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Teager–Kaiser energy operator signal conditioning improves EMG onset detection

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Abstract Accurate identification of the onset of muscle activity is an important element in the biomechanical analysis of human movement. The purpose of this study was to determine if inclusion of the Teager–Kaiser energy operator (TKEO) in signal conditioning would increase the accuracy of popular electromyography (EMG) onset detection methods. Three methods, visual determination, threshold-based method, and approximated generalized likelihood ratio were used to estimate the onset of EMG burst with and without TKEO conditioning. Reference signals, with known onset times, were constructed from EMG signals collected during isometric contraction of the vastus lateralis ($n = 17$). Additionally, vastus lateralis EMG signals ($n = 255$) recorded during gait were used to evaluate a clinical application of the TKEO conditioning. Inclusion of TKEO in signal conditioning significantly reduced mean detection error of all three methods compared with signal conditioning without TKEO, using artificially generated reference data (13 vs. 98 ms, $p < 0.001$) and also compared with experimental data collected during gait (55 vs. 124 ms, $p < 0.001$). In conclusion, addition of TKEO as a step in conditioning surface EMG signals increases the detection accuracy of EMG burst boundaries.

Keywords Electromyography ·
Teager–Kaiser energy operator · Muscle onset detection ·
Signal processing

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Introduction

Surface electromyography (EMG) is widely used to study biomechanical and neurological aspects of human movement (De Luca 1997). One application of surface EMG analysis to human movement is to determine the temporal characteristics of muscle recruitment that can provide insights into motor control strategies. For example, temporal analysis of muscle recruitment elucidated the mechanism of an age-related increase of muscle co-activation during locomotion (Hortobagyi and DeVita 2000; Hortobagyi et al. 2009; Mian et al. 2006), and revealed unique muscle activation patterns associated with clinical conditions such as stroke (Babyar et al. 2007; Cheng et al. 2004), Parkinson's disease (Chen et al. 2001; Kumru et al. 2004), cerebral palsy (Tedroff et al. 2006, 2008). It also allowed the quantification of electromechanical delay (Conforto et al. 2006; Howatson et al. 2008) under a variety of conditions, an important input variable in musculoskeletal modeling. Temporal analysis of EMG signals used in these and other studies required an accurate identification of onset, offset, and duration of the EMG burst.

Several computerized algorithms are used to determine the boundaries of an EMG burst including threshold-based

(Hodges and Bui 1996) and advanced statistical methods (Lee et al. 2007; Micera et al. 1998; Roetenberg et al. 2003; Staude 2001). High baseline noise and low amplitude of recorded EMG signals can increase the magnitude of the error in detecting the onset of the EMG burst. The accuracy of these methods is normally validated by creating several versions of an artificial signal that contain different signal-to-noise ratios (SNR). However, computerized algorithms can fail to accurately detect burst onset in experimental data, indicating that some of these techniques may not be sensitive enough to improved SNR. In several studies, EMG burst properties were analyzed with visual inspection instead of a computerized algorithm (Clancy et al. 2004; Latash et al. 1995; Tedroff et al. 2008; Vasseljen et al. 2006), suggesting that algorithm validation using artificially generated EMG signals may not be sufficient to test robustness and accuracy of onset detection techniques.

Recently, Teager–Kaiser energy operator (TKEO) was proposed to improve SNR and minimize erroneous EMG onset detection (Li et al. 2007). The non-linear TKEO, introduced by Kaiser (Kaiser 1990; Kaiser 1993), measures instantaneous energy changes of signals composed of a single time-varying frequency. Lately, the application of TKEO was extended to detect abrupt changes in broadband biological signals (i.e., spike detection of neurological signals) (Atit et al. 1999; Mukhopadhyay and Ray 1998; Sherman et al. 1998). One advantage of TKEO output, compared with other onset detection methods, is that the calculated energy is derived from instantaneous amplitude and instantaneous frequency of the signal. Therefore, TKEO may improve our ability to analyze muscle activity as depolarization of the muscle cell membrane during contraction produces rapid fluctuations in signal's amplitude and frequency. TKEO, thus, emphasizes both properties of motor unit action potentials, amplitude and frequency, whereby SNR is improved and onset detection, theoretically, becomes more accurate (Li and Aruin 2005).

Previous studies reported improvement of onset detection accuracy after TKEO compared to other popular methods (Li et al. 2007). Our preliminary data (Solnik et al. 2008), however, suggest that the use of TKEO may be most effective when it is included as a part of signal conditioning of conventional onset detection methods. Our expectation was that any method, including threshold-based and statistical techniques, incorporating TKEO as a step in conditioning of EMG data would increase signal quality, hence the accuracy of onset detection. Therefore, the purpose of the present study was to compare the accuracy of EMG onset detection with and without TKEO conditioning applied to three onset detection algorithms.

Methods

Participants and testing protocols

To broaden our analysis, we assessed TKEO effectiveness in two sets of data containing different subjects and test conditions. The first set included young and middle aged adults performing isometric quadriceps contractions and the second set included older adults walking at three speeds. All participants were healthy and mobile. A geriatrician, based on a physical exam, excluded individuals with orthopedic and neurological abnormalities, past lower extremity surgeries, or other complications that would have interfered with the motor tasks. All participants signed written informed consent according to university policy.

Seventeen healthy participants volunteered for the isometric contractions experiment (8 males, 9 females, age 48 ± 23 years, mass 69 ± 12.3 kg, height 170.8 ± 8.9 cm). Surface EMG activity was recorded from the vastus lateralis of the dominant leg during a 4-s effort that started with a brief period of rest and was followed by a near-maximal voluntary isometric contraction (MVC), creating a distinct onset of the EMG burst. The subject was seated in a chair with the knee joint fixed at 70° of flexion. After a few practice trials at levels perceived to be 50, 75, and 90% of the subjects' MVC, participants performed the test contraction by attempting to extend the knee against manual resistance at the ankle. Additionally, to evaluate TKEO conditioning in a clinical application, we also used experimental data from a previous study (Hortobagyi et al. 2009). Vastus lateralis EMG signals from 17 old adults (10 female and 7 male, age 78 ± 1.33 years, mass 68.1 ± 3.75 kg, height 1.65 ± 0.03 m) were recorded while subjects walked on a 16 m walkway equipped with a force plate. Force plate data were used only to identify heel strike and extract vastus lateralis EMG burst for one gait cycle. Each subject walked five times at three velocities (1.2, 1.5, and 1.8 m/s), producing 255 EMG signals.

EMG data processing

Before data collection, patients' skin over the vastus lateralis was shaved, rubbed with abrasive skin prep, and cleaned with alcohol to improve the electrode–skin contact and minimize skin impedance. Bipolar, disposable, pre-gelled Ag/AgCl surface electrodes with 20 mm distance between electrode centers were placed on the belly of the vastus lateralis. The exact placement of the electrodes followed the recommendations by Surface Electromyography for the Non-Invasive Assessment of Muscles (SENIAM 2008). The reference electrode was placed over the proximal end of the fibula of the same leg. Signals were analog filtered at 10–500 Hz (with first order filter at lower

cutoff frequency and sixth order filter at higher cutoff frequency), amplified 2000× and sampled at 1 kHz using a TeleMyo 900 telemetric hardware system (Noraxon USA, Inc., Scottsdale, AZ, baseline noise < 1 uV RMS, Common Mode Rejection min. 85 dB through 10–500 Hz operating range).

EMG signals were recorded as each of 17 subjects performed one near-maximal voluntary isometric contractions, starting with 1 s of rest interval to establish baseline. The raw signals were visually inspected and the pre-contraction portions of the baseline as well as the steady portions of the EMG burst were identified. The baseline and the EMG burst from each recorded signal was then used to construct 17 reference EMG signals by adjoining the baseline and the burst portion at a known onset time t_0 (see Fig. 1). Length of the EMG baseline, EMG burst, and position of the true onset t_0 varied for all reference signals. The known, true onset times, t_0, were used as a reference to quantify the accuracy of estimated onset times t_1 identified by three onset detection methods.

The precise EMG onset was not known in the experimental signals recorded from old adults during gait. In these trials, we determined the onset time, t_0, by visual detection because computerized techniques should detect EMG onset close to the onset time selected by individuals with EMG expertise (Staude et al. 2001).

SNR of the reference signals was calculated to test the influence of signal quality on onset detection accuracy. The SNR of the signals was defined as:

$$SNR = \left(\frac{A_{signal+baseline}}{A_{baseline}} \right)^2$$

where A is RMS amplitude. All data analysis was performed in MATLAB (MathWorks, Natick, MA).

Data conditioning and onset detection methods

We defined the EMG onset as a first recorded activity of motor unit action potentials. We selected three popular onset detection methods: visual detection (VD) (Vasseljen et al. 2006), threshold-based method (TH) (Hodges and Bui 1996), and approximated generalized likelihood ratio (AGLR) (Micera et al. 1998; Staude et al. 2001; Staude and Wolf 1999; Staude 2001) to test the influence of TKEO calculations on the robustness and accuracy of the detection algorithms. Usually, the initial step in computerized onset detection method is conditioning of data. This step serves to condition EMG signals to minimize background noise, reduce movement artifacts and facilitate EMG onset detection. Two types of signal conditioning (with and without TKEO) were applied to the reference signals.
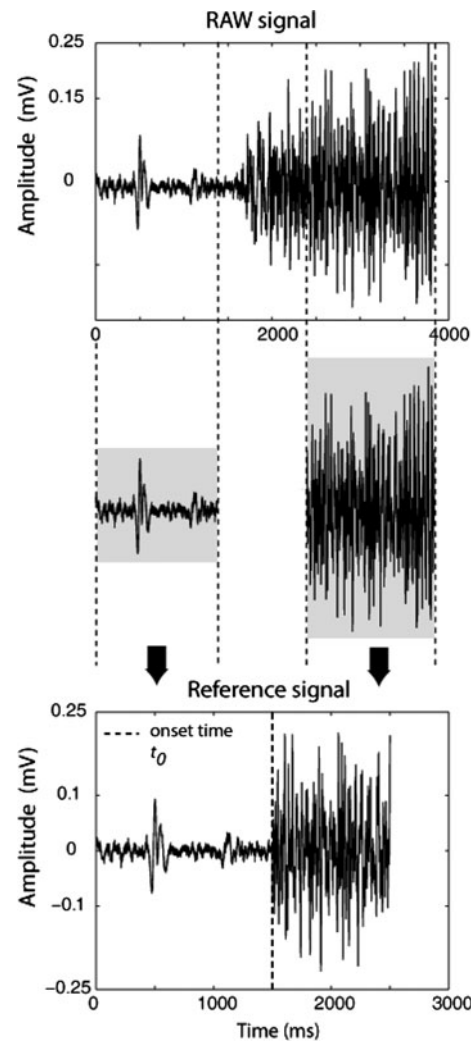

Fig. 1 Construction of the reference signal. From the raw signal (*top panel*), a portion of the baseline and a portion of the EMG burst was selected (*middle panel*) and re-joined at the known onset time t_0 (*bottom panel*). To demonstrate the importance of signal conditioning, the baseline in this example contains fluctuations in the signal amplitude. These fluctuations were not associated with the muscle contraction

Conditioning without TKEO, included traditional data processing that was specific and adequate for each detection algorithm. For VD, standard conditioning consisted of band-pass filtering of the EMG signals at 30–300 Hz (6th order Butterworth filter), which facilitates manual onset determination (Dick et al. 1986; Latash et al. 1995). For TH, conditioning included band-pass filtering at 30–300 Hz (6th order Butterworth filter), and rectification and low-pass filtering at 50 Hz (2nd order Butterworth, zero-phase forward and reverse filter). Such conditioning reduces high frequency noise and provides smoothed envelope of the signal (Hodges and Bui 1996). Conditioning for AGLR included band-pass filtering of the signal at

30–300 Hz (6th order Butterworth filter) to remove motion artifacts, enhance spectral resolution, and improve application of statistical methods (Staude et al. 2001). Reference signals after conditioning without TKEO formed one of two sets of data.

A second set of data was created by processing the reference signals using conditioning that incorporated TKEO. This process also differed from previous conditioning protocols that used TKEO on its own (Kaiser 1990, 1993; Maragos et al. 1993). The discrete TKEO Ψ was defined as:

$$\psi[x(n)] = x^2(n) - x(n+1)x(n-1)$$

where x is the EMG value and n is the sample number. TKEO was always applied after the signal was band-pass filtered. After applying TKEO, the signal conditioning followed the same steps as the conditioning procedure without TKEO. Figure 2 shows two types of signal conditioning for TH method. Two sets of data consisted of 17 reference signals conditioned with and without TKEO. Both sets of signals were later fed into three onset detection methods.

Visual detection

Two individuals with expertise in EMG data analysis evaluated two types of reference signals, one with and one without TKEO conditioning. An interactive graphical user interface was created in Matlab that displayed individual EMG traces on the computer monitor. Experts determined onset times, t_1, by moving the mouse cursor (with 1 ms resolution) and marked the earliest rise of the muscle electrical activity above the baseline (Brown and Frank 1987; Horak et al. 1984). All signals were plotted separately in random order and without time scale to remove any bias. Estimated onset times detected by experts for each trial were averaged and stored for further accuracy evaluation.

Threshold-based method

Mean μ and standard deviation σ of the baseline for each reference signal after both types of conditioning were computed. The threshold T was determined as

$$T = \mu + h\sigma$$

where h is a preset variable, defining level of the threshold.

The estimated onset time t_1 was identified as the first point when the smoothed signal exceeded the threshold T for more than 25 consecutive samples. For conditioning without TKEO, h was set to 3 (Tedroff et al. 2006). All parameters of the TH algorithm were set to maximize the t_1 accuracy, and were based on recommendations by Hodges and Bui (1996). After TKEO processing, threshold was set at $h = 15$ due to very low magnitude of the baseline.

Fig. 2 Conditioning of the reference signal with (*right panel*) and without (*left panel*) Teager–Kaiser energy operator (TKEO) to detect burst onset using the threshold-based method. Conditioning without TKEO included band-pass filtering at 30–300 Hz (6th order Butterworth filter), and rectification and low-pass filtering at 50 Hz (2nd order Butterworth, zero-phase forward and reverse filter). Conditioning with TKEO consisted of the same steps with an additional TKEO calculation after bandpass filtering. After conditioning with and without TKEO, the two signals were subjected to the onset detection algorithm

Previous authors' (Li et al. 2007) tested threshold levels ranged from 3 to 23 times the standard deviation for signals after TKEO conditioning. They have found that threshold values ranging from 6 to 8 introduced the minimal detection latency. However, for our set of EMG data, threshold level $h = 15$ was found the most robust and introduced the smallest detection errors. All other parameters were the same for both data sets.

Approximated generalized likelihood ratio

AGLR (Staude et al. 2001; Staude and Wolf 1999; Staude 2001) is based on statistical testing of the null hypotheses H_0 and the alternate hypothesis H_1 describing the statistical properties of series of EMG samples x_1, x_2,…,x_k. H_0 indicates no change within the analyzed portion of the EMG signal, and H_1 indicates that change has occurred in the tested portion of the signal. Two hypotheses were tested using a log-likelihood ratio test $g(n)$:

$$g(n) = \ln\left(\prod_{n=1}^{k} \frac{p_1(x_n)|H_1}{p_0(x_n)|H_0}\right) \begin{smallmatrix} > \\ < \end{smallmatrix} h$$

where ln represents natural logarithm, $x(n)$ represents series of EMG samples, p_1 and p_0 represent probability density functions associated with hypotheses H_1 and H_0, respectively. When log-likelihood $g(n)$ becomes higher than preset threshold h, then hypothesis H_1 is more probable and signal change is detected. AGLR algorithm performs hypothesis testing in a sliding window of size L, over the series of EMG data. Log-likelihood ratio is calculated from L samples for every window step. After a signal change is detected, the estimated onset time t_1 is found by maximizing likelihood estimators for each sample from last window position. For the AGLR algorithm, the window size was set at $L = 25$ ms, and detection threshold was set $h = 14$ (Roetenberg et al. 2003). AGLR parameters were the same for data conditioned with and without TKEO.

Accuracy and statistical analysis

For reference signals, estimated onset times, t_1, from all detection methods were compared with the true onset times, t_0. In order to quantify accuracy of the detection
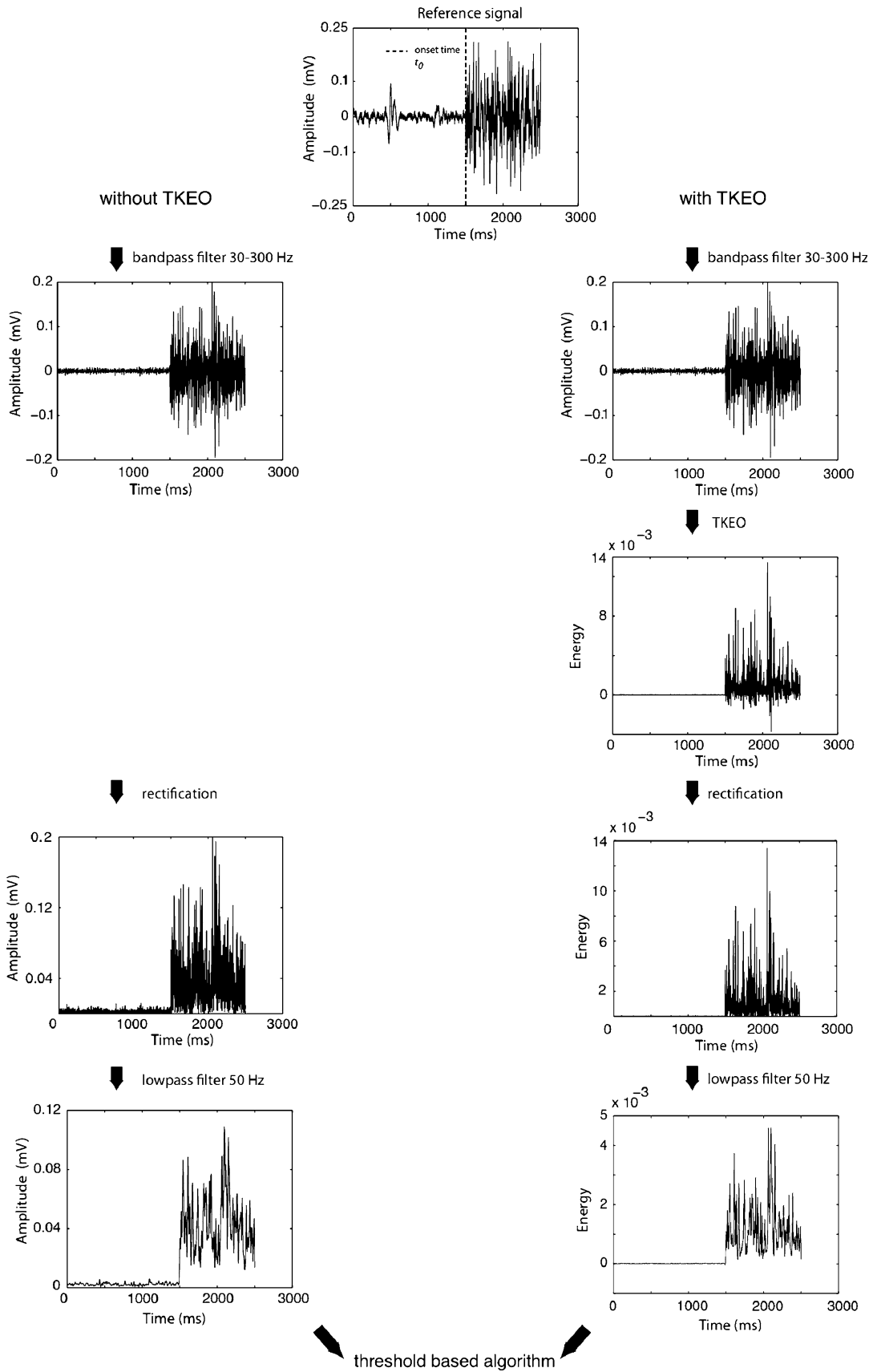
methods before and after TKEO calculations, detection error $\varepsilon = |(t_0 - t_1)|$ was calculated for both conditionings. We used the absolute difference between true and estimated onset times to obtain the detection error magnitude (in milliseconds) and avoid cancelation of negative and positive values in the statistical analysis.

Detection errors were compared with an *onset method* (3) by *conditioning* (2) ANOVA with repeated measures on both factors. In order to fulfill assumptions of homogeneity of variance and normality, detection errors were log-transformed before ANOVA was calculated (Ferguson 1976). In addition, Pearson correlation was used to test the relationship between signal quality, defined as SNR, and accuracy of the onset detection methods, identified by the detection error, ε. The level of significance was set at $p < 0.05$ in all statistical analyses.

For experimental signals recorded during gait, visually detected t_0 onset times on raw signals without TKEO conditioning were used to evaluate accuracy of two computerized detection methods with and without TKEO conditioning. Detection errors were compared with a *computerized onset method* (2) by *conditioning* (2) ANOVA with repeated measures on both factors. Paired Student t test was used to assess the effect of TKEO conditioning on SNR. A post-hoc test with Bonferroni adjustment for multiple comparisons was used for pairwise comparisons.

Results

Experiment using isometric contractions

The accuracy of onset detection improved in all methods when TKEO was included in the signal *conditioning* (detection error decreased from 98 to 13 ms, $F = 31.79$, $p < 0.001$). There was a significant *onset method* main effect among VD, TH and AGLR (14, 123.5, and 28 ms, respectively, $F = 16.49$, $p < 0.001$).

The *conditioning* type by *detection method* interaction was not significant ($F = 0.932$, $p = 0.404$). The mean detection errors for all methods with and without TKEO signal conditioning are shown in Table 1. Post-hoc tests revealed that AGLR detection errors were significantly lower than TH and VD ($p < 0.001$ and $p < 0.01$, respectively) and TH detection errors were not significantly different from VD ($p > 0.05$). SNR was not related to accuracy of any computerized onset detection methods ($r = -0.06$, $p = 0.81$ for AGLR and $r = -0.171$, $p = 0.51$ for TH).

Experiment using gait data

Signal conditioning with TKEO improved SNR from 12.3 to 357.7 ($p < 0.001$). The detection error decreased significantly after TKEO conditioning (124 vs. 55 ms, $F = 132.8$, $p < 0.001$). Method main effect was significant between detection methods (101 ms for TH vs. 78 ms AGLR, $F = 27.5$, $p < 0.001$). The *conditioning* type by *detection method* interaction was significant ($F = 113.7$, $p < 0.001$). The mean detection error with and without TKEO was 45 ± 80 versus 157 ± 118 ms for TH and 66 ± 64 versus 90 ± 105 ms for AGLR (see Fig. 3). Post-hoc tests revealed that AGLR detection errors were significantly lower than TH ($p < 0.001$).

Discussion

Our results confirmed that signal conditioning with TKEO significantly improved accuracy of three popular onset detection methods (VD, TH, and AGLR) and in two test conditions, isometric contractions and level walking. An accurate identification of EMG burst boundaries is an important element in the biomechanical analysis of human movement. Delayed or premature detection of the muscle activation can lead to potentially misleading conclusions on motor control strategies. Erroneous EMG burst onset detection can have a major impact on age- and disease-related differences in muscle recruitment patterns and co-activation during movements such as gait, postural tasks, and rapid limb movements (Hortobagyi and DeVita 2000; Howatson et al. 2008; Latash et al. 1995).

We examined the possibility that signal conditioning with TKEO improves the precision of onset detection using VD, TH, and AGLR. As suggested by Li et al. (2007), in this study we defined EMG onset when the first motor unit was firing. TKEO may universally improve EMG burst onset detection because TKEO incorporates both amplitude and frequency components of motor unit activity. Our results showed that TKEO amplifies energy of action potential spikes and therefore helps to differentiate between relaxed and contracted state of the muscle, and improves accuracy of all three onset detection methods.

Several studies have used VD to determine the onset of EMG burst (Latash et al. 1995; Tedroff et al. 2008; Vasseljen et al. 2006). Benefits of this technique include low computational demand and an ability to exclude obviously erroneous burst onsets (i.e., due to movement artifacts). Drawbacks of this method include operator errors that can bias data and the excessive time needed to process a large number of trials. TKEO improved VD onset detection because it suppressed noise amplitude during steady state portion of the EMG signal and amplified the EMG burst. Together, these steps helped two experts determine the start of the EMG burst more accurately.

TH is an objective onset detector that relies on computer analysis and does not depend on the experience or skills of

Table 1 Accuracy of onset detection of reference signals processed with two types of conditioning

Reference Signal	VD		TH		AGLR		SNR
	wo/TKEO (ms)	w/TKEO (ms)	wo/TKEO (ms)	w/TKEO (ms)	wo/TKEO (ms)	w/TKEO (ms)	
1	−41	−5	47	13	−5	6	42.7
2	−17	1	4	1	7	−1	11.9
3	−35	−4	35	8	2	2	23.4
4	−17	−3	385	377	−334	−3	19.7
5	−32	−3	44	7	−24	−3	96.9
6	−23	−10	11	7	2	1	6.6
7	−13	−12	11	7	2	1	4.3
8	−34	−6	445	8	−29	−1	27.4
9	−24	−3	272	5	−470	−3	9.5
10	−16	−10	13	7	−1	5	8.9
11	−8	−8	1,398	9	1	1	4.5
12	−17	−10	497	7	−21	−3	10
13	−6	−1	6	6	2	3	8.1
14	−20	−12	16	8	−8	2	13.6
15	−14	−12	497	8	1	2	18.1
16	−15	−6	8	6	3	3	17.9
17	−20	−11	16	9	−4	1	8.8
Mean (μ)	21	7	218	29	54	2	19.5
SD (σ)	10	4	359	90	133	1	22.2

For explanatory purpose, data shown in the table represent a signed difference $(t_0 - t_1)$ in milliseconds between known onset time and estimated time detected by three methods

Mean (μ) and SD (σ) represent average and standard deviation of detection errors, $\varepsilon = |(t_0 - t_1)|$

VD visual detection, *TH* threshold based method, and *AGLR* approximated generalized likelihood ratio. *w/TKEO* and *wo/TKEO* conditioning with and without TKEO, respectively, *SNR* signal-to-noise ratio (unitless)
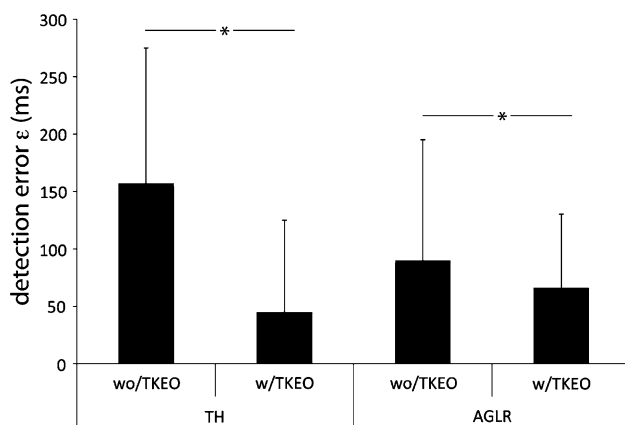

Fig. 3 Mean (±SD) detection errors, ε, with (w/TKEO) and without (wo/TKEO) TKEO conditioning of experimental gait EMG signals ($n = 255$) for threshold based (TH) and approximated generalized likelihood ratio (AGLR) onset detection methods. *$p < 0.001$

the examiner. TH methods are not computationally demanding and are easy to implement during EMG signal analysis. However, several studies reported more inaccurate results when EMG signals with low SNR were used (Lee et al. 2007; Micera et al. 1998; Staude et al. 2001).

Our results showed that signal conditioning with TKEO significantly improves the accuracy of the TH method. Reduced baseline amplitude after TKEO, heightened selectiveness of the threshold, calculated from standard deviation of the steady state portion of the EMG signals led to increased consistency of estimated onset times, t_1. Similar results have been previously reported by Li et al. (2007) on artificial EMG signals. Also, Lauer and Prosser (2009) showed that threshold method after TKEO detected EMG onsets closer to those identified by visual detection on EMG signals recorded from children with cerebral palsy. Our preliminary data (Solnik et al. 2008) suggest that the use of TKEO is effective when it is included as a part of signal conditioning of threshold-based methods. This study confirmed the previous findings and extended them by providing a comprehensive evaluation of the TKEO effect on the popular VD, TH, and AGLR methods. We also evaluated their robustness and accuracy on experimental EMG data from gait and a set of artificial EMG data.

AGLR is a sophisticated method and provides superior results compared to TH methods (Lee et al. 2007; Roetenberg et al. 2003; Staude 2001). AGLR is more

Fig. 4 Reference signals 7 and 8 conditioned with (*right panel*) and without (*left panel*) Teager–Kaiser energy operator (TKEO). Signal-to-noise ratio (SNR) of Reference signal 7 was lower than SNR of Reference signal 8 (4.3 vs. 27.4, respectively). Therefore, onset threshold (*horizontal dashed line*) is lower for Reference signal 8 than onset threshold for Reference signal 7. Low threshold is more sensitive to random increases of signal amplitude that are not associated with a muscle contraction. As a result, estimated onset time t_1 was prematurely detected in Reference signal 8 when conditioned without TKEO. Conditioning with TKEO improved the estimated onset time t_1
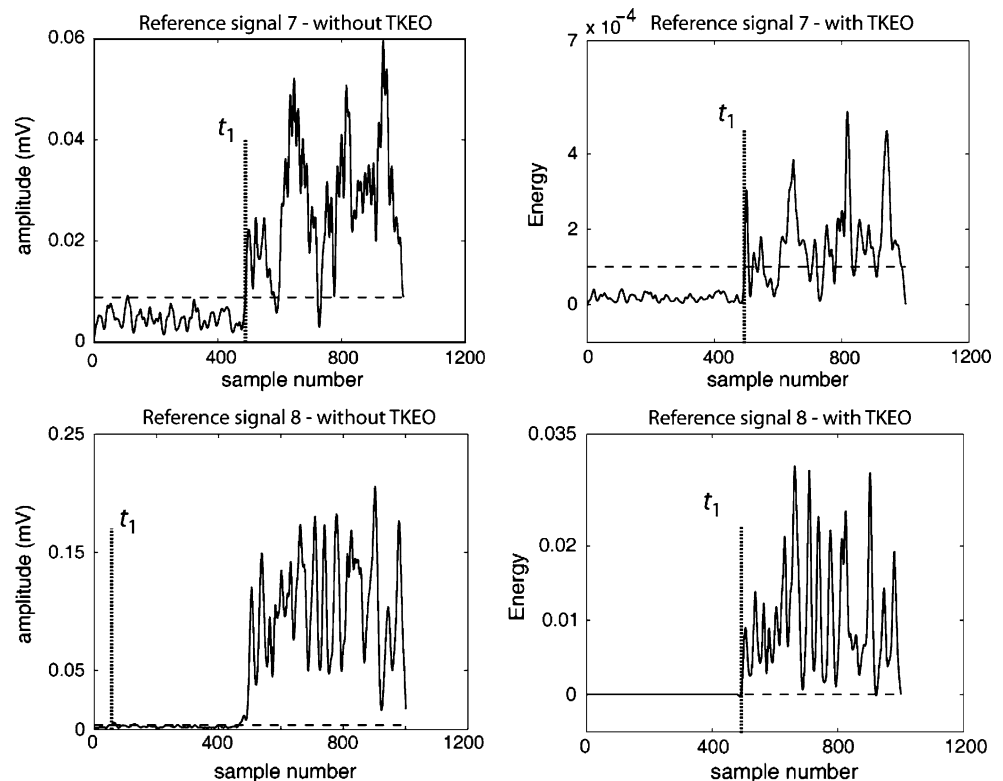
computationally demanding than TH, and involves statistical testing using generalized likelihood ratio. TKEO suppresses noise during the steady state portion of the signal, which resulted in narrowing of baseline probability distribution and widening of the EMG burst probability distribution. This process changed statistical properties of the EMG signals and improved AGLR detection, which uses probability density functions to test two hypotheses associated with active and inactive part of the EMG.

In several clinical conditions, including movement disorders, preparatory muscle contractions that are not germane to the analysis often precede the target EMG bursts. TKEO processes EMG bursts without discriminating between non-relevant preparatory and the target, main EMG burst. EMG bursts that are not relevant to the research question or a clinical condition can be excluded from the onset detector's output in post processing. For example Merlo et al. (2003) proposed the use of double threshold method coupled with specific postprocessor settings to merge activity bursts or to exclude bursts as noise-related spikes. Bonato et al. (1998) used a post processor to reject erroneous onsets by defining particular detection criteria based on a muscle's functions in gait. Indeed, the difficulty in identifying relevant periods of muscle activity can complicate the use of any onset detection methods in clinical conditions.

During clinical recordings of the EMG signals, it can be often difficult to identify obvious baseline noise section,

when muscles are not active. In our study, we tested the influence of TKEO on computerized techniques that required baseline noise identification. TH requires information about the background activity to create the threshold and AGLR uses information from the baseline and needs baseline noise to create probability density function of signal samples during muscle inactivity for statistical comparison with EMG burst. TKEO, however, tracks instantaneous energy changes of the signal and does not require any assumptions about pre-contraction part of the EMG signal or the baseline noise. Therefore, TKEO conditioning can be coupled with other detection methods that find onset without any initial assumptions about background activity, i.e. the basic randomization method (Thexton 1996).

Previous studies validated detection algorithms by changing SNR of artificial signals (Lee et al. 2007; Li et al. 2007; Staude et al. 2001). Our results, however, show that SNR is not the only factor that affects onset detection when experimental EMG signals are used. Computerized algorithms are more likely to fail due to random variations in the baseline, most often generated by electrode or electrode cable movement over the skin. Results show that TH is more sensitive than AGLR to these random increases of signal amplitude that are not associated with a muscle contraction, and therefore generates more false onset detections (see Fig. 4). To increase accuracy after conditioning without TKEO, one would need to visually inspect

onset detection results and fine-tune parameters of the algorithm when necessary (i.e., selectively increase threshold value). Tedroff et al. (2006) reported that to limit detection errors produced by TH method, two examiners were involved in reviewing EMG records with estimated onsets. Since the result of TKEO is proportional to the product of amplitude and frequency of the signal, and random variations of the baseline usually have lower frequency than the EMG signal, conditioning with TKEO flattens baseline during the steady state. Therefore, signal conditioning with TKEO reduces false onset detection, increases robustness of computerized methods and makes data analysis less time-consuming.

One limitation of the present study is the way we created reference signals. Reference signals were constructed from a portion of the baseline and a steady portion of the muscle contraction. As a result, the amplitude of the EMG signal rapidly changed, and represented an extremely fast ramping of muscle contraction. As errors in onset detection occurred early relative to the actual onset, a lack of gradual increase in signal amplitude could limit errors associated with later onset detection. For this reason, we also performed an analysis on experimental data. EMG signals collected during gait included variety of physiological transition rates from baseline to EMG burst instead of an abrupt change in the EMG activity. The results were similar in the artificially constructed and experimental data and confirmed our expectation that TKEO increases signal quality, therefore the accuracy of onset detection.

Another possible limitation is that we did not condition EMG signals with a whitening filter. Several studies that used artificial EMG signals (Lee et al. 2007; Staude et al. 2001; Staude and Wolf 1999; Staude 2001) proposed using an adaptive whitening filter as part of the data conditioning with AGLR. We tested a few trials with signal whitening and did not observe significant improvements in accuracy after such filtering. This observation agreed with the results obtained by Roetenberg et al. (2003) who analyzed EMG signals recorded during gait, and considered signal whitening not worth the computational effort. In contrast, TKEO calculations can be easily implemented into the data conditioning process without a significant increase in computational demand.

In conclusion, TKEO improved the accuracy of EMG burst onset detection in all three methods. TKEO improved robustness and selectivity of these popular onset detection methods without increasing complexity of the onset detection algorithms. We suggest that TKEO should be incorporated in standard EMG onset detection algorithms.

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