Joint force estimation using time-varying SEMG feature in fatiguing contraction

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Abstract— **Many studies have estimated joint force using surface electromyography (SEMG), however, the time-variant characteristic of SEMG is not considered. The change of SEMG amplitude is one of manifestations of muscle fatigue. This study proposes a force estimation method using SEMG in fatiguing contraction. The SEMG amplitude is used to determine the signal states by *k*-means clustering method. According to the signal state changes, the corresponding gain is used to estimate the force. The target contraction is an isometric abduction of an index finger in static and dynamic force conditions for 5 healthy subjects. The estimation performance was evaluated by percentage of root mean squared error (RMSE). The RMSE for the proposed method is 2.5±1.0% under static condition and 8.8±1.2% under dynamic condition. The accuracy using a constant gain calculated at initial time was used to compare with the proposed method. The RMSE are 8.9±2.2% under static condition and 10.1±2.4% under dynamic condition. The proposed method had better performance in both conditions.**

I. INTRODUCTION

Surface electromyography (SEMG) signals, which represent the amount of muscle contraction, can be measured while patients cannot move their body but contract their muscles [1]. SEMG signals have been used to estimate movement intents (e.g., joint force) for control signals of assistive robotics such as powered exoskeletons and rehabilitation devices. Many studies have been performed to estimate joint force using SEMG [2]–[5]. The variability of SEMG is a challenging issue in the activities of daily living and in clinical applications because this variability can deteriorate the estimation accuracy of the movement intention and can cause the rehabilitation program to malfunction.

In previous studies, however, the time-variant characteristic of SEMG was not considered. The features of signal, such as its amplitude and frequency range, can be varied by muscle fatigue despite the usefulness of the signals; the changes of the SEMG amplitude and mean frequency indicate the muscle fatigue [6]. The time and frequency components of the SEMG signals were analyzed to detect the muscle fatigue in static and dynamic contraction [7]. The increase of SEMG amplitude and the decrease of SEMG mean frequency are regarded as signs of muscle fatigue [8]. Because of the variability of signal, accurate detection of fatigue state and change in signal-force relationship is unavoidable.

Soo et al. reported a force estimation model for hand grip force estimation during fatiguing contraction [9], [10]. In fatigue condition, the low frequency amplitude was increased because of the mean frequency shift of the SEMG. However, the high frequency amplitude was not changed between fatigue and non-fatigue condition. They redefined the frequency range (242-365 Hz) to extracted stable SEMG signals not changed due to muscle fatigue. However, this method extracts the part of the SEMG and limits the information of manifestation of muscle fatigue.

In this paper, we propose the method of joint force estimation using time-varying SEMG features in fatiguing contraction. The signal states were classified by using the amplitude of mean absolute value (MAV) and *k*-means clustering method. The gain, which is relation between the force and MAV, was calculated in advance for each signal state. According to the signal state changes, the corresponding gain was used for estimating force. The proposed force estimation method was validated during isometric index finger abduction.

II. MATERIALS AND METHODS

A. Experimental setup and protocol

We recruited 5 healthy volunteers (right-handed, 26.2±1.3 years old) who had no previous experiences with our experiments. The protocol (KH2010-25) was approved by the Institutional Review Board at KAIST. Written informed consent and assent were obtained from the subjects.

The experimental setup is illustrated in Fig. 1 [11]. A force sensor (651AL, Ktoyo, Korea) was used to measure the isometric abduction force of the index finger. The SEMG of the first dorsal interosseous (FDI) muscle, responsible for the flexion and abduction movement at the metacarpophalangeal (MCP) joint, was recorded using a bipolar sensor (DE-2.1 sensor; Delsys Inc., USA) and was amplified 1,000 times using a Bagnoli^{TM} system (Delsys Inc., USA). The position of the electrodes was chosen to be on the belly of the FDI muscle when the subjects performed the isometric abduction of the index finger. The force signal was sampled at 1 kHz and were low-pass filtered using a finite impulse response (FIR) filter with a corner frequency of 20 Hz. The SEMG signals were sampled at 1 kHz and were band pass filtered using an FIR filter with a frequency range between 20 and 400 Hz. The MAV was extracted with a time windows of 200ms in duration for every 50ms. The MAV was calculated using the equation below.

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$$MAV_i = \frac{1}{N}\sum_{k=1}^{N}\left|x_i(k)\right|$$

where $x_i(k)$ is k^{th} signal sample, i is i^{th} window, and N is the number of samples in window.

The subjects were asked to sit comfortably on a chair and to relax their upper limbs. The right index finger was positioned in a custom-fit ring fixed to a force sensor. Other fingers and the forearm were fastened to the table using bands. The subjects were then instructed to follow the target force. The subject's force measured by the sensor and the target force were displayed on the monitor. The subjects performed maximal voluntary isometric contraction (MVIC) 3 times prior to the main experiments. After the MVIC measurement, the subjects performed two experimental sessions: in the first session, the subjects were instructed to sustain a contraction force of 50% MVIC for 100 s (static force). Second, the subjects were asked to follow sinusoidal signals, for which the frequency was 0.25 Hz duration of 100 s; the force varied from 0 to 50% MVIC. We encouraged subjects to track the target force as closely as they can. The SEMG and the force signals were normalized for each subject using the maximum values measured during the MVIC.

C. Classification of signal states

Even before a subject realizes fatigue in his/her muscle, the SEMG signal starts to change during work. The purpose of classification of signal states is to monitor the signal condition and switch between gains, which calibrates the MAV for force estimation. The signal states can be defined as shown below.

$$\begin{Bmatrix} s_t^k \text{ for static force} \\ s_c^k \text{ for dynamic force} \end{Bmatrix} \quad (1)$$

where k is signal state, t is time, and c is the cycle.

The signal states were determined based on the amplitude of MAV. For static force, the signal state was divided for each time step (every 50 ms). For dynamic force, the signal state was divided for each cycle. The peak of the MAV of each cycle was used to classify the signal state. The segmentation of cycles was divided manually because the duration of cycles is not consistent.

The MAV was used for state classification using the k-means clustering method [12]. The k-means clustering aimed to group data points into k number of states in which each data point belongs to a state of the nearest cluster. Fig. 2 shows that the signal is classified into 4 states based on the amplitude of MAV during static force. Dotted lines indicate thresholds between states. Fig. 3 shows the 4 signal states using different markers (circle, square, cross, and asterisk). The number of states, which is k, was changed from 2 to 20 and we selected 10 as the maximum number of states based on root mean squared error (RMSE) of force estimation. Although the number of states is greater than 10, the RMSE showed no significant difference. The signal states were classified based on the amplitude of MAV. The MAV can change to each time step as shown in Fig. 2 and Fig. 3. The states were not consistent according to time. This index represents only the magnitude of MAV and helps to find the corresponding gain for estimating force.

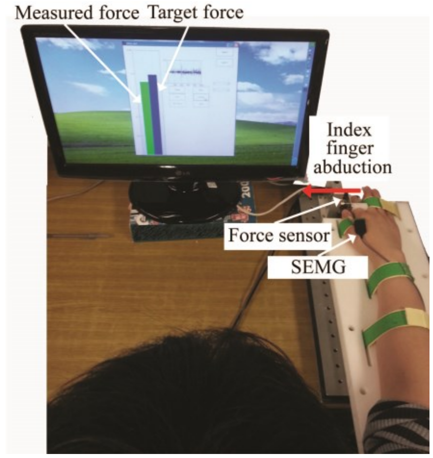

Fig. 1. Experimental setup.

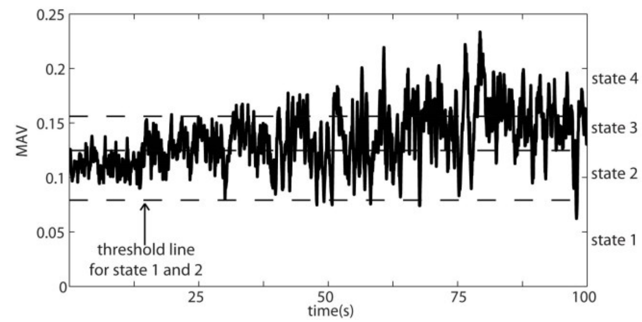

Fig. 2. Example of 4 signal states for static force. Dotted lines are boundary between two states (s1).

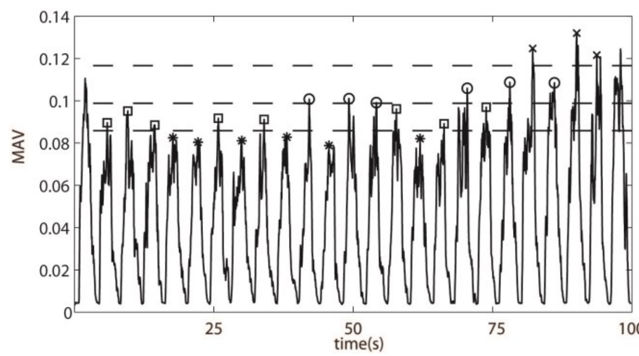

Fig. 3. Example of 4 signal states for dynamic force. The marker types at peak of each cycle indicate the signal states (s1 data).

D. Force estimation according to signal states

The gain was calculated using a linear equation with the measured force and MAV.

$$gain = force / MAV \quad (2)$$

For static force, the centers of each state were used for calibration. Depending on a signal state, the corresponding gain is used to estimate the measured force. For dynamic force, the entire data of the first cycle of each signal state was used for calibration. The first and last cycles were removed for force calibration because these cycles did not guarantee the

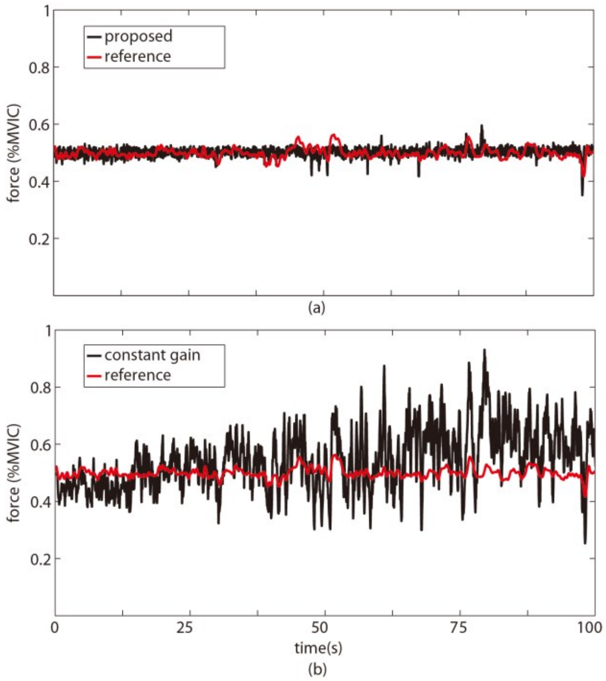

Fig. 4. Force estimation for static force using (a) the proposed method when signal states were classified to 10 signal states and (b) the conventional method (s1 data).

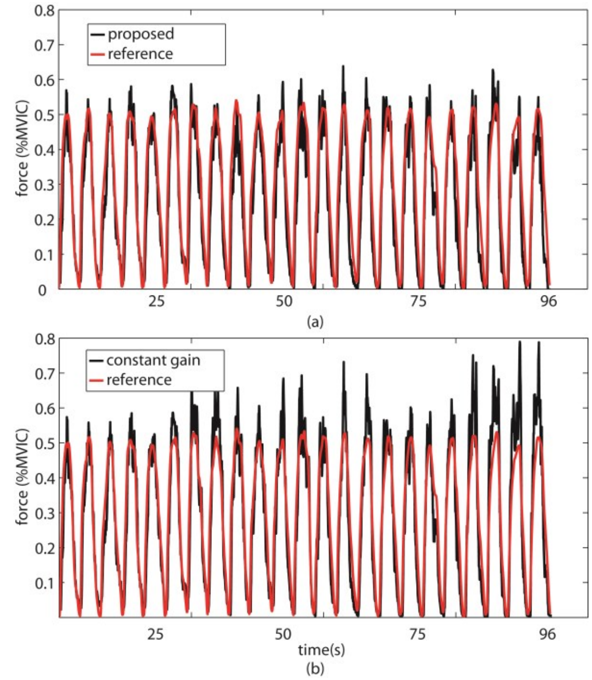

Fig. 5. Force estimation for dynamic force using (a) the proposed method when signal states were classified to 10 signal states and (b) the conventional method (s1 data).

TABLE I. THE PERFORMANCE COMPARISON FOR THE PROPOSED METHOD AND THE CONVENTIONAL METHOD USING RMSE AND CORR.

	Static condition	
	RMSE	
	Proposed	Control
s1	3.20	11.19
s2	1.40	10.68
s3	2.20	9.53
s4	3.80	6.36
s5	2.00	6.96

Dynamic condition			
RMSE		CORR	
Proposed	Control	Proposed	Control
9.62	11.13	0.88	0.87
7.30	7.39	0.94	0.94
7.92	8.36	0.88	0.88
10.10	13.48	0.88	0.89
9.19	9.99	0.86	0.88

whole cycle duration. The estimated force can be calculated as shown below.

$$\left\{\begin{array}{l} f_t = gain_k \times MAV_t \ \ for\ static\ force \\ f_t = gain_k \times MAV_c,\ for\ dynamic\ force \end{array}\right\} \quad (3)$$

where k is signal state, t is time, and c is cycle.

In addition, we performed a comparison study to determine whether the proposed estimation model is more effective than conventional methods [13]. In conventional methods, the gain was calculated by the MAV from the first time step for static force and from the first cycle for dynamic force. The gain was consistent for entire data regardless of time. This method cannot consider the time-varying features of SEMG, thus the error might increase during usage.

III. RESULTS AND DISCUSSION

Fig. 4 and Fig. 5 show the example of the estimated force for static force and dynamic force by using the proposed method and the conventional method with constant gain. Fig. 4 (a) shows that the estimated force is constant compared with the measured reference force because the gain was changed according to the signal state. Fig. 4 (b) shows the estimated force by constant initial gain increases according to time. The amplitude of MAV of s1 increased over time because the difference between the reference and the estimated force increased.

In dynamic condition, the proposed method worked better than the conventional method based on the difference between force sensor and estimation value at peaks. The force estimation with constant gain shows large peak values, which increased up to 0.8 in Fig. 5 (b). The difference increased as time increased. However, the errors between the measured force and estimated force were less than static condition in both methods as shown in Fig. 5 (a) and (b).

All subjects had better performance using the proposed method in both conditions as shown in Table I. Based on RMSE, static condition shows better performance than dynamic condition. On the other hand, the conventional method had similar the RMSE values compared with the proposed method in dynamic condition. The reason of this result is because fatigue was not induced equally over both conditions. The dynamic condition was composed of small force which is less than 50% MVIC for most part except the peaks. The correlation values were similar in both methods. The phase of force increase and decrease were not different because the force was estimated using the linear equation for both methods.

IV. Conclusion

We proposed the joint force estimation using time-varying SEMG features in fatiguing contraction. 5 healthy subjects performed the isometric index finger abduction in static and dynamic force condition. The time-varying characteristic of SEMG was considered to estimate the force. The amplitude of SEMG is used to determine the signal states by the *k*-means clustering method. According to the change of signal states, different corresponding gain is used to estimate the force. The estimation performance was evaluated by the percentage of root mean squared error (RMSE). The proposed method had better performance compared to the conventional method, which used a constant initial gain. The proposed method could be widely applied to estimate the force in fatiguing conditions.

In further studies, the potential use of this approach with unknown signals (e.g., non-sinusoidal or impulsive force profiles, different/reduced cycle time) should be validated for practical application to control of prosthesis. By considering more features such as frequency and changing rate of features, the proposed method will also be applied to force-varying conditions, mimicking practical usages.

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