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Muscle Activity Onset Time Detection Using Teager-Kaiser Energy Operator

Xiaoyan Li, Alexander S. Aruin

Abstract **– This study presents a novel method, characterized with simple implementation, to automatically detect the onset time of muscle activity using surface electromyogram (EMG) signals. The method applied Teager-Kaiser energy operator (TKEO) to highlight the motor unit activities by simultaneously considering the amplitude and frequency information of the surface EMG, and therefore increase the prospects of muscle activity detection. A robust threshold-based algorithm was then applied to the TKEO output to locate the onset time of muscle activity. The validity of the proposed method was illustrated using both experimental surface EMG recordings and various surface EMG simulations.**

I. INTRODUCTION

Surface electromyogram (EMG) recording is a widely used approach to obtain physiological or clinical information about nerve and muscle functions [1]. One important application of surface EMG is the precise detection of motor events, such as the determination of the exact onset and offset times of a muscle contraction, which is a prerequisite in studies of motor control and performance. However, due to the stochastic characteristics of the surface EMG, onset detection is a very challenging task, especially when surface EMG response is weak. Under conditions where the signal to noise ratio (SNR) is very low, it is prone to false detection by visual inspection of the signal or by simply setting an amplitude threshold to determine if the muscle activity occurs [2]. To overcome this difficulty, more complicated methods such as wavelet template matching [3] and statistical criterion determination [4-7] have been proposed to improve the onset time detection. These methods usually require much computation cost, and their performances are largely related to *a priori* knowledge of the signal.

In this study, we propose a novel method to robustly and efficiently detect the onset time of muscle activity by applying Teager-Kaiser energy operator (TKEO) to the surface EMG signal. The performance of the onset time detection using various simulated surface EMG signals and experimental surface EMG records indicate that TKEO dramatically improves the SNR of the signal and therefore increases the prospects of onset time detection, especially at low SNRs.

Xiaoyan Li is with the Department of Bioengineering, University of Illinois at Chicago, Chicago, IL 60612 USA (phone: 312-355-0902; fax: 312-996-4583; e-mail: xli25@uic.edu).

Alexander S. Aruin is with the Department of Physical Therapy and Department of Bioengineering, University of Illinois at Chicago, Chicago, IL 60612 USA (e-mail: aaruin@uic.edu).

II. METHODOLOGY

A. Teager-Kaiser Energy Operator (TKEO)

The history of the Teager-Kaiser energy operator (TKEO) goes back to the Teager's experiments in 1983 arguing that the production of speech involved nonlinear processes against the linear theory used by the models at that time [8, 9]. In 1990, Kaiser first derived the TKEO in discrete domain to compute the energy generator of a sound [10, 11]. The algorithm was later extended to cover continuous signals [11].

The discrete TKEO Ψ is defined in time domain as:

$$\Psi_d[x(n)] = x^2(n) - x(n+1)x(n-1) \tag{1}$$

For a given signal with amplitude A and frequency ω_0,

$$x(n) = A(n)\cos(w_0(n) + \theta) \tag{2}$$

Applying the signal into equation (1), the energy operator can be rewritten as:

$$\Psi_d[x(n)] \approx A(n)^2 \sin^2(w_0(n)) \tag{3}$$

Therefore, the output of TKEO is proportional to the product of the instantaneous amplitude and frequency of the input signal. TKEO has been widely used in speech signal analysis including AM-FM demodulation [12], stop classification of the speech, estimation of the speech formats and recently in detection of neural spikes and spiky waveforms in electroencephalogram signals [13-15].

B. Muscle Activity Onset Time Detection Using TKEO

When a motor unit action potential fires, it is usually accompanied by an instantaneous increase in signal amplitude and frequency. In this study, taking advantage of the property of TKEO, we explored to detect the onset time of muscle activity by simultaneously considering the instantaneous frequency and amplitude information of the surface EMG. First, TKEO was applied to the surface EMG signal to highlight the motor unit activities by making the action potential spikes more conspicuous. Then a threshold level in the TKEO output was determined by

$$DF = u_0 + j \cdot o_0 \tag{4}$$

where u_0 and o_0 are the mean and the standard deviation of the TKEO output of the noise when there is no muscle activity, j is a preset variable which is to be determined empirically. The onset time of the muscle activity was determined as the point where the TKEO output exceeded the preset threshold.

C. Surface EMG Simulation

To evaluate the onset time detection performance, simulated surface EMG signals were generated by the simulation software (SiMyo) developed by Institu de Myologie in Paris, France [16, 17]. Detailed theoretical bases can be found in [17]. The model simulates surface EMG signals that origin from intracellular potentials passing through volume conductor such as muscle, fat and skin tissues, and finally detected by a single differential amplifier.

Each signal was simulated by superposition of different numbers of individual motor unit action potentials by adjusting the number of active motor units (recruitment) and their mean inter-spike-interval (IPI) between action potentials (firing rate). IPIs were randomized by a Gaussian distribution. The IPI variation was extracted from a zero mean Gaussian distribution, the standard deviation of which was computed as 10% of the mean IPI. Each segment of simulated EMG recording was 1 s long. Five groups of simulated surface EMG signals each containing 3 segments were generated in a way that the first group contained 100 motor unit action potentials, and the following groups contained 200, 300, 400, 500 motor unit action potentials respectively.

To simulate the surface EMG signals with different noise levels, Gaussian noise was generated separately using Matlab 6.5. The standard deviation of the noise was determined in such a way that the noise level resulted in surface EMG signals of different SNRs varying from 2 dB to 10 dB.

C. Experimental Surface EMG Recording

The real surface EMG signals used in this study were taken from the experiments designed for exploring the feed-forward postural control mechanisms [18, 19]. Precise onset and offset detection of the muscle activity using surface EMG signal is a prerequisite in accurately determining the time order of the postural muscle activation.

Four healthy subjects without any known neurological or muscle disorders participated in this study. Subjects were given informed consent form approved by the Institutional Review Board of the University of Illinois at Chicago.

Subjects were asked to release a 5-lb load with forearm extended as fast as possible. Onset of the load release (perturbation) was measured by a miniature unidirectional accelerometer (Sensotec) taped to the load. Six channels of surface EMG signals were recorded from the following muscles: Rectus Abdominis (RA), Erector Spinae (ES), Rectus Femoris (RF), Biceps Femoris (BF), Soleus (SOL), and Tibialis Anterior (TA). All the signals were sampled at 1000 Hz with 16-bit resolution. The data were analyzed off-line with the customized software based on the Labview and Matlab 6.5.

D. Performance Evaluation

To better evaluate the performance of the proposed method, we also implemented several already established surface EMG onset time detection methods as a comparison. These methods include the conventional or general amplitude thresholding of raw surface EMG, thresholding in wavelet transform domain using wavelets similar to surface motor unit action potentials, and the onset time detection using statistical criteria, i.e. generalized likeliness ratio, which utilizes *a priori* knowledge of the signal. Detailed description of these methods can be referred in [6, 7]. In this study, parameters of these methods were selected to achieve the optimal performance.

III. RESULTS

Simulated Surface EMG and TKEO Output

First, the onset time detection based on TKEO was applied to the simulated surface EMG signals contaminated by different noise levels. The onset time of the simulated surface EMG was defined as the occurrence of the first motor unit action potential in the signal. Surface EMG signals at different noise levels were used to evaluate the detection performance. Fig. 1 shows two simulated signals with different SNRs (top) and their corresponding TKEO outputs (bottom). It is indicated that when the SNR is low, it is very difficult to detect the onset time by comparing the amplitude of background noise and muscle activity. However, by computing the TKEO outputs of the simulated data, we can observe that the difference between background noise and muscle activity is apparent since the TKEO is not only sensitive to the instantaneous amplitude but also to the instantaneous frequency of the signal. As the frequency of muscle activity is higher than that of background noise, the TKEO output of muscle activity is becomes more evident compared with the background noise. Therefore, it is relatively easy to separate muscle activity from background noise.

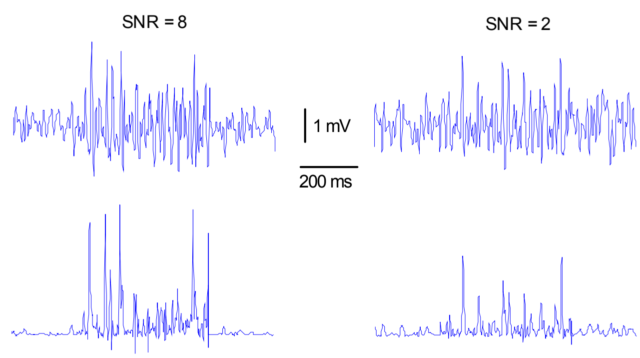

Fig. 1. Simulated surface EMG signals of different SNRs (top) and their corresponding TKEO outputs (bottom)

Optimal Thresholding of TKEO Outputs

The threshold for TKEO output used in determining the muscle activity onset time was decided according to *Equ.*3. The mean and the standard deviation of the TKEO outputs of the background noise could be obtained by applying TKEO to the segment which contains no muscle activity. The threshold was then decided by j. In general, j was chosen to be greater than 3. For the signals with different noise levels, the threshold was adjusted by varying j in order to achieve optimal performance. Fig. 2 displays the absolute value of latency changes as SNR of the data decreases from 10 to 2 dB and j varies from 3 to 30. Latency τ is defined as the absolute value of the difference between true onset and detected onset time instant $|t_{true} - t_{detected}|$. Two error types, false alarm and delayed estimation of onset time, were not distinguished in the onset detection. For any given j, the latency decreases as SNR of the simulated data increases. When SNR of the data is above 8 dB the latency decreases to near zero for j greater than 8. On the other hand, when SNR of the signal is less than 8 dB, the latency first decreases and then increases dramatically with j. The smallest latency occurs when j approaches 7. So according to Fig. 2, we observed that j could be set around 7 to achieve robust and optimal performance.

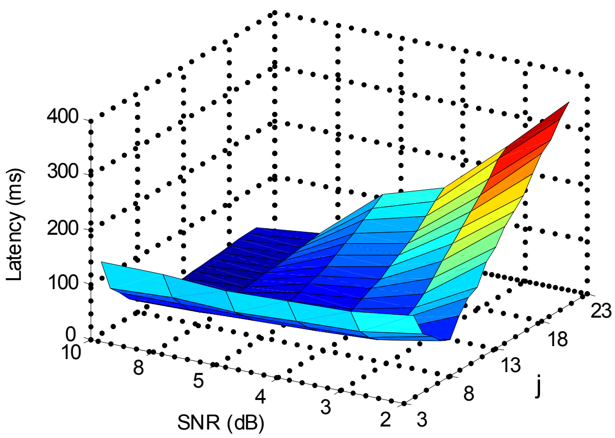

Fig. 2. Three-dimensional plot of the onset time detection of simulated surface EMG signals

Comparison of Different Methods

Using the simulated surface EMG signals, we tested the onset time detection performance of several established methods for comparison with the proposed method based on TKEO. The general thresholding of raw EMG signal (Gen), the statistical criterion determination using generalized likeliness ratio (GLR), and wavelet transform based matching (WT) were implemented respectively to detect the onset time of the simulated surface EMG signals. Parameters for each method were adjusted to achieve the best performance.

Table 1 represents the comparison of different methods. It indicates that as the SNR increases from 2dB to 10dB, the latency decreases in all methods. When the SNR of signal is relatively high, the GLR method achieves the best performance for onset detection as the means and standard deviation of latency are smaller than those of other methods. The method based on TKEO has the second best performance among the listed four methods (j=7). However, In the case of poor signal quality, TKEO achieves the best performance for onset time detection, indicating its ability in dealing with low SNR signals.

Table 1. Onset time estimation (in latency) using different methods (mean±std)

SNR (dB)	Latency (ms)			
	Gen	GLR	WT	TKEO
2	162.46±191.58	45.77±10.32	80.85±41.06	28.76±30.59
3	127.55±159.45	41.93±10.74	55.84±25.89	27.99±28.68
4	100.10±120.32	38.71±10.63	53.96±26.07	26.02±28.52
5	83.69±97.75	34.50±10.61	51.44±26.82	25.81±28.40
8	50.11±39.17	20.44±9.87	48.57±28.29	22.81±27.50
10	41.02±35.74	11.28±7.55	43.11±27.75	19.06±24.78

Onset Detection of Experimental Surface EMG

Application of TKEO for experimental muscle activity onset detection is presented here. Fig. 3 shows an example of the surface EMG signals detected from a pair of postural muscles. It is observed that before the mechanical onset (the onset of arm movement), the TA is already activated and SOL is suppressed. The onset time instance of the TA and offset of the SOL are different. The order of muscle activity is an activation of TA followed by the suppression of the SOL.

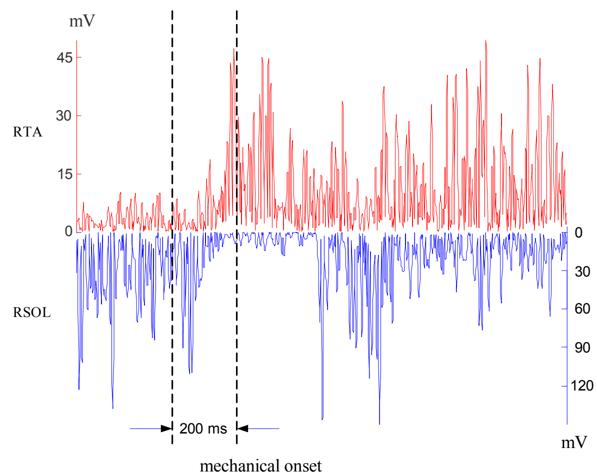

Fig. 3. Surface EMG signals collected from a pair of postural muscles

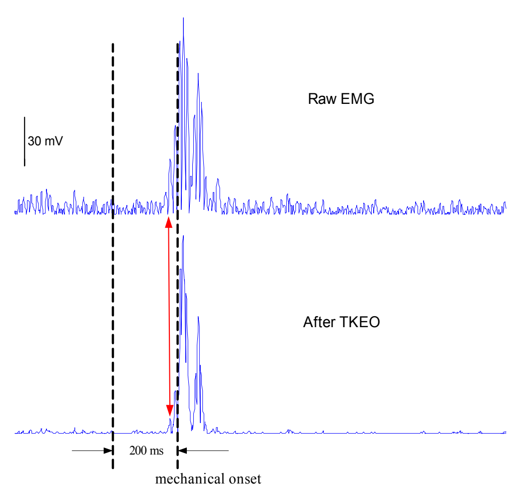

Fig. 4. TKEO based onset time detection of the TA muscle.

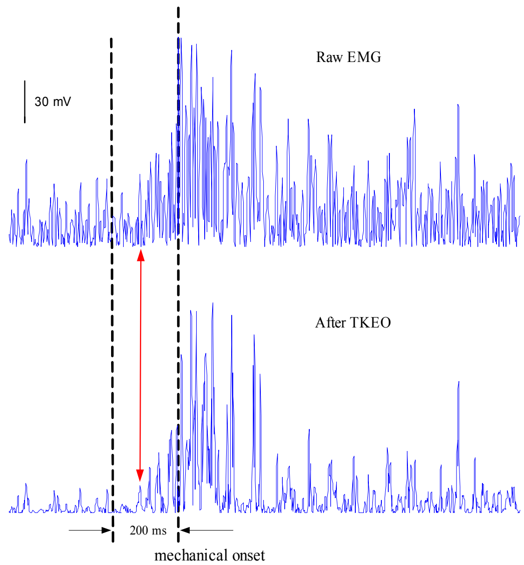

Fig. 5. TKEO based onset time detection of RF muscle

Fig. 4 and Fig. 5 present two examples of the onset time detection process based on TKEO. The search window of the muscle activity onset detection begins 200ms before mechanical onset time instant and ends 200ms after the mechanical onset. Both the TA and BF are activated before the arm movement. The result shows the activations of TA start earlier than those of RF.

IV. Discussion

It is extremely important to precisely detect the muscle activity onset time for investigation of postural adjustments. For example, the movement of releasing a load with arms extending forward creates a backward perturbation toward the subject. To minimize the perturbation, a forward moment about the ankle joint is anticipated from the muscle activities of TA (activation) and SOL (suppression) in Fig. 3. The precise onset detection of muscle activity, giving the time order of muscle activity, provides more information in postural adjustments.

Many efforts haven been focused on the detection of onset time of muscle activity by processing surface EMG signals. However, most of the proposed methods only achieve satisfactory results when the SNR of the signal is sufficiently high. In the current study, based on the observation that the firing of action potential provides the temporal increase of the signal amplitude and frequency, we proposed to use TKEO to make the motor unit action potentials more conspicuous while suppressing the noise. The thresholding was applied to the TKEO output rather than directly to the raw EMG signal. The computer simulations together with the real surface EMG processing prove that the proposed surface EMG onset time detection method based on TKEO achieves good performance even in the situations where the SNR of the signal is poor. In addition, the proposed method is characterized with simple implementation. No *a priori* knowledge about the processed surface EMG signal is required.

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