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Novel Algorithm for Real-Time Onset Detection of Surface Electromyography in Step-Tracking Wrist Movements*

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Abstract— **We present a novel algorithm for real-time detection of the onset of surface electromyography signal in step-tracking wrist movements. The method identifies abrupt increase of the quasi-tension signal calculated from sEMG resulting from the step-by-step recruitment of activated motor units. We assessed the performance of our proposed algorithm using both simulated and real sEMG signals, and compared with two existing detection methods. Evaluation with simulated sEMG showed that the detection accuracy of our method is robust to different signal-to-noise ratios, and that it outperforms the existing methods in terms of bias when the noise is large (low SNR). Evaluation with real sEMG analysis also indicated better detection performance compared to existing methods.**

I. INTRODUCTION

SURFACE electromyography signal, sEMG, can be used for various applications, including diagnosis and evaluation of patients with neurological diseases, studying motor control, and serving as input signal for the control of robotic devices. Detecting the onset of increased muscle activity is required for interpreting temporal information such as the beginning and duration of motion or cocontraction. Real-time onset detection is particularly important if the signal is used for controlling devices like prostheses [1] or for predictive haptic displays [2] (as in the example depicted in Fig. 1).

Methods for onset detection in sEMG have been studied intensively in the last decade [3]–[5]. Existing methods can be categorized into two types: one type is threshold-based where muscle activation onset is detected when the sEMG signal exceeds critical threshold [6]. The other type is based on a statistically optimal decision: it assumes statistical properties of signals, estimates the parameters of the assumed distributions, and detects onset when these parameters change. The performance of existing methods has been compared [3], [4], but the most appropriate method have not been established because the performance is very sensitive to noise in the signals.

During movement, muscles are recruited gradually, and the temporal properties of this recruitment are expressed in the sEMG signal [7]. Thus, sEMG under a specific movement would reflect its temporal characteristics. Based on this assumption, we propose a robust real-time sEMG onset detection method by beginning-of-motion template matching.

Fig. 1. The initial state of step tracking movement, in which a user is asked to move his hand from point-to-point, while holding haptic device

II. ONSET DETECTION OF SEMG

A. Movement theory applied to sEMG quasi-tension

Step tracking movements in which a user is asked to move his hand from point-to-point have been studied extensively, and various computational models have been suggested to describe their trajectories [8], [9], [11]. The Minimum Acceleration with Constraints model [11] suggests that at the beginning of movement, the third derivative of position, jerk, changes abruptly from zero to some constant value, resulting in a position trajectory that can be described as a cubic power of time after onset. This model was used to develop an algorithm for automatic, offline, movement onset detection based on regression [10]. Here, we assume that muscle tension, which can be represented as a convolution of sEMG and impulse response of a single motor unit [12], [13], increases similarly to displacement in the beginning of motion [14]. Thus, tension y can be represented as:

$$y(t) = \begin{cases} 0 & t < t_0 \\ at^3 & t \geq t_0. \end{cases} \quad (1)$$

where a is a coefficient of cubic function, and tension y increases abruptly at the onset of sEMG time t_0.

B. Curve fitting for onset detection

To identify sEMG activity onset, we propose a method based on fitting a piecewise linear regression around the suspected onset time. Similarly to the offline algorithm in [10], our method uses a template consisting of a flat region before onset, and a cubic power of time after it. Fig. 2 illustrates the process of curve fitting. The method employs a sliding test window, and finding the least square error approximation of the quasi-tension profile with the template curve. Increase in the size of the coefficient of the cubic region indicates onset of muscle activation. Our method

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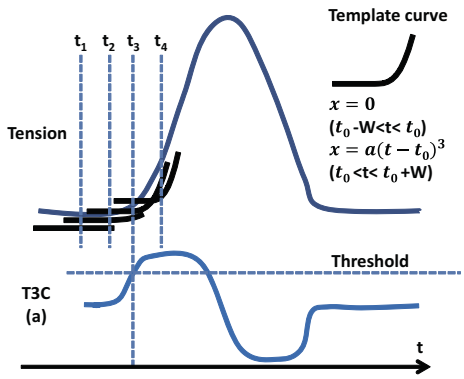

Fig. 2. Onset detection by sliding template curve (upper right corner) fitting to a window of quasi-tension signal (upper trace). The coefficient of the cubic function segment (lower trace) increases at movement onset.

detects onset of sEMG activity when this coefficient exceeds a threshold h_T. Because our method uses the coefficient of the regression between tension and a cubic function of time, in the remainder of the paper we refer to it by the name T3C algorithm.

The T3C algorithm for detecting the onset time of sEMG activity, t_0, can is as follows. First, a quasi-tension signal, y_k is calculated from the sEMG signal x_k by convolution with an impulse response w_k of a single muscle unit recruitment, i.e.:

$$y_k = \sum_{i=1}^{M} w_i x_{k-i}; \qquad w_k = \frac{k}{T_c} e^{-\frac{k}{T_c}} \tag{2}$$

where M is the number of samples for convolution, and T_c is the time constant of the impulse response. T_C was set to be 50 [13], and M to be 300. Then, for a window of length $2W_T$ the quasi-tension is fitted with a flat region of length W_T and a cubic function of time of length W_T:

$$\bar{y}_k = \frac{1}{W_T} \sum_{i=k-2W_T+1}^{k-W_T} y_i \tag{3}$$

$$g_k = \min_a \sum_{i=1}^{W_T} \| \, y_{k-W_T+i} - \bar{y}_k - a(i\Delta T)^3 \, \|^2, \tag{4}$$

where ΔT is a sampling time. Finally, the onset is detected when g_k exceeds the threshold h_T for the first time:

$$k_d = \min_k \{k \geq 2W_T : g_k \geq h_T\} \tag{5}$$

and the estimated time of onset can be calculated as:

$$\hat{k}_0 = k_d - W_T + 1. \tag{6}$$

The values of h_T and W_T were set empirically to be 0.5×10^5 N/s^3 and 10, respectively. In future studies, we will explore optimization of these parameters.

III. EVALUATION OF DETECTION PERFORMANCE ON SIMULATED SEMG

A. Signal generation

As a first step for assessing of robustness and accuracy of our proposed algorithm and comparing its performance to other existing methods, we used simulated sEMG signals. The main advantage of using simulated sEMG is that the correct onset time is known. In addition, it allows for controlling signal parameters like signal-to-noise ratios (SNR) and rise time.

As in previous studies, we use a model that is based on white noise, whose variance is modulated by muscle activation [3], (Fig. 3). The signal has some quiet state variance σ^2_{noise}, and at movement onset the variance increases gradually until reaching the active state variance $\sigma^2_{\text{noise}} + \sigma^2_{\text{signal}}$. Thus, the variance of sEMG signal, σ^2 can be written as:

$$\sigma^2(k) = \sigma^2_{\text{noise}} + \sigma^2_{\text{signal}} u(k, \tau, k_0), \tag{7}$$

where $u(k, k_0)$ describes the dynamic profile of muscle activation, characterized by the transition function $r(k, \tau, k_0)$ as:

$$u(k, \tau, k_0) = \begin{cases} 0 & k < k_0 \\ r(k, \tau, k_0) & k_0 \leq k < k_0 + \tau/\Delta T \\ 1 & k \geq k_0 + \tau/\Delta T \end{cases} \tag{8}$$

where τ is the rise time.

Most studies assume a linear transition function during the rise time [3]. However, nonlinear transition is physiologically more plausible, because muscle units are recruited gradually in accordance with the size principle, where smaller units are recruited first [7]. We compare three transition types. One is linear, following [3], and the other two are smooth nonlinear transitions: one that is based on a function that models a point-to-point movement that minimizes the jerk [8], and the other is a sinusoid. These are formally described as:

1) Linear transition

$$r(k, \tau, k_0) = (k - k_0)\Delta T/\tau \tag{9}$$

2) Minimum-jerk transition

$$\begin{aligned} r(k, \tau, k_0) &= 10((k - k_0)\Delta T/\tau)^3 \\ &\quad - 15((k - k_0)\Delta T/\tau)^4 + 6((k - k_0)\Delta T/\tau)^5 \end{aligned} \tag{10}$$

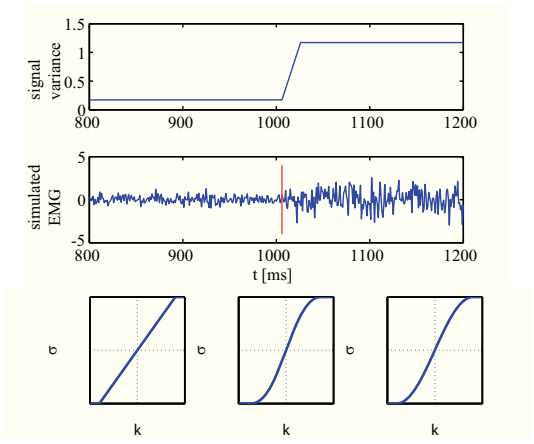

Fig. 3. Simulated EMG signals. Upper and middle panels depict example of one signal with linear ramp modulation of white noise variance. Lower panels depict three ramp functions used in this study: (left to right) linear, minimum-jerk, and sinusoidal.

3) Sinusoidal transition

$$r(k,\tau,k_0) = 0.5(\sin(\pi(k-k_0)\Delta T/\tau + \pi/2) + 1). \quad (11)$$

To normalize the signals, σ_{signal} was always set to 1, while σ_{noise} was determined based on SNR, such that:

$$\text{SNR} = 10 \cdot \log_{10} \frac{\sigma^2_{\text{signal}}}{\sigma^2_{\text{noise}}} [\text{dB}]. \quad (12)$$

B. Procedures

We generated simulated sEMG signals with varying rise times τ distributed uniformly between 5 and 30 ms, and varying SNR distributed uniformly between 4 and 12 dB. To assess the dependency of accuracy on SNR, we fixed the rise time at $\tau = 20$ ms, and the analysis of dependency on rise time was performed with fixed SNR of 6 dB. We repeated the simulation 100 times for each condition, and then examined the distributions of detected onset errors. Because an accurate detection algorithm needs to be unbiased and precise, we examined the central tendency as well as the dispersion of error distribution. Because the distributions were not symmetrical, we chose the *median* and *interquartile range* (the difference between the first, 25%, and third, 75% quartiles of the ordered errors) as the statistics of interest for comparison between different detection algorithms.

We compared the performance of our method with two additional methods: mean tension *Change Ratio* [3] and variability threshold *Hodges* method [6]. The *Change Ratio* method detects onset time when a sufficiently large change of mean tension occurs. Namely, after calculating the tension signal from (2) the ratio of mean tension before and after suspected onset time is calculated,

$$\bar{y}_k = \frac{1}{W_C} \sum_{i=k-2W_C+1}^{k-W_C} y_i, \quad \bar{z}_k = \frac{1}{W_C} \sum_{i=k-W_C+1}^{k} y_i \quad (13)$$

$$g_k = \bar{z}_k / \bar{y}_k, \quad (14)$$

and the onset is detected when g_k exceeds the threshold h_T:

$$k_d = \min_k \{k \geq 2W_C : g_k \geq h_C\} \quad (15)$$

and the estimated time of onset can be calculated as:

$$\hat{k}_0 = k_d - W_C + 1, \quad (16)$$

where h_C and W_C were set to 5 and 10, respectively.

The *Hodges* method detects onset time based on a change of the mean value of rectified and filtered sEMG signal, y_k, that exceeds a threshold that depends on the initial standard deviation of y_k [6]. Namely, the mean, $\hat{\mu}_0$, and standard deviation, $\hat{\sigma}_0$, of the first M samples of y_k are calculated, and a test function is calculated according to:

$$g_k = \frac{1}{\hat{\sigma}_0}(\bar{y}_k - \hat{\mu}_0), \quad \bar{y}_k = \frac{1}{2W_H} \sum_{i=k-2W_H+1}^{k} y_i. \quad (17)$$

The onset is detected when g_k exceeds a threshold,

$$k_d = \min_k \{k \geq 2W_H + M : g_k \geq h_H\}. \quad (18)$$

and the estimated time of onset can be calculated as:

$$\hat{k}_0 = k_d - W_H + 1 \quad (19)$$

We set W_H to 10, similarly to the other methods, and followed [3], set h_H to 2.5, and used a 6$^{\text{th}}$-order Butterworth low pass filter with 50 Hz cutoff frequency to calculate y_k.

C. Results

Fig. 7 (a) shows the cumulative distribution function (CDF) of the onset detection error, defined as $P_a = P(|\hat{k}_0 - k_0| \leq a)$, where $\hat{k}_0$ and k_0 are the detected and real onset time, respectively. This distribution function was calculated based on 1,000 sEMG simulations with sinusoidal transition, SNR = 6dB and τ = 20ms. The CDF of the T3C method is leftmost, indicating superior detection performance.

Fig. 4 shows evaluation of the onset error as a function of SNR. The median of the T3C method was smaller than the other methods at small SNR (i.e. large noise), indicating that our method is robust to noise, while the interquartile range was similar among the methods. Fig. 5 shows evaluation of the onset error as a function of rise time, and reveals that the T3C method has the smallest median. The median of detected onset value in all methods increases with increasing rise time, while the interquartile range remains roughly the same. Short rise time in a simulated sEMG signal represents fast activation of motor units due to fast movement, and therefore, onset must be detected promptly to allow fast response. Therefore, the fact that the onset is detected earlier at small values of rise time indicates that all the methods are effective in detecting the onset of rapid movements.

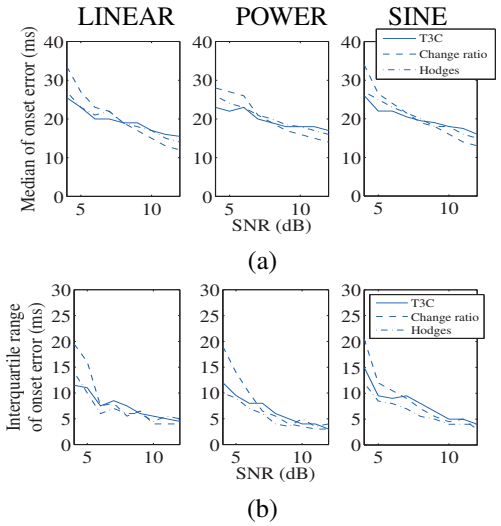

Fig. 4. Performance evaluation based on simulated sEMG: (a) median and (b) interquartile range of the onset error as a function of SNR with fixed rise time at 20 ms

IV. EVALUATION OF DETECTION PERFORMANCE ON REAL SEMG

A. Data acquisition

The system consists of an amplifier with electrodes (BA1104-CM, TEAC), A/D converter (AIO-163202FX-USB, Contec) to measure sEMG of ulnar flexor muscle

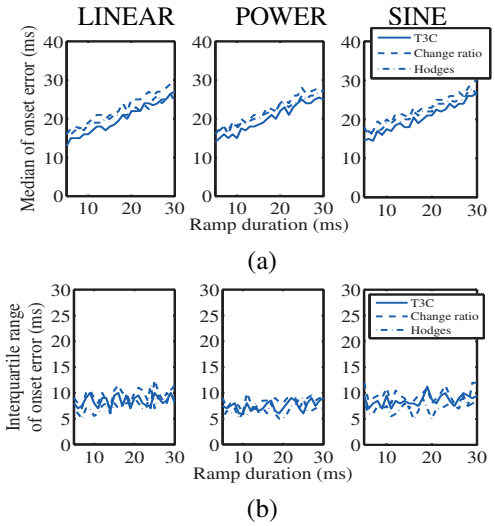

Fig. 5. Performance evaluation based on simulated sEMG: (a) median and (b) interquartile range of the onset error as a function of rise time with fixed SNR at 6 dB

at 1 KHz, 3D position input device (PHANToM Omni, SensAble), and a computer with a visual display.

B. Procedures

We recorded sEMG of superficial flexor muscle of fingers and ulnar flexor muscle of right arm as representative muscles that are activated during palmer flexion, with consideration of the order of contribution of muscles to flexion. The sEMG was recorded while the participant was performing a wrist step-tracking movement while holding a haptic device, as depicted in Fig. 1. In each movement, a round origin and target were displayed, and the participant was asked to reach the target and return to the origin as quickly as possible. To allow sufficient sample size for evaluation of onset detection performance, the participant performed 500 step-tracking movements. Then, we applied all three algorithms to detect sEMG activation onset and compared it to the correct onset time that was determined by visual inspection.

C. Results

An example of one measured signal is depicted in Fig. 6. Fig. 7 (b) depicts the CDF of the onset detection error. Consistent with simulated sEMG evaluation, the CDF of our the T3C method is leftmost, indicating overall superior detection performance.

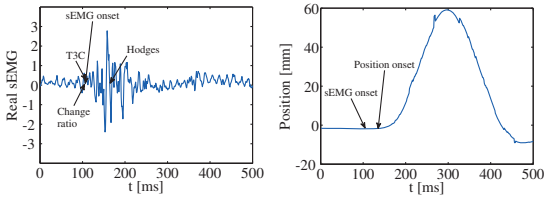

Fig. 6. An example of signals generated during one forth-and-back wrist movement: a sEMG signal (A), and its corresponding movement trajectory (B). Visually inspected onset times of sEMG and position are included.

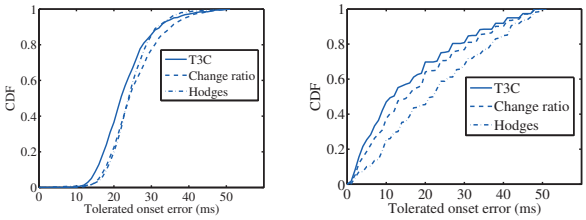

Fig. 7. CDF of the onset error in case of (a) simulated sEMG with $\tau = 20$ ms and $SNR = 6$ dB, (b) real sEMG signals

V. CONCLUSIONS

We propose a novel, movement-similarity based, method for real-time onset detection in sEMG. We evaluated the performance of this method in comparison with two existing methods using both simulated and real sEMG signals. Simulated sEMG evaluation revealed that our method is robust to noise, and in low SNR, its performance is superior in terms of bias. Real sEMG recordings evaluation, based on comparison to visual offline detection, also supports the conclusion that our proposed method is more accurate in onset detection than other methods.

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