filter model [11] is realized in Algorithm 1 [Figure 2(b)]. The nomenclature of the Kalman filter variable was written in Table 1.

![Figure 2](image-url). (a) The block diagram of linear Kalman filter, (b) the algorithm of Kalman filter.

| Algorithm 1: Kalman Filter |
|---------------------------|
| Init: \( \hat{x}_{k-1} = 0; F_{k-1} = 0; \) |
| Input: \( z_k = E \) |
| Output: \( \hat{x}_k \) |
| 1. For \( k \rightarrow 0 \) to \( N \) do |
| 2. \( \hat{x}_k = \hat{x}_{k-1} \) |
| 3. \( F_k = F_{k-1} + Q \) |
| 4. \( K_k = F_k (F_k + R)^{-1} \) |
| 5. \( \hat{x}_k = \hat{x}_k + K_k (z_k - \hat{z}_k) \) |
| 6. \( F_k = F_K (1 - K_k) \) |
| 7. End |

| Table 1. The nomenclature of Kalman filter |
|-------------------------------------------|
| \( \hat{x}_k \) | Estimated state |
| \( \hat{x}_{k-1} \) | A priori estimated state |
| \( \hat{x}_k \) | Previous estimated state |
| \( \hat{x}_k \) | Error covariance |
| \( \hat{x}_k \) | A priori error covariance |
| \( \hat{x}_k \) | Previous error covariance |
| \( \hat{x}_k \) | Kalman gain |
| \( \hat{x}_k \) | Input measurement |
| \( \hat{x}_k \) | Input control |

where \( x_i \) is the \( i \)-th EMG sample.
3. Results and Discussion

3.1. Estimating the Elbow Joint Angle

Before the Kalman filtering process, the EMG features were normalized within the range between 0 and 1, as shown in figure 3 (a). Figure 3 (a) shows that the SSC features indicated by little rectangular obviously can follow the movement of the elbow joint angle (indicated by the red color line) but with noise. In this figure 3(a), the Pearson’s correlation coefficient and RMSE values were 0.847 and 24.03°, respectively. In order to improve the performance of the estimation, the EMG features extracted using SSC were filtered using Kalman filter as shown in figure 3 (b). After the Kalman filtering process, the performance of the estimation was increased as follows: the Pearson’s correlation coefficient and RMSE values were 0.967 and 8.76°, respectively.

Figure 3. A typical of motion period of 6 seconds. (a) The normalize EMG features, (b) The Kalman filtered EMG features.

In figure 3, the small rectangle indicates as the EMG features, the dashed line shows the estimated elbow-joint angle from EMG features, and the red line indicates the measured elbow-joint angle. To obtain the optimum of the estimation, the Kalman filter parameters consists of the process noise Q and the measurement noise R were tuned to a certain value which resulted in the best performance. After the Kalman filtering process, the predicted angles almost coincide with the estimated angles with small of error [Figure. 3(b)].

3.2. Evaluation of the proposed method

The variation of the performance was examined by calculating the Pearson’s correlation coefficient (CC) and RMSE for each cycle of motion during ten continuous cycles. Figures 4(a) and (b) and figures 5(a) and (b) show the variation of the CC and the RMSE before and after Kalman filtering. Before the Kalman filtering process, the mean of CC were 0.85±0.036, 0.88±0.021, and 0.88±0.021 for motion periods of 12 seconds, 8 seconds and 6 seconds, respectively and the mean of RMSE were 25.64±2.47, 23.13±1.96, and 22.15±1.99 for motion periods of 12 seconds, 8 seconds and 6 seconds, respectively.
High accuracy of elbow joint estimation is very important in the development of the exoskeleton robot or prosthetic devices. As shown in Table 2, the mean of RMSE of the estimated angle for 12 seconds, 8 seconds and 6 second periods are 10.39°±0.60°, 9.89°±0.37° and 10.26°±0.82°, respectively. This work was comparable with previous related work. Tang et al. [4] reported similar results for three different speeds of motion with mean RMSE of 12.42°, 9.67° and 10.70° for 8 seconds, 4 seconds and 2 seconds period. In their study, the EMG signal collected from biceps, triceps, anconeus and brachialis muscles were extracted in order to obtain the features and to use as the input for the ANN classifier.

Table 2. The summary of the CC and RMSE values after the Kalman filtering process for the motion periods of 12, 8, and 6 seconds.

| Descriptive Stat. | CC          | RMSE (°)   |
|-------------------|-------------|------------|
|                   | 12 sec.     | 8 sec.     | 6 sec. | 12 sec. | 8 sec. | 6 sec. |
| Mean              | 0.95        | 0.96       | 0.96   | 10.39   | 9.89   | 10.26  |
| Standard Deviation| 0.021       | 0.010      | 0.016  | 0.60    | 0.37   | 0.82   |
| Maximum           | 0.97        | 0.98       | 0.98   | 13.25   | 11.85  | 15.90  |
| Minimum           | 0.90        | 0.95       | 0.93   | 7.66    | 8.13   | 7.48   |

Table 2 shows that the CC values were higher than 0.9, these indicate that the estimated and measured angle has a high relationship. The consistency of the proposed method was tested for the three different periods namely 12, 8, and 6 seconds. Statistical analysis of single factor ANOVA showed that there was no significant difference of RMSE as well as CC for three different periods of motion (p-value>0.05).

Although the results were very promising for a better performance, there were some factors needs to consider. These factors were the muscle fatigue [12], skin conductance, electrode placement [2] and the number of subjects. Next work, it also needs to explore the Kalman filter parameters such as Q-
parameter and R-parameter to optimize the estimation algorithm. Furthermore, this proposed method (SSC-KF) can be applied to any devices based on myoelectric control to get a natural control.

4. Conclusion
This study has demonstrated the effectiveness of the proposed method by using a combination of the Sign Slope Change features and Kalman filtering. The elbow joint angle was estimated using the EMG signal generated from biceps alone. The EMG signals were extracted using the Sign Slope Change and optimized using Kalman filter. Statistical analysis proved that there is no significant difference of RMSE between periods of motion. The performance of the estimation was increased after the Kalman filtering process by 59.45%, 57.23%, and 53.66% for motion period of 12, 8, and 6 seconds, respectively. In next work, this proposed method can be implemented in prosthetics and robotic exoskeleton design.

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