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Onset detection in surface electromyographic signals across isometric explosive and ramped contractions: a comparison of computer-based methods

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Abstract

Objective. Accurate identification of surface electromyography (EMG) muscle onset is vital when examining short temporal parameters such as electromechanical delay. The visual method is considered the 'gold standard' in onset detection. Automatic detection methods are commonly employed to increase objectivity and reduce analysis time, but it is unclear if they are sensitive enough to accurately detect EMG onset when relating them to short-duration motor events. *Approach*. This study aimed to determine: (1) if automatic detection methods could be used interchangeably with visual methods in detecting EMG onsets (2) if the Teager–Kaiser energy operator (TKEO) as a conditioning step would improve the accuracy of popular EMG onset detection methods. The accuracy of three automatic onset detection methods: approximated generalized likelihood ratio (AGLR), TKEO, and threshold-based method were examined against the visual method. EMG signals from fast, explosive, and slow, ramped isometric plantarflexor contractions were evaluated using each technique. *Main results*. For fast, explosive contractions, the TKEO was the best-performing automatic detection method, with a low bias level (4.7 ± 5.6 ms) and excellent intraclass correlation coefficient (ICC) of 0.993, however with wide limits of agreement (LoA) (-6.2 to $+15.7$ ms). For slow, ramped contractions, the AGLR with TKEO conditioning was the best-performing automatic detection method with the smallest bias (11.3 ± 32.9 ms) and excellent ICC (0.983) but produced wide LoA (-53.2 to $+75.8$ ms). For visual detection, the inclusion of TKEO conditioning improved inter-rater and intra-rater reliability across contraction types compared with visual detection without TKEO conditioning. *Significance*. In conclusion, the examined automatic detection methods are not sensitive enough to be applied when relating EMG onset to a motor event of short duration. To attain the accuracy needed, visual detection is recommended. The inclusion of TKEO as a conditioning step before visual detection of EMG onsets is recommended to improve visual detection reliability.

Introduction

Surface electromyography (EMG) is a widely used measurement technique for determining muscle activity in biomechanics, biomedical, and areas of sports sciences (De Luca 1997). Surface EMG is primarily employed to examine neurological and biomechanical aspects of human movement (Hermens *et al* 2000, Raez *et al* 2006, Massó *et al* 2010, Tillin *et al* 2010, Hannah *et al* 2012, Ahmadian *et al* 2013, Chowdhury *et al* 2013). An important application of EMG is the precise detection of temporal characteristics of muscle recruitment, such as muscle activity onset and offset times. Temporal characteristics are a prerequisite for studies of motor control and performance. Due to the stochastic characteristics of the EMG signal, onset detection can be challenging, especially when the signal-to-noise ratios are low. Temporal analysis of surface EMG data has been widely employed to quantify electromechanical delay (EMD), which is the delay between muscle activation and force production (Cavanagh and Komi 1979). Many studies have used EMD as a determinant of musculoskeletal performance across a variety of tasks and muscles. Accurate identification of EMG onset is vital when examining temporal parameters such as EMD, where the delay period between EMG onset and force may be as low as 10 ms for voluntary contractions (Tillin *et al* 2010). EMG onset is one of the most commonly studied parameters in surface EMG analysis; however, methods of detection vary across the literature. The importance of accurate onset detection is contextualized in limb movement studies when comparing muscle activation patterns associated with clinical conditions (e.g. Parkinson's disease, cerebral palsy) with normal function, and how this affects movement outcomes (Chen *et al* 2001, Kumru *et al* 2004). The large variability of the EMG signal across different muscles, populations, and movement tasks makes EMG onset identification quite difficult (Robichaud *et al* 2009, Yang *et al* 2017). A detection method with high validity and reliability would enable comparisons between muscles, participants, and experimental conditions across research studies.

Since EMG signals are prone to sources of noise, precise identification of onset is difficult. Manual visual identification is commonly considered the 'gold standard' method for detecting EMG onset (Van Boxtel *et al* 1993, Hodges and Bui 1996, Staude 2001, Allison 2003). This method involves a skilled experimenter examining the EMG trace and visually determining when the onset has occurred using a preset criterion (e.g. earliest detectable rise, last peak/trough before the signal deflects from baseline noise). Visual onset identification is considered more sensitive and accurate in detecting EMG onsets as it is not as influenced by signal-to-noise ratio or movement artefacts, whereas onset detections can be skewed using automated methods (Hodges and Bui 1996, Allison 2003). However, visual detection is time-consuming and involves a risk of subjective bias. Furthermore, the accuracy of visual detection is based on the experience of the assessor and includes variability from human error and error between researchers. This variability is prominent under conditions where the signal-to-noise ratio is very low (Winter 1984).

Automatic computer-based detection methods are commonly employed in detecting EMG onset in an attempt to increase the objectivity, reduce experimenter bias, and optimize analysis time. Several automatic detection methods have been employed, including the threshold-based method (TBM) (Hodges and Bui 1996) and advanced statistical methods (Staude 2001, Staude *et al* 2001, Lee *et al* 2007) and more recently the Teager–Kaiser energy operator (TKEO). The TBM involves deriving a threshold from muscle baseline signal amplitude characteristics (usually the mean and a multiple of the standard deviation) and determining the onset of the EMG burst when the trace exceeds this threshold. TBM's of EMG onset detection are robust when the signal traces have a high signal-to-noise ratio coupled with fast rates of amplitude increases (Hodges and Bui 1996, Allison 2003). However, as these algorithms utilize baseline amplitude characteristics, the subsequent threshold value is sensitive to changes in the baseline amplitude. A low level of baseline amplitude reduces the detection threshold and can result in early-onset detection, while high baseline amplitude has the opposite effect and may result in the late detection of the true onset (Hodges and Bui 1996, Allison 2003). The outcome of such threshold errors is most notably the systematic shortening or lengthening of derived EMD. There is little consensus about the criteria and parameters (e.g. processing methods, the magnitude of deviation from the baseline to indicate the threshold value, number of subsequent samples the EMG trace must exceed the threshold) for EMG onset detection using TBM. Previous research evaluating variations of the parameters and their influence on onset detection of a postural task highlighted that several parameter combinations could accurately approximate the onset times (Hodges and Bui 1996). Another automatic detection method utilized in EMG onset detection is the approximated generalized likelihood ratio (AGLR). From a statistical standpoint, EMG onset detection can be considered a binary testing problem between the null hypothesis H_0 indicating no statistical change within the analyzed portion of the EMG signal and H_1 signaling a statistical change in the analyzed segment of the signal. AGLR is based on statistical testing of the null hypotheses (H_0) and the alternate hypothesis (H_1) and outlines the statistical properties of an EMG series of samples. AGLR has demonstrated improvements in the accuracy of EMG onset detection compared to the TBM (Staude 2001, Roetenberg *et al* 2003, Lee *et al* 2007, Solnik *et al* 2010). Despite these improvements, AGLR and TBM both lack the desired accuracy to be used interchangeably with visual detection. AGLR is similarly reliant on baseline signal information in the detection of EMG onset. Additionally, the rate of amplitude increase can significantly influence the accuracy of the automatic detection methods, particularly for TBM. During slow, ramped contractions, the amplitude increase is more gradual than during fast, explosive contractions, which can result in delayed onset detection (Horak *et al* 1984, DiFabio 1987). Thus, the accuracy of onset detection may be reduced when automatic detection methods are used to detect EMG onset across contraction types with varying rates of amplitude increase (e.g. fast, explosive contraction versus slow, ramped contraction).

Recently, the TKEO has been proposed to reduce erroneous EMG onset (Li *et al* 2007). TKEO measures instantaneous energy changes in signals composed of a single-time varying frequency. During muscle contraction, when a motor unit action potential fires, it is accompanied by an instantaneous increase in signal frequency and amplitude. TKEO accentuates the frequency and amplitude properties of motor unit action potentials by making action potential spikes sharper and narrower (Li and Aruin 2005). As the frequency of muscle activity is higher than background noise activity, the TKEO output of muscle activity is more pronounced versus the background noise. The suppression of baseline noise and accentuation of muscle activity reduces erroneous onsets attributed to baseline variability observed in other automatic detection methods (i.e. TBM). By applying the TKEO as a method of EMG onset detection, previous studies have reported improvements in detection accuracy (Li *et al* 2007). Recognizing that the TKEO can improve EMG signal-to-noise ratio, previous research demonstrated that TKEO is most effective when used as a step in signal conditioning. EMG signal conditioning using TKEO showed marked improvements in the accuracy of visual, TBM, and AGLR compared to conditioning methods without TKEO (Solnik *et al* 2010). TKEO has demonstrated improvements in onset detection accuracy most notably on the AGLR method on EMG signals reconstructed from isometric contractions in able-bodied adults (Solnik *et al* 2010). Interestingly, the accuracy of visual detection compared to the true onset times also improved following TKEO conditioning. It is unclear whether this accuracy remains across experimental EMG data of varying signal-to-noise ratio and varying rate of amplitude increase (i.e. fast, explosive and slow, ramped).

In studies of motor control and performance, the precise determination of motor events such as muscle contraction onset is vital. Motor events, such as EMD, produce values as low as 10 ms (Tillin *et al* 2010). Thus, it is reasonable to propose that detection biases not exceed 2–3 ms in order to validate an automatic detection method. While research has identified automatic detection methods that can detect true onset within this bias range for constructed EMG signal (Solnik *et al* 2010), this has yet to be demonstrated for experimental data. EMD measures differ across studies, with various contraction types (i.e. fast and explosive, ramped and maximal, and involuntary) used to measure this delay period. The selection of the most accurate method for onset detection across different EMD measures is a prerequisite for a valid study outcome. The accuracy of any EMG onset detection algorithm is largely dependent on the amplitude increase of the EMG signal. This varies between muscle contraction types. Fast, explosive contractions can be more accurately determined due to abrupt amplitude increases than slow, ramped contractions with a slower amplitude increase (Van Boxtel *et al* 1993). Previous studies have examined the accuracy of various automatic detection methods across contraction types (explosive and ramped), with the best-performing method producing EMG onsets that matched visual within 10 ms in more than 80% of trials (Van Boxtel *et al* 1993). When examining motor control parameters such as EMD, this onset bias is too large. The TKEO measures instantaneous energy changes in the signal and emphasizes action potential spikes, but has not previously been examined across contraction types. The use of the TKEO as a conditioning step or as a detection method may improve detection accuracy when comparing EMG onsets across contraction types where the amplitude increase in the EMG trace varies (i.e. fast, explosive versus slow, ramped).

The current research aims to examine if automatic detection methods, namely TKEO, AGLR, and TBM, could be used interchangeably with visual detection of EMG onsets across experimental isometric contractions. Initial evidence suggests TKEO as a conditioning step improves EMG onset detection accuracy across visual and automatic detection methods (Solnik *et al* 2010). This study also compares the accuracy of all detection methods with and without TKEO as a conditioning step. For application in research involving short delay periods (i.e. EMD), automatic onset detection bias must not exceed 2–3 ms when compared with visual. Determining an automatic onset detection method that is consistently reliable for EMG onset detection across muscle contraction tasks of varying amplitude increase may enable more accurate, quicker, and objective comparisons of motor events across studies.

Methods

Participants

Following approval by the local University Research Ethics committee, fourteen participants (7 ♂, 7 ♀, 26 $\pm$ 3 years, 169.4 $\pm$ 6.6 cm, 70.1 $\pm$ 6.9 kg) of similar low-to-moderate levels of habitual physical activity were recruited for the study. The Victorian Institute of Sport Assessment-Achilles (VISA-A) questionnaire was used to screen for any Achilles tendinopathy pain (Robinson *et al* 2001). Participants were excluded if they had experienced a lower-leg injury in the previous six months. Additionally, participants were excluded if they demonstrated symptoms of Achilles tendinopathy pain, determined as a VISA-A score under 90 (Iversen *et al* 2012). All participants signed a written consent form before data collection commenced.

Experimental protocol

Following a familiarization day where participants were accustomed to the two contraction types, participants returned to the lab for a testing session during which data for both contraction types were collected. Participants were secured lying prone in a calibrated dynamometer (Con-trex, Dubendorf, Switzerland). The dynamometer and ankle joint (at neutral angle) axes of rotation were aligned, with the knee joint fixed at 180° in full extension. The ankle was securely fastened with two straps, one 2 cm proximal to the medial malleolus and one 3 cm proximal to the head of the first metatarsophalangeal joint. A waist belt and shoulder straps were used to minimize upper body movement. Firstly, participants completed a standardized warm-up of the plantarflexors of the right leg with a series of submaximal contractions. Fast, explosive isometric contractions were performed at three different joint angles (10° plantarflexion, 0° anatomical zero, and 10° dorsiflexion) following the warm-up. For each contraction, participants were instructed to relax as much as possible and, following an auditory signal, attempt to plantarflex their ankle as 'fast and hard' as possible, with the emphasis on 'fast'. Contractions were separated with a 30 s rest period and five were performed at each joint angle. Following the explosive contractions at each joint angle, slow, ramped (maximal voluntary) contractions were performed. Participants completed three at each joint angle, separated with a 30 s rest period. The instruction for this contraction was to plantarflex the ankle as 'hard' as possible without concern for the rate of force development, reaching maximum torque in ~2 to 3 s. The order of joint angles for both contraction types was performed in a randomized order.

EMG collection and data processing

Surface EMG data were recorded from the soleus, lateral gastrocnemius, and medial gastrocnemius of the right leg using a DELSYS Trigno EMG-system (Delsys, Boston, MA). Surface EMG for the Non-Invasive Assessment of Muscles (SENIAM) guidelines guided the placements of the electrodes. Ultrasonography was used to identify the largest muscle belly and orientation of the muscle fibers for more precise electrode placement. Before electrode attachment, the skin was prepared by shaving, light abrasion, and cleansing with 70% ethanol to improve electrode-skin conductivity. EMG signals were amplified (×100; differential amplified, 20–450 Hz), sampled at 2000 Hz, and interfaced with LabChart 8 software using wireless communication. Two hundred and fifty-two data sets (one trial × two conditions × three angles × three muscles × 14 participants) were selected from the available data for analysis. Data were separated into two categories of 126 traces based on the contraction type. EMG signals were band-passed filtered in both directions between 10 and 400 Hz using a fourth-order Butterworth digital filter. All data treatment and onset detection were performed in MATLAB (R2019a, MathWorks, Massachusetts, USA) using a custom-written script. The anonymized data that support the findings of this study are openly available at the following link: (https://figshare.com/articles/dataset/Participant_data/13482429). The MATLAB script used for analysis is also available at this link.

EMG data conditioning and onset detection methods

All EMG traces were evaluated using manual visual detection, TBM, and AGLR. These detection algorithms were tested after two types of signal conditioning (without TKEO and with TKEO) across both contraction types. Additionally, all EMG traces were evaluated with TKEO as a detection method, following conditioning without TKEO. EMG conditioning minimizes background noise, reduces movement artefacts, and can facilitate onset detection. For signals conditioned without TKEO, data conditioning involved processing methods specific to the detection method. Regardless of the detection method, all signals were firstly band-passed filtered at 10–400 Hz (4th order Butterworth filter). For visual detection, the data was rectified following the band-pass filter but not further filtered. This has been previously recommended to facilitate visual onset detection (Dick *et al* 1986, Latash *et al* 1995) and avoids biasing the agreement of the visual detection and the computer-based methods (TBM, TKEO, AGLR), by ensuring similar filtering methods are used. For TBM and AGLR, after the band-pass filter, data was rectified and low-pass filtered at 50 Hz (2nd order Butterworth, zero-phase forward and reverse filter). Fast, explosive and slow, ramped contractions conditioned using the aforementioned conditioning methods formed the first set of data.

For the second set of data, fast, explosive and slow, ramped contractions were conditioned with TKEO as a step in the conditioning process. For all detection methods, TKEO was applied after the signal was band-pass filtered (10–400 Hz, 4th order Butterworth filter). The discrete TKEO Ψ is defined as

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

with x representing the EMG value and n the sample number. After TKEO conditioning, each detection method followed the same process of conditioning as conditioning without TKEO. Once the onset detection methods (visual, TBM, AGLR) were conditioned both without TKEO and with TKEO, onsets were detected across both conditioning and contraction types. In the event an onset detection could not be determined by any of the onset detection methods, a missing value was recorded for statistical analysis. EMG traces where onset detection was obscured by a movement artefact were eliminated. This enabled a true comparison of the methods to detect EMG onset accurately. A sample trace demonstrating the detection methods with and without TKEO conditioning is presented in figure 1.

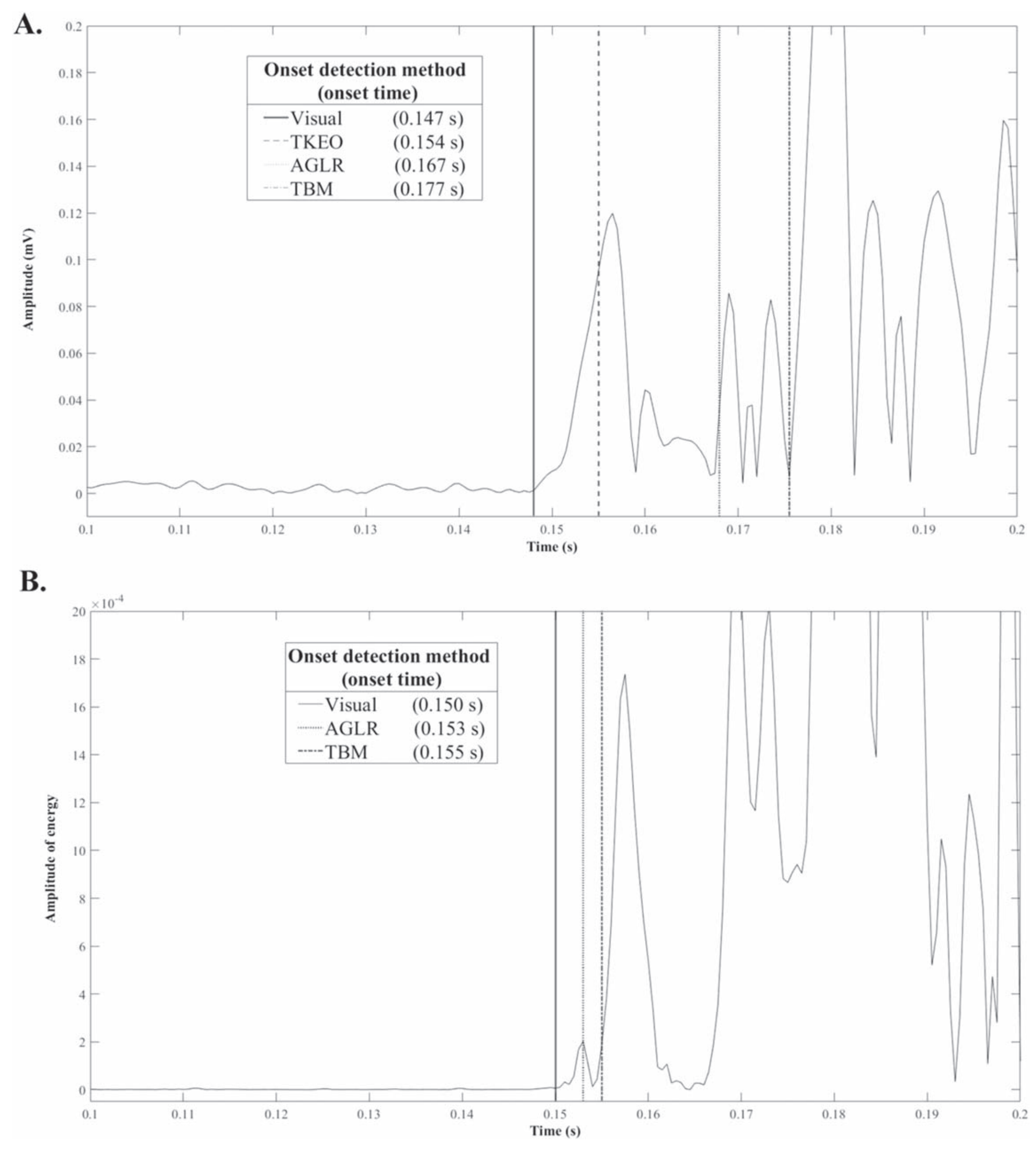

Figure 1. Representative EMG traces from a single trial for (A) fast, explosive contractions without TKEO conditioning (B) fast, explosive contraction with TKEO conditioning. Onset estimates of visual, AGLR, TKEO and TBM (best-performing) are indicated in the legend for the selected trial.

Visual detection

An individual with expertize in EMG analysis visually determined the onset of all data traces. A custom-written script in MATLAB displayed individual EMG traces on the computer monitor enabling onset detection to the nearest millisecond. EMG traces for each muscle were plotted separately in random order to remove any bias. For visual identification of onset, the criteria used by Tillin *et al* (2010) was employed. Initially, EMG signals were viewed with a constant y-axis scale of 10 mV and an x-axis scale of 500 ms. These scales enabled clear visualization of the pattern of noise and enabled signal onset detection. Signal onset was determined as the last peak or trough before the signal deflected away from baseline noise. To determine the reliability of visually identifying EMG onsets, the examiner determined the onset times for a random sample of fourteen explosive contractions (42 onsets) and fourteen maximal voluntary contractions (42 onsets) one week after the initial analysis. A second individual with EMG expertize visually determined onsets of a sample of ten explosive contractions (30 onsets) and ten maximal voluntary contractions (30 onsets), blinded to the other reviewers' onsets to examine inter-rater reliability. Both intra and inter-rater reliability analyses was performed for traces conditioned without TKEO and with TKEO to examine could TKEO conditioning improve visual detection reliability.

Approximated generalized likelihood ratio

AGLR involves statistical testing of the null hypotheses H_0 and alternate hypothesis H_1 of the statistical properties of a series of EMG samples $Y_1, Y_2, \ldots, Y_R$. The null hypothesis H_0 is related to the muscle being relaxed with no change in the statistical properties of the sequence and the alternate hypothesis H_1 relates to a contracted state with a change in statistical properties. AGLR tests the two hypotheses using a log-likelihood ratio test $g(k)$:

$$g(\mathrm{k}) = \ln\left(\prod_{k=1}^{r} \frac{p1(Yn)|H1)}{p0(Yn)|H0)}\right) \underset{<}{>} h, \tag{2}$$

where ln represents the natural logarithm, $Y(n)$ represents the series of EMG samples, $p1$ and $p0$ represent the probability density function aligned with hypothesis H_1 and H_0 respectively. The AGLR functions whereby when the log-likelihood $g(k)$ exceeds the preset threshold h, then hypothesis H_1 is more probable and a signal change is detected. The AGLR hypothesis test is performed over a predefined sliding window of size L. A log-likelihood ratio is calculated for every location of the window along the series of EMG data. Once a signal change is detected, the precise EMG onset time (t_1) is estimated by maximizing the likelihood estimators for each sample from the last window position. The window size was set at $L = 25$ ms, and the detection threshold level was set at $h = 6$ for fast, explosive contractions and $h = 10$ for slow, ramped contractions. These thresholds were selected as they introduced the smallest detection errors for the respective contraction type.

Threshold-based method

The TBM used the mean (μ) and standard deviation (σ) of each trace baseline activity level to compute the onset. The threshold T was determined as

$$T = \mu + h.\sigma, \tag{3}$$

where h is a variable determining the threshold level. The TBM involves identifying the onset as the point where the mean of a specified number of samples exceeds baseline activity by a specified number of standard deviations. Twelve different combinations of parameters were evaluated using the TBM. The parameters examined correspond to those, which tend to vary between studies employing the TBM. The first parameter investigated was the number of samples assessed in the sliding window (10, 25, 50 ms or 20, 50, 100 samples). The threshold level (magnitude of the deviation from the baseline) was also assessed (1, 2, 3, 5 SD). All 12 possible combinations of these two parameters were examined.

Teager–Kaiser energy operator

TKEO was employed as both a conditioning step and a detection method in the current study. As a detection method, TKEO facilitates detection by emphasizing the frequency and amplitude properties of motor unit action potentials and improving the signal-to-noise ratio. Thus, the output of TKEO is proportional to the product of the instantaneous amplitude and frequency. The discrete TKEO Ψ is defined as

$$\Psi[x(n)] = x^2(n) - x(n+1)x(n-1), \tag{4}$$

with x representing the EMG value and n the sample number. This method of onset detection involves applying the TKEO to each EMG trace and detecting the onset as the point where the TKEO output exceeds a preset threshold. Similar to the TBM, the threshold level was determined by

$$T = \mu + h.\sigma. \tag{5}$$

In the case of TKEO, h is a preset variable, which previous authors (Li and Aruin 2005) recommend is determined empirically. For this dataset, a threshold level of $h = 3$ for the explosive (fast) contractions and $h = 2$ for the maximal voluntary (slow, ramped) contractions introduced the smallest detection errors.

Statistical analysis

Visual detection is widely employed in EMG onset detection studies and is considered the 'gold standard' for onset detection (Hodges and Bui 1996, Allison 2003, Tillin *et al* 2010, Hannah *et al* 2012). Previous research has suggested that the accuracy of visual detection could be improved following conditioning with TKEO, particularly for signals with a low SNR (Li *et al* 2007, Solnik *et al* 2010). To evaluate the reliability of the visual onset detection with and without TKEO conditioning, across both contraction types, single and average intraclass correlation coefficients (ICC) and the typical error of measurement (TE) were calculated to examine intra-rater and inter-rater reliability respectively. When conditioned using TKEO, visual detection demonstrated improved inter-rater and intra-rater reliability compared to visual detection conditioned without TKEO. Thus, visual detection with TKEO conditioning was used as the criterion method to compare with the automatic detection methods. Onset delays for automatic detection methods conditioned without TKEO (AGLR, TBM, and TKEO) and with TKEO (AGLR and TBM) were calculated against visual onsets for both fast, explosive and slow, ramped trials. EMG onset bias ($\bar{d}$) was examined as the mean and standard deviation of the difference between visual and automatic onset methods. Agreement between visual onset detection and each automatic detection method for all EMG traces was examined using Bland–Altman 95% limits of agreement (LoA) (Bland and Altman 1986) and ICC with 95% confidence intervals (CI) (Atkinson and Nevill 1998). The LoA provide an interval within which 95% of the differences between the onset detection methods are expected to lie. ICC was used to examine the absolute agreement between onset detection methods, specifically a two-way mixed-effects model. Technical error of measurement (TEM) was evaluated between visual onset and each automatic detection method. TEM is an accuracy index and expresses the error margin between measurement methods (Perini *et al* 2005). TEM essentially provides a measure of standard deviation between repeated measures. Absolute and relative TEM were calculated with the following formulas:

$$\text{Absolute TEM} = \sqrt{\frac{\sum d^2}{2n}}, \tag{6}$$

where Σd^2 = summation of deviations squared, and n = number of samples measured.

$$\text{Relative TEM (\%)} = \frac{\text{TEM}}{\text{VAV}} \times 100, \tag{7}$$

where TEM = technical error of measurement expressed in %, and VAV = variable average value.

The variable average value (VAV) was needed for the calculation of relative TEM. To calculate the VAV, it was necessary to obtain the mean of the two measurements (visual onset and automatic computer-determined onset) for each EMG trace. Once the mean value of each trace was calculated, the averages obtained were summed up and divided by the number of traces in the sample, generating the VAV. All analyses were undertaken on the data separated by contraction type (fast, explosive and slow, ramped) and conditioning type (with TKEO conditioning and without TKEO conditioning). All analyses were performed using SPSS version 26 (SPSS Inc., Chicago, IL) and Microsoft Excel (Microsoft Excel, Microsoft Corporation, Redmond, WA, USA).

Results

Reliability—visual method

Both visual detection without TKEO conditioning and with TKEO demonstrated excellent agreement. The intra-rater reliability of the visually determined EMG onset without TKEO conditioning were determined individually for fast, explosive (TE = 0.6 ms; ICC = 0.998; ICC_{CI} = 0.997–0.999) and slow, ramped (TE = 3.3 ms; ICC = 0.999; ICC_{CI} = 0.998–1.000) contractions. Inter-rater reliability between the two raters was also determined individually for the fast, explosive contractions (TE = 1.4 ms; ICC = 0.994; ICC_{CI} = 0.856–0.997) and slow, ramped contractions (TE = 3.1 ms; ICC = 0.997; ICC_{CI} = 0.996–0.998).

Visually determined EMG onset with TKEO conditioning displayed improved agreement across measures compared with visually determined without TKEO conditioning. The intra-rater reliability demonstrated improvements for fast, explosive (TE = 0.3 ms; ICC = 1.000; ICC_{CI} = 1.000–1.000) and particularly slow, ramped (TE = 0.6 ms; ICC = 1.000; ICC_{CI} = 1.000–1.000) contractions. Inter-rater reliability was improved for both fast, explosive (TE = 1.1 ms; ICC = 0.999; ICC_{CI} = 0.997–1.000) and slow, ramped contractions (TE = 1.5 ms; ICC = 0.999; ICC_{CI} = 0.998–1.000).

Eliminated onsets

Trials were removed from the analysis if an onset was not detected using the automatic detection methods or if a movement artefact significantly skewed the onset. Across automatic detection methods, onset detection following TKEO conditioning reduced the number of trials screened out or where no onset was detected (table 1). For signals conditioned without TKEO, the number of trials that produced no onset was highest for the fast, explosive contractions and occurred most frequently in the 5 SD/50 ms parameter combination, potentially due to the conservative nature of the threshold and the short duration of the movement task. Trials screened out (table 1) due to a movement artefact skewing the onset across automatic detection methods was higher for the slow, ramped contractions (6% of all trials—with TKEO conditioning, 23% of all trials—without TKEO conditioning) when compared with the fast, explosive contractions (8% of all trials—with TKEO conditioning, 12% of all trials—without TKEO conditioning). Automatic compared with visual onsets lower and upper LoA, mean bias ± SD, ICCs and 95% CI, and TEM (absolute and relative) are provided in table 2 (fast, explosive—without TKEO processing), table 3 (fast, explosive—with TKEO processing) table 4 (slow, ramped—without TKEO processing) and table 5 (slow, ramped—with TKEO processing).

Fast, explosive contractions

EMG onset analysis for fast, explosive contractions indicated that the TKEO as a detection method and the AGLR with TKEO conditioning achieved the best agreement for onset time detection when compared to visual

Table 1. Eliminated EMG traces across automatic detection methods.

Detection method			Fast, explosive				Slow, ramped			
			With TKEO conditioning		Without TKEO conditioning		With TKEO conditioning		Without TKEO conditioning	
Method	SD	Window width	No onset	Screened out	No onset	Screened out	No onset	Screened out	No onset	Screened out
TKEO	2/3[a]	10	—	—	0	1	—	—	0	2
AGLR	6/10[b]	25	0	6	0	5	0	11	2	15
SD	1	10	0	14	0	96	0	4	0	77
SD	1	25	2	10	3	1	0	6	0	14
SD	1	50	0	4	3	12	1	0	3	32
SD	2	10	0	9	2	17	0	4	0	15
SD	2	25	0	2	5	1	0	2	0	17
SD	2	50	4	2	8	22	1	5	4	43
SD	3	10	0	3	2	1	0	3	0	1
SD	3	25	1	0	4	4	0	0	1	26
SD	3	50	1	0	2	34	4	0	12	50
SD	5	10	0	0	2	0	0	1	0	3
SD	5	25	0	0	2	7	0	3	2	35
SD	5	50	2	0	97	3	4	5	19	56

Note. No onset: algorithm returned no onset value; Screened out: onset screened out of analysis due to movement artefact producing skewed onset.

[a] TKEO 2 SD used for slow, ramped, TKEO 3 SD used for fast, explosive.

[b] AGLR 6 SD used for fast, explosive, AGLR 10 SD used for slow, ramped.

Table 2. Agreement and descriptive statistics for automatic detection methods compared with visual for fast, explosive contractions—without TKEO processing.

Detection method			Limits of agreement (ms)		Bias (ms)			ICC 95% CI		TEM	
Method	SD	WW	LloA	UloA	Mean	SD	ICC	Lower	Upper	Absolute	Relative
AGLR	6	25	−10.1	41.7	15.8	13.2	0.949	0.519	0.984	14.5	7.4%
TKEO	3	10	−6.2	15.7	4.7	5.6	0.993	0.966	0.997	5.2	2.7%
SD	1	10	−108.6	163.3	27.4	69.4	0.320	−0.005	0.593	52.0	29.4%
SD	1	25	−51.3	78.4	13.5	33.1	0.860	0.772	0.910	25.2	12.7%
SD	1	50	−49.7	122.3	36.3	43.9	0.716	0.285	0.865	40.2	19.0%
SD	2	10	−41.7	40.2	−0.8	20.9	0.941	0.915	0.959	14.7	7.8%
SD	2	25	−38.8	79.7	20.4	30.2	0.855	0.636	0.928	25.7	12.8%
SD	2	50	−28.9	106.6	38.8	34.6	0.777	0.129	0.917	36.7	17.4%
SD	3	10	−25.4	35.7	5.1	15.6	0.967	0.949	0.978	11.6	6.0%
SD	3	25	−37.3	91.0	26.8	32.7	0.820	0.452	0.919	29.9	14.6%
SD	3	50	−20.4	112.7	46.2	34.0	0.715	−0.026	0.900	40.5	19.2%
SD	5	10	−13.4	38.6	12.6	13.3	0.959	0.753	0.985	12.9	6.5%
SD	5	25	−17.2	78.0	30.4	24.3	0.850	0.152	0.950	27.5	13.3%
SD	5	50	−15.3	121.0	52.9	34.8	0.702	−0.060	0.901	44.6	20.8%

Note. Abbreviations: SD = standard deviation; WW = window width, LloA = lower limits of agreement, UloA = upper limits of agreement, ICC = intraclass correlation coefficient, TEM = technical error of measurement.

(tables 2, 3). TKEO had a low level of bias (4.7 ± 5.6 ms) with excellent ICC (0.993; ICC_{CI} = 0.977–0.997) and a low relative TEM (5.2%) compared with other automatic detection methods. The LoA (−6.2 to +15.7 ms) were wide under the current criteria of EMD calculation (table 2). AGLR with TKEO conditioning had a lower level of bias (2.0 ± 8.4 ms) compared to the TKEO detection method. Excellent ICC (0.991; ICC_{CI} = 0.986–0.994) and a low relative TEM (6.0%) were also reported for this detection method. The LoA (−14.4 to +18.3 ms) were wide under the current criteria and wider than the TKEO detection method (table 3). The TBM parameters, which resulted in the best agreement with the visual method for fast, explosive contractions was SD5/50 ms with TKEO conditioning. This TBM produced wider LoA (−21.5 to +17.4 ms) when compared with the TKEO detection method and AGLR (with TKEO conditioning) levels of agreement with visual onsets. Bias for the

Table 3. Agreement and descriptive statistics for automatic detection methods compared with visual for fast, explosive contractions—with TKEO processing.

Detection method			Limits of agreement (ms)		Bias (ms)			ICC 95% CI		TEM	
Method	SD	WW	LloA	UloA	Mean	SD	ICC	Lower	Upper	Absolute	Relative
AGLR	6	25	−14.4	18.3	2.0	8.4	0.991	0.986	0.994	6.0	3.2%
SD	1	10	−784.9	−512.8	−648.8	69.4	0.000	−0.002	0.003	461.4	−335.7%
SD	1	25	−874.5	1.2	−436.6	223.4	−0.007	−0.041	0.038	346.5	−982.7%
SD	1	50	−558.0	268.6	−144.7	210.9	0.106	−0.040	0.253	180.4	157.3%
SD	2	10	−905.3	−80.4	−492.9	210.4	−0.004	−0.029	0.029	378.7	−642.0%
SD	2	25	−647.8	221.1	−213.4	221.6	0.055	−0.055	0.176	217.1	269.6%
SD	2	50	−249.4	173.3	−38.1	107.8	0.421	0.257	0.558	80.6	47.9%
SD	3	10	−741.1	186.2	−277.5	236.5	0.027	−0.052	0.121	257.4	531.0%
SD	3	25	−464.9	262.5	−101.2	185.6	0.126	−0.025	0.277	149.0	109.1%
SD	3	50	−86.4	70.9	−7.8	40.1	0.831	0.768	0.878	28.8	15.7%
SD	5	10	−470.9	255.3	‘−107.8	185.3	0.131	−0.022	0.283	151.1	113.4%
SD	5	25	−234.2	181.3	−26.5	106.0	0.392	0.238	0.528	77.0	44.2%
SD	5	50	−21.5	17.4	−2.0	9.9	0.987	0.982	0.991	7.1	3.8%

Note. Abbreviations: SD = standard deviation; WW = window width, LloA = lower limits of agreement, UloA = upper limits of agreement, ICC = intraclass correlation coefficient, TEM = technical error of measurement.

Table 4. Agreement and descriptive statistics for automatic detection methods compared with visual for slow, ramped contractions—without TKEO processing.

Detection method			Limits of agreement (ms)		Bias (ms)			ICC 95% CI		TEM	
Method	SD	WW	LloA	UloA	Mean	SD	ICC	Lower	Upper	Absolute	Relative
AGLR	10	25	−158.1	326.3	84.1	123.6	0.728	0.420	0.857	105.3	24.6%
TKEO	2	10	−83.0	120.2	18.6	51.8	0.956	0.928	0.972	38.8	9.7%
SD	1	10	−213.4	156.4	−28.5	94.3	0.794	0.633	0.889	68.8	22.3%
SD	1	25	−121.8	278.0	78.1	102.0	0.791	0.445	0.901	90.5	22.0%
SD	1	50	−109.3	357.7	124.2	119.1	0.683	0.086	0.868	121.3	27.1%
SD	2	10	−187.5	202.0	7.2	99.4	0.854	0.790	0.900	70.1	18.8%
SD	2	25	−117.0	325.0	104.0	112.8	0.735	0.227	0.885	108.2	25.4%
SD	2	50	−83.8	387.5	151.8	120.2	0.669	−0.024	0.876	136.6	29.1%
SD	3	10	−128.6	203.5	37.4	84.7	0.879	0.791	0.925	65.2	16.7%
SD	3	25	−94.5	290.6	98.0	98.2	0.779	0.222	0.912	97.9	23.0%
SD	3	50	−50.9	349.1	149.1	102.0	0.640	−0.072	0.873	127.4	28.6%
SD	5	10	−133.7	278.7	72.5	105.2	0.785	0.500	0.890	90.1	22.1%
SD	5	25	−72.5	309.4	118.4	97.4	0.745	0.043	0.908	108.2	24.4%
SD	5	50	−78.9	445.9	183.5	133.9	0.456	−0.097	0.765	159.9	37.7%

Note. Abbreviations: SD = standard deviation; WW = window width, LloA = lower limits of agreement, UloA = upper limits of agreement, ICC = intraclass correlation coefficient, TEM = technical error of measurement.

5 SD/50 ms detection method (−2.0 ± 9.9 ms) was similar to the two best-performing methods for fast, explosive contractions (tables 2, 3). Across automatic detection methods, the TKEO detection method most closely estimated visual onset with narrower LoA compared to the other automatic detection methods (AGLR or SD5/50 ms). Figure 2(A) demonstrates the TKEO agreement with visual onset for fast, explosive contractions using a Bland–Altman plot and LoA.

Slow, ramped contractions

TKEO (detection method), AGLR, and all TBM parameters produced wide LoA, large bias, and high levels of TEM when examining the agreement between automatic detection methods and visual for onsets of EMG during slow, ramped contractions (tables 4, 5). Of the automatic detection methods, the AGLR with TKEO conditioning produced the smallest bias (11.3 ± 32.9 ms) and narrowest LoA (−53.2 to 75.8 ms) with excellent ICC (0.983; ICC_{CI} = 0.971–0.989). Figure 2(B) demonstrates the AGLR agreement with visual onset for slow, ramped contractions using a Bland–Altman plot and LoA. The method which produced the next best agreement

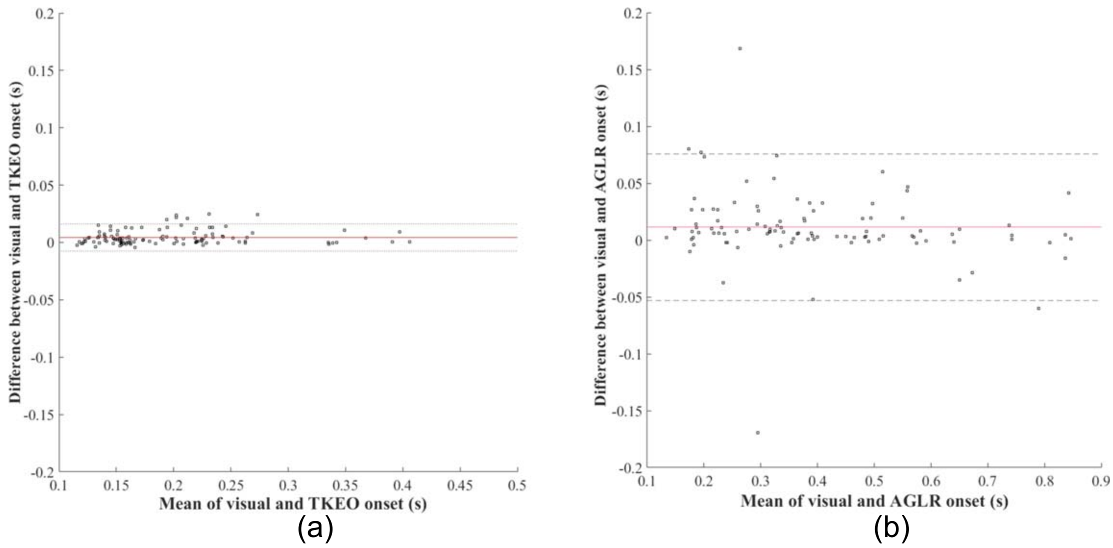

Figure 2. Bland–Altman plot displaying agreement between visual and best-performing automatic detection method for (A) fast, explosive contractions (TKEO as a detection method) and (B) slow, ramped contractions (AGLR after TKEO conditioning).

Table 5. Agreement and descriptive statistics for automatic detection methods compared with visual for slow, ramped contractions—with TKEO processing.

Detection method			Limits of agreement (ms)		Bias (ms)			ICC 95% CI		TEM	
Method	SD	WW	LloA	UloA	Mean	SD	ICC	Lower	Upper	Absolute	Relative
AGLR	10	25	−53.2	75.8	11.3	32.9	0.983	0.971	0.989	24.5	6.2%
SD	1	10	−1171.9	−501.0	−836.4	171.1	0.001	−0.006	0.012	603.6	−1316.0%
SD	1	25	−1196.2	4.6	−595.8	306.3	−0.002	−0.036	0.044	473.3	603.1%
SD	1	50	−833.3	415.5	−208.9	318.6	0.196	0.002	0.374	268.6	96.0%
SD	2	10	−1185.5	−180.1	−682.8	256.5	0.004	−0.018	0.035	515.5	1665.4%
SD	2	25	−901.6	366.1	−267.8	323.4	0.177	−0.030	0.369	296.1	120.1%
SD	2	50	−322.8	244.7	−39.1	144.8	0.726	0.618	0.805	105.6	29.0%
SD	3	10	−982.6	265.8	−358.4	318.5	0.158	−0.065	0.371	338.3	171.6%
SD	3	25	−632.5	362.4	−135.0	253.8	0.402	0.178	0.574	202.6	64.0%
SD	3	50	−142.8	131.8	−5.5	70.1	0.923	0.891	0.947	49.5	13.0%
SD	5	10	−657.6	356.1	−150.8	258.6	0.343	0.112	0.527	211.0	69.2%
SD	5	25	−344.9	251.9	−46.5	152.2	0.730	0.617	0.810	112.1	31.1%
SD	5	50	−78.5	102.2	11.9	46.1	0.966	0.950	0.977	33.5	8.6%

Note. Abbreviations: SD = standard deviation; WW = window width, LloA = lower limits of agreement, UloA = upper limits of agreement, ICC = intraclass correlation coefficient, TEM = technical error of measurement.

with visual, similar to the fast, explosive analysis, was SD 5/50 ms with TKEO conditioning (−78.5 to +102.2 ms).

Discussion

The present study examined if automatic detection methods, namely AGLR, TKEO, and various iterations of the TBM, could be used interchangeably with visual in detecting EMG onset across contraction types. The goal was to validate an automatic method of detection that is reliable and agrees well with visual onset detection across contraction types. Additionally, the research examined if TKEO as a conditioning step would improve onset detection accuracy across contraction types. The results demonstrated that when examining fast, explosive contractions, TKEO as a detection method provides a better alternative to the AGLR and TBM. For slow, ramped contractions, the AGLR with TKEO as a conditioning step performed best of the automatic detection methods. Although AGLR demonstrated the best onset detection performance of the automatic detection methods for slow, ramped contractions, it was more common for the measurement to be less accurate than the best-performing method (TKEO) for fast, explosive contractions. Our results demonstrated that signal conditioning with TKEO improved the accuracy of visual and AGLR across both contraction conditions. TBM demonstrated improved detection accuracy for the 5 SD/50 ms iteration but did not improve for all other iterations. As TBM is largely determined using baseline amplitude, the reduced baseline amplitude following TKEO conditioning resulted in consistent underestimations of the true onset. The accurate identification of EMG burst boundaries is a crucial element of the biomechanical analysis of human movement. Inappropriate selection of the analysis technique can induce errors of 16.9% to EMD measures based on the present data or 10.1% when applied to EMD data for a heel-lift experiment (Crotty *et al* 2019) when the best-performing automatic method was employed. Motor events of durations as short as EMD would require automatic detection methods to have detection bias in the region of 2–3 ms compared with the visual method to justify implementation. The automatic detection methods did not produce this level of agreement. Therefore, it is recommended that visual inspection following TKEO conditioning is the best method for accurate and reliable onset detection across contraction types.

Determining EMG onset using automatic computer-based methods has been widely examined throughout the literature with varying levels of success (Hodges and Bui 1996, Staude *et al* 2001, Allison 2003, Solnik *et al* 2010). The majority of automatic detection algorithms are robust and produce a good agreement with visual methods when EMG signals exhibit rapid amplitude increases and a large signal-to-noise ratio (Staude *et al* 2001). The findings align with this as fast, explosive contractions exhibited narrower LoA and smaller onset biases across computer-based methods when compared to slow, ramped contractions (tables 2–5). These results are comparable to Van Boxtel *et al* (1993), who reported the accuracy of several automatic detection methods in determining EMG onset was lower for slow than fast contractions. Additionally, a larger number of trials were screened out of the slow, ramped contractions due to skewed onsets stemming from smaller signal-to-noise ratios (table 1). Similarly, Hodges and Bui (1996) screened out a higher number of traces with no discernible onset in a group of low signal-to-noise ratio compared to the high signal-to-noise ratio trials. The evidence indicates that high baseline noise and low rates of EMG amplitude are the main factors inducing errors in the automatic detection of EMG onset. The TBM is particularly affected by this as onset biases increased with respect to baseline noise due to the necessarily higher thresholds for the signals conditioned without TKEO (Dotan *et al* 2016). Conditioning with TKEO amplifies the energy of action potential spikes and assisted automatic methods in determining muscle onset. This resulted in a reduced number of trials screened out across contractions (table 1).

The susceptibility of TBM to EMG trace characteristics (i.e. signal-to-noise ratio, and rate of amplitude increase) in identifying EMG onset was evident from the results of this study. Across the majority of thresholds (1/2/3/5 SD) and window width (10/25/50 ms) parameters examined, onsets significantly varied from visually determined EMG onsets. The combination of TBM parameters which performed best across contraction conditions was 5 SD/50 ms with TKEO conditioning (tables 3, 5). This was unexpected since it was hypothesized that contractions of different signal-to-noise ratios, and rate of amplitude increase would produce different optimal parameters. Similar results were reported by Hodges and Bui (1996) with considerable overlap between the optimal TBM parameters for EMG traces with high and low background activity. For fast, explosive contractions 5 SD/50 ms demonstrated excellent levels of agreement (ICC $=$ 0.987), and low bias (-2.0 ± 9.9 ms), but with wide LoA (-21.5 to $+$ 17.4 ms). For slow, ramped contractions 5 SD/50 ms was the next best-performing automatic method after AGLR (with TKEO conditioning) and demonstrated excellent levels of agreement (ICC $=$ 0.966) but with large bias (-11.9 ± 46.1 ms), and wide LoA (-78.5 to $+$ 102.2 ms). The general problem of the threshold method is that the threshold level is adapted to the background noise and as a result varies with the signal-to-noise ratio. A higher noise level (decreased SNR) in the calculated TBM onsets' without TKEO conditioning resulted in Type II errors, leading to delayed or missed onset detections (tables 2, 4). TKEO conditioning works to enhance signal amplitude and frequency, thus improving the signal-to-noise ratio. While TKEO conditioning improved detection accuracy for the 5 SD/50 ms iteration, improvements were not extended to other iterations. The lower noise level (improved SNR) in the calculated TBM onsets' with TKEO conditioning resulted in Type I errors and early-onset detection when the muscle was inactive (tables 3, 5). Additionally, low threshold levels (1 SD) and smaller window widths (10 ms) increased Type I errors and early detection by identifying erratic bursts of activity as the onset. Higher threshold levels (5 SD) and large window widths (50 ms) ignored short EMG bursts and tended to delay accurate onset identification. Overall, the measurement was less accurate when the rate of amplitude increase was low versus fast, ramping traces. When relating EMG onset to a motor event or when comparing muscle onsets with differing rates of EMG amplitude increase, the results suggest the iterations of the TBM examined are not accurate enough to be used interchangeably with visual detection.

AGLR involves statistical testing using a generalized likelihood ratio and has demonstrated increased onset detection accuracy compared with TBM (Staude *et al* 2001, Roetenberg *et al* 2003, Solnik *et al* 2010). Both AGLR and TBM utilize baseline information in the detection process. However, AGLR is more robust to changes in signal parameters (i.e. signal-to-noise ratio, change dynamics) compared with TBM (Staude *et al* 2001, Solnik *et al* 2010). Using AGLR, the automatic detection accuracy improved compared to TBM across both contraction types. For fast, explosive contractions, the results showed that AGLR with TKEO conditioning demonstrated excellent levels of agreement (ICC = 0.991) and low bias (2.0 ± 8.4 ms) with visual onset detection. Comparable results using AGLR with TKEO conditioning have been reported by Solnik *et al* (2010), with low bias (2.0 ± 1.0 ms) on signals reconstructed from isometric contractions. For slow, ramped contractions, AGLR with TKEO conditioning was the best-performing automatic method. The results demonstrated that AGLR produced the lowest bias (11.3 ± 32.9 ms) and excellent agreement levels (ICC = 0.983). AGLR performed well compared with visual detection, however wide LoA for both fast, explosive (−14.4 to +18.3 ms) and slow, ramped (−53.2 to +75.8 ms) contractions and large average detection errors make it unsuitable to be used interchangeably with visual. The average detection error ($\varepsilon = |(\text{Automatic onset—Visual onset})|$) of AGLR for slow, ramped contractions was 19.9 ms. Implementing this method of onset detection would induce, on average, a percentage change in EMD value of 38.2%. While AGLR was the best-performing automatic method for slow, ramped contractions, the large errors in EMD calculation that could be produced by using this method make it unsuitable.

Recent research has proposed TKEO as a viable automatic method of EMG onset detection (Li *et al* 2007). TKEO improves the signal-to-noise ratio by suppressing the noise and amplifying the EMG burst. The results confirm previous suggestions that TKEO is not as influenced by signal baseline characteristics for onset detection compared to other automatic detection methods. TKEO resulted in the best agreement for onset time detection of fast, explosive contractions. The results show that TKEO produced excellent levels of agreement (ICC = 0.993) and low bias (4.7 ± 5.6 ms) with visual. Similar results reported by Li *et al* (2007) examined EMG onset using TKEO on artificial signals. They observed increased consistency of onset times to within 19.1 ± 24.8 ms when TKEO was implemented across signals of varying signal-to-noise ratio. The current results highlight that TKEO was less accurate for slow, ramped contractions producing large bias (18.6 ± 51.8 ms), and wide LoA (−83.0 to +120.2 ms). While TKEO performed best against visual for fast, explosive contractions, wide LoA (−7.5 to +16.1 ms), and large average detection error indicate that it may not be used interchangeably with visual detection when examining motor events, such as EMD. The average detection error in determining EMG onset for fast, explosive contractions was 4.9 ms for TKEO. On average, this could cause a percentage change in EMD value of 16.9%. While results from this study confirmed previous findings that TKEO improves detection performance, it also extended them by providing results indicating TKEO can improve performance detection for fast, explosive contractions. However, TKEO lacks the accuracy desired to be used interchangeably with visual when examining motor events of short duration.

Motor events, such as EMD, produce values as low as 10 ms (Tillin *et al* 2010). Thus, it is reasonable to propose that detection biases not exceed 2–3 ms to validate an automatic detection method. Similar to previous research on automatic detection methods, this study demonstrated to attain the level of accuracy needed for motor events, visual detection of EMG onsets is recommended. As visual detection is both objective and dependent on rater experience, future researchers must employ methods to examine rater reliability (inter and intra) for EMG onset detection. Examining rater reliability is imperative before any detailed onset analysis of an EMG dataset. This strategy assists in limiting the operator error bias that can influence conclusions on onset measures. Previous research demonstrated that including TKEO as a conditioning step can improve the accuracy of onset detection for the visual method, by suppressing baseline noise amplitude and amplifying the EMG burst (Solnik *et al* 2010) The results from this study provide further support for including TKEO as a conditioning step prior to visual detection, with improved inter-rater and intra-rater reliability across both contraction types. While visual without TKEO conditioning demonstrated excellent results, the improvements observed from visual detection with TKEO conditioning are important when examining short muscle delay periods, such as EMD. Additionally, the inclusion of the TKEO as a conditioning step improved AGLR detection across contraction types (tables 3, 5). As AGLR utilizes baseline information the TKEO assisted in narrowing the baseline probability distribution and widening the EMG muscle activity probability distribution (Solnik *et al* 2010), thus improving AGLR detection. However, TKEO as a conditioning step did not improve the accuracy of TBM. The TBM is more sensitive to random variations in the baseline signal. Following TKEO conditioning, reduced baseline amplitudes' led to a bias toward early detection compared to TBM detection without TKEO conditioning (tables 2–5). Potentially this is due to the low thresholds used in the current study. This study examined the conventional iterations of TBM (1, 2, 3, 5 SD) widely employed in EMG research. Previous research indicates that thresholds of 6–8 (Li *et al* 2007) or even as high as 15 (Solnik *et al* 2010) are required following TKEO conditioning due to the low magnitude of the baseline.

Conclusion

In this study, the acceptability of AGLR, TBM, and TKEO as alternatives to visual EMG onset detection were examined across contractions of varying rates of amplitude increase. Additionally, the accuracy of EMG onset detection with and without TKEO conditioning applied to the detection methods was examined. For fast, explosive contractions, TKEO as a detection method demonstrated the best accuracy with visual onsets. For slow, ramped contractions, AGLR with TKEO conditioning demonstrated the best accuracy. However, the automatic methods are not sensitive enough to be applied as the detection method when relating EMG onset to a movement or motor event of short duration. This study confirmed manual visual detection should be applied in the analysis of such biomechanical events. As seen in this study and recommended by previous research (Solnik *et al* 2010), including TKEO as a step of the signal conditioning process can suppress noise amplitude during the steady-state portion of the EMG trace, and amplify the EMG burst. Inclusion of TKEO in signal processing can assist in optimizing the visual detection procedure and reduce onset biases due to objectivity, especially for signals of low signal-to-noise ratio and slow amplitude increases. Problems in visual detection can arise in signals with low signal-to-noise ratio and slow rate of EMG amplitude increase. However, the TKEO as a conditioning step demonstrated improved inter-rater and intra-rater reliability for visual detection across contractions of varying rates of amplitude increase. Thus, it is recommended to employ this as a conditioning step prior to visual detection in future studies examining EMG onset. Improvements in detection accuracy were demonstrated with TKEO as a detection method and as a conditioning step for automatic detection methods (i.e. AGLR). Future research should assess the applicability of TKEO in determining muscle onsets and offsets in dynamic tasks. Previous research has demonstrated improvements in onset detection in EMG on walking gait following TKEO as a conditioning step for automatic detection methods (Solnik *et al* 2010). The use of TKEO either as a detection method or as a conditioning step may be a viable option for detecting kinematic events such as EMG onset in high-speed dynamic conditions (e.g. sprinting). In actions as such, the EMG signal amplitude increases are fast and the accuracy of onset is not as vital as in motor events, such as EMD.

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