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Teager–Kaiser Operator improves the accuracy of EMG onset detection independent of signal-to-noise ratio

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A temporal analysis of electromyographic (EMG) activity has widely been used for non-invasive study of muscle activation patterns. Such an analysis requires robust methods to accurately detect EMG onset. We examined whether data conditioning, supplemented with Teager–Kaiser Energy Operator (TKEO), would improve accuracy of the EMG burst onset detection. EMG signals from vastus lateralis, collected during maximal voluntary contractions, performed by seventeen subjects (8 males, 9 females, mean age of 46 yrs), were analyzed. The error of onset detection using enhanced signal conditioning was significantly lower than that of onset detection performed on signals conditioned without the TKEO (40 ±99 ms vs. 229 ±356 ms, *t*-test, $p = 0.023$). The Pearson correlations revealed that neither accuracy after enhanced conditioning nor accuracy after standard conditioning was significantly related to signal-to-noise ratio (SNR) ($r = -0.05$, $p = 0.8$ and $r = -0.19$, $p = 0.46$, respectively). It is concluded that conditioning of the EMG signals with TKEO significantly improved the accuracy of the threshold-based onset detection methods, regardless of SNR magnitude.

Key words: *Teager–Kaiser Operator, EMG onset detection, signal conditioning*

1. Introduction

Surface electromyography (EMG) is widely used for the non-invasive study of muscle activation patterns. One popular application of surface EMG is the temporal analysis of muscle activation in terms of burst onset, duration, and offset. For example, the temporal analyses of muscle activation patterns recorded during gait provide insights into the changes in neuromuscular strategies that occur with age [1], and onset measurements are also needed for the determination of electromechanical delay under highly various conditions [2]. However, temporal analysis of surface EMG data requires computational algorithms that allow activation onset to be accurately and robustly determined. A number of algorithms are being used to detect EMG onsets [3], including the error-prone but simple visual inspection and threshold-based methods [4]. Recently, a new method, the nonlinear Teager–Kaiser Energy Operator (TKEO), has been proposed to increase the accuracy of the onset detection by improving the signal-to-noise ratio (SNR) of the EMG signal [5]. However, the method was validated using primarily simulated EMG data. Therefore, the purpose of the present study was to examine whether the TKEO calculation improves onset detection in true EMG signals and to determine whether SNR affects the accuracy of the onset detection.

2. Methods

2.1. Testing protocol

Seventeen subjects volunteered in the study (8 males, 9 females, mean age of 46 years). Surface EMG data

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were recorded from the dominant-leg vastus lateralis (VL) during a maximal voluntary contraction while the subject was seated on a chair. The knee joint was fixed at 70° of flexion. Subjects were asked to contract the knee extensors for 4 seconds by attempting to extend their knee against manual resistance at the ankle.

2.2. Recording of EMG activity

Bipolar, disposable, pre-gelled Ag/AgCl surface electrodes (Noraxon USA, Inc., Scottsdale, AZ) were placed on the belly of the vastus lateralis with 20 mm inter-electrode distance. The exact placement of the

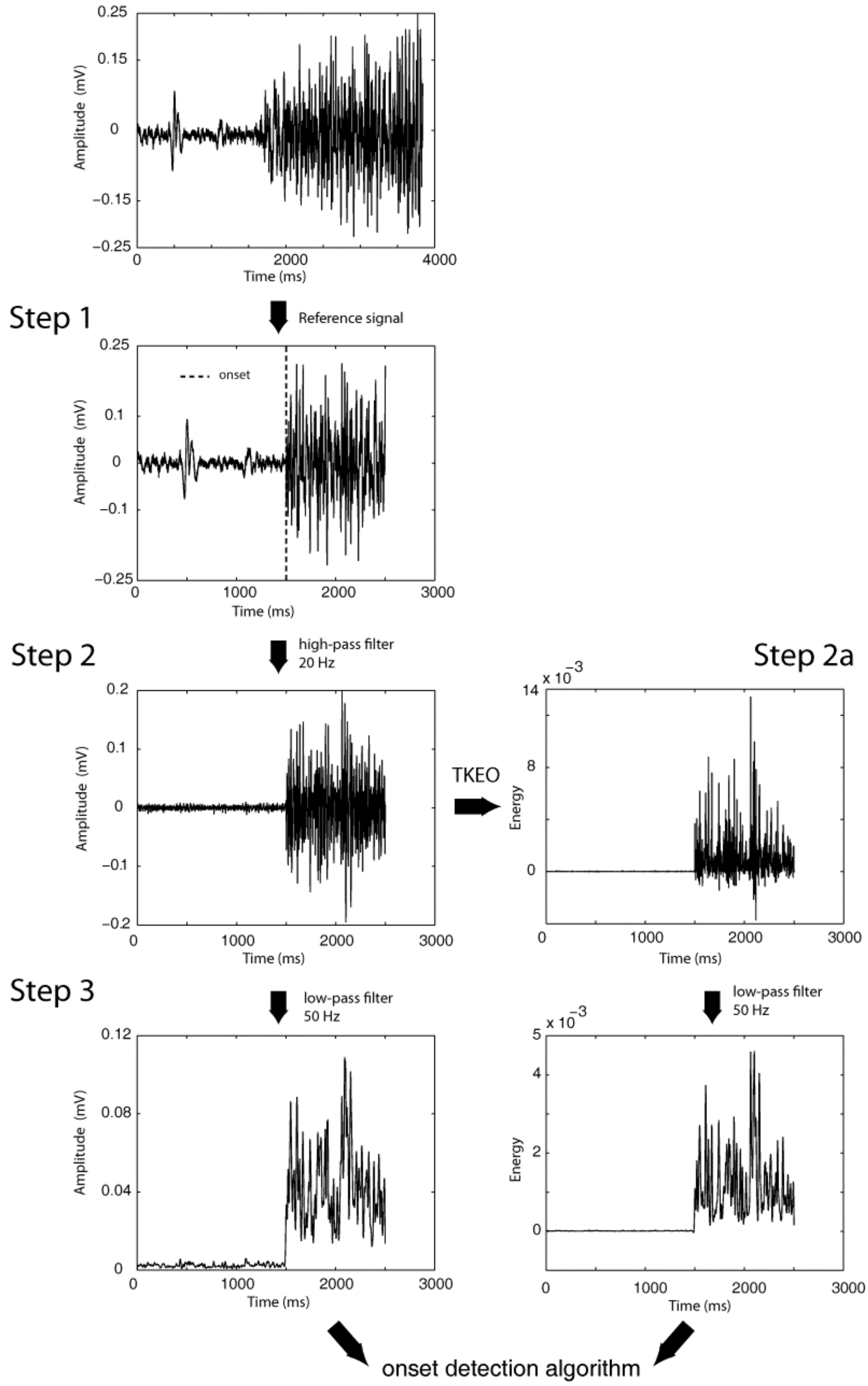

Fig. 1. Analysis and conditioning of EMG signal. A reference signal with the known onset of the burst was constructed from a raw signal (Step 1). In order to remove motion artifacts, the signal was high-pass filtered (Step 2). Additional conditioning (Conditioning 2) by TKEO was used to create the second set of signals (Step 2a). Finally, both sets of signals (from Conditioning 1 and Conditioning 2) were smoothed with a low-pass filter (Step 3) and transferred to the onset detection algorithm

electrodes followed the recommendations of the Surface Electromyography for the Non-Invasive Assessment of Muscles (SENIAM) [6]. The reference electrode was placed on the proximal end of the fibula of the same leg. Signals were band-pass analog filtered at 10–500 Hz and sampled at 1 kHz with a gain of 1000 using TeleMyo 900 telemetric hardware system (Noraxon USA, Inc., Scottsdale, AZ). The recording of the EMG signal started one second before the onset of muscle contraction and provided data for baseline and background activity at rest.

2.3. Signal analysis

We compared two signal conditioning methods: Conditioning 1 and Conditioning 2. Conditioning 1 consisted of three steps (figure 1). After the EMG data were collected, the signal was visually inspected, the pre-contraction part of the baseline as well as the steady portion of the EMG burst were determined. The baseline and the EMG burst were then used to construct a "reference EMG signal" by adjoining the baseline portion and the burst portion with a known onset point of the burst (Step 1). Steps 2 and 3 consisted of conditioning the reference signal, as proposed by HODGES and BUI [4]. The 6th order, high-pass filter at 20 Hz was applied to remove motion artifacts (Step 2) and then the signal was smoothed with the 6th order, zero-phase low-pass filter at 50 Hz (Step 3). Conditioning 2 started after Step 2 by subjecting the adjoined and high-pass filtered signal to TKEO (figure 1, Step 2a). The discrete TKEO Ψ was defined as:

$$\Psi[x(n)] = x^2(n) - x(n+1)x(n-1)\,, \qquad (1)$$

where x is the EMG value and n is the sample number [6].

After data conditioning, the onset of the EMG burst was identified as the time point when the smoothed signal exceeded the threshold of 3 standard deviations of the baseline for more than 25 consecutive samples. Due to very low magnitude of the baseline, the threshold of signal after Conditioning 2 was defined as 15 deviations of the baseline [5]. The signal-to-noise ratio (SNR) of the collected, raw EMG signals was defined as:

$$\mathrm{SNR} = \left(\frac{A_{\mathrm{Signal}}}{A_{\mathrm{Baseline}}}\right)^2, \qquad (2)$$

where A is the amplitude.

All data analysis was performed in MATLAB (The MathWorks Inc., Natick, MA). The difference (error) between the onsets determined after Conditioning 1 relative to the known onset time and the difference between the onsets determined after Conditioning 2 relative to the known onset time were compared with a paired t-test. The Pearson correlation coefficient (r) was calculated to test the relationship between signal quality, defined as SNR, and accuracy of the onset detection. The level of significance was set at $p < 0.05$ in all statistical analyses.

3. Results

The table shows the accuracy of the detected onsets using Conditioning 1 and Conditioning 2, with the addition of signal to noise values. Conditioning 2 resulted in more accurate onset detection than Conditioning 1 (40 ±99 ms vs. 229 ±356 ms, $p = 0.023$). The Pearson correlations revealed that neither accuracy after Conditioning 1 nor after Conditioning 2 was significantly related to SNR ($r = -0.05$, $p = 0.8$ and $r = -0.19$, $p = 0.46$, respectively).

Table. Accuracy of onset detection after Conditioning 1 and Conditioning 2

Subject	Conditioning 1 (ms)	Conditioning 2 (ms)	SNR
1	47	13	42.7
2	4	1	11.9
3	35	8	23.4
4	385	377	19.7
5	44	7	96.9
6	11	7	6.6
7	11	7	4.3
8	445	8	27.4
9	272	5	9.5
10	13	7	8.9
11	1398	9	4.5
12	497	7	10.0
13	6	6	8.1
14	16	8	13.6
15	497	8	18.1
16	6	4	17.9
17	209	206	8.8
mean	229	40	20
sd	356	99	22

SNR – signal to noise ratio.

4. Discussion

The main finding of the present study is that TKEO significantly improved the detection of EMG burst onset, regardless of SNR magnitude. Previous methods

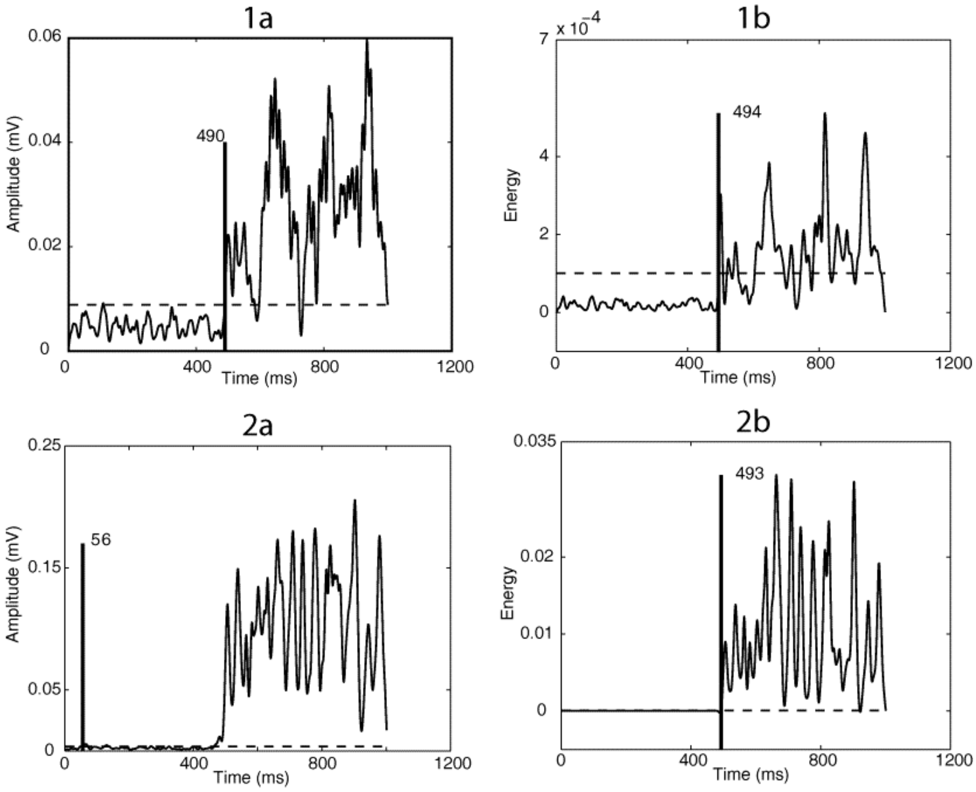

Fig. 2. A typical example of the onset detection using data with low (top row, SNR = 4.3) and high (bottom row, SNR = 27.4) signal quality. The results of onset detection are shown after Conditioning 1 (1a, 2a) and Conditioning 2 (1b, 2b). Horizontal, dashed line represents threshold and solid, vertical line indicates the detected EMG burst. The true EMG burst onset was set at 500 ms in both cases

of EMG onset validation relied primarily on the notion that SNR can bias EMG burst onsets [3], [5]. However, the present study showed that when real EMG signal is used, the SNR is not the most critical factor affecting onset detection. Threshold-based methods are more likely to produce error due to random variations in the baseline (figure 2). These variations are often generated by electrode movement over the skin or excessive movement of the electrode cable, and are usually of lower frequency than the EMG burst. By compressing the energy of the baseline, EMG onset analysis supplemented with the TKEO reduced the error.

In conclusion, the results of this study showed that the conditioning of the EMG signals by TKEO significantly improved the accuracy of threshold-based onset detection methods. We anticipate that the improvements in onset detection can be even greater for EMG data recorded during dynamic activities, because it would increase the random variations of the baseline through electrode and wire vibrations or movements.

Acknowledgements

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