Application of the Teager–Kaiser Energy Operator
in an autonomous burst detector to create onset and offset profiles
of forearm muscles during reach-to-grasp movements

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Purpose: The primary aim of this study is to investigate the potential benefit of the Teager–Kaiser Energy Operator (TKEO) as data pre-processor, in an autonomous burst detection method to classify electromyographic signals of the (fore)arm and hand. For this purpose, optimal settings of the burst detector, leading to minimal detection errors, need to be known. Additionally, the burst detector is applied to real muscle activity recorded in healthy adults performing reach-to-grasp movements. *Methods:* The burst detector was based on the Approximated Generalized Likelihood Ratio (AGLR). Simulations with synthesized electromyographic (EMG) traces with known onset and offset times, yielded optimal settings for AGLR parameters "window width" and "threshold value" that minimized detection errors. Next, comparative simulations were done with and without TKEO data pre-processing. Correct working of the burst detector was verified by applying it to real surface EMG signals obtained from arm and hand muscles involved in a sub-maximal reach-to-grasp task, performed by healthy adults. *Results:* Minimal detection errors were found with a window width of 100 ms and a detection threshold of 15. Inclusion of the TKEO contributed significantly to a reduction of detection errors. Application of the autonomous burst detector to real data was feasible. *Conclusions:* The burst detector was able to classify muscle activation and create Muscle Onset Offset Profiles (MOOPs) autonomously from real EMG data, which allows objective comparison of MOOPs obtained from movement tasks performed in different conditions or from different populations. The TKEO contributed to improved performance and robustness of the burst detector.

Key words: electromyography, AGLR, Teager–Kaiser, timing, reach, grasp

Abbreviations

AGLR	–	Approximated Generalized Likelihood Ratio
APL	–	Abductor Pollicis Longus
ECR	–	Extensor Carpi Radialis
ECU	–	Extensor Carpi Ulnaris
EDC	–	Extensor Digitorum Communis
(s)EMG	–	(surface) ElectroMyoGraphy
FCR	–	Flexor Carpi Radialis
FCU	–	Flexor Carpi Ulnaris
HO	–	Hand opening
MAP	–	Muscle Activation Pattern
MCP3	–	MetaCarpoPhalangeal joint 3
MOOP	–	Muscle Onset Offset Profile
RD	–	Reaching distance
RMS	–	Root Mean Squared
SNR	–	Signal-to-Noise Ratio
STD	–	Standard deviation
TKEO	–	Teager–Kaiser Energy Operator

1. Introduction

Surface electromyography (sEMG) is widely used to study physiological processes involved in movement execution [11]. Electromyographic signals are related to force production [12] and muscle fatigue [24] and are often used to study muscle activation patterns (MAPs) after neurological disorders such as spinal cord injury [6] and stroke [18]. Timing of muscle activation can help in understanding motor deficits after neurological injury, and planning therapeutic interventions such as (multichannel) electrical stimulation to support arm and hand function [7], [8].

Muscle onset and offset times are often studied by means of visual inspection [4]. However, this method is prone to intuitive, heuristic and subjective judgment of the researcher or clinician and has poor reproducibility. In the past decades, computer assisted methods [4], [22] have been developed to objectively quantify muscle onset and offset times, such as a simple threshold algorithm [4], a double threshold algorithm [1], Teager–Kaiser Energy Operator (TKEO) [9] and the Approximated Generalized Likelihood Ratio (AGLR) [23].

The AGLR algorithm [23] detects changes in signal variance. In the case of sEMG onset and offset detection, two hypotheses (H_0 and H_1), describing the statistical properties of two probability density functions, represent the state of the muscle. The null hypothesis H_0 corresponds to a muscle in a relaxed state; H_1 corresponds to a muscle in contracted state. In the detection and estimation phases of the AGLR algorithm, a fixed window of length "L" is shifted along the input signal. When the log-likelihood ratio test, comparing the probability density functions of H_0 and H_1, exceeds a threshold "h", a change in signal variance is detected and the H_1 hypothesis is accepted that the muscle is contracted. The exact change time "t_0" of signal variance is estimated by a maximum likelihood ratio. The output of the AGLR algorithm is influenced by the threshold "h" and window length "L". These parameters need to be chosen a priori [22], [23] and determine the sensitivity, false positive and false negative detection ratios of the algorithm. To increase robustness and decrease sensitivity to artifacts, the signal can benefit from pre-processing before it is analyzed by the AGLR algorithm. A promising pre-processor is the nonlinear Teager–Kaiser Energy Operator [5].

The TKEO calculates the energy of a signal, based on its amplitude and frequency content. It was first used in speech signal analysis [14], and more recently in EMG analysis [9]. The discrete TKEO is defined as

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

in which $x(n)$ is the amplitude on discrete time "n" and $x(n-1)$ and $x(n+1)$ are the preceding and succeeding samples, respectively. Li and Aruin [9] explored the possibility to detect muscle onset times by applying the TKEO to simulated and human EMG signals, and thresholding the TKEO signals. Onset detection errors were smaller after applying the TKEO, compared to only thresholding the raw EMG signals [10]. Solnik et al. [21] observed that EMG onset detection improved after applying TKEO in three different methods (visual inspection, single threshold and AGLR) and that improvement was independent of the signal-to-noise-ratio (SNR) [20]. Solnik et al. used modified sEMG signals, obtained from lower extremity muscles such as the quadriceps and vastus lateralis during maximal voluntary contractions. A burst detector consisting of AGLR and TKEO has not been previously tested on (rather slowly varying) sEMG signals that were obtained from upper extremity muscles during a sub-maximal movement task, which corresponds better with the functional nature of most upper extremity movements while performing daily activities.

Objective

The primary aim of this study is to investigate the added value of applying TKEO data pre-processing to an AGLR-based method for burst detection in surface EMG of the hand and forearm, during submaximal movements. As a first step, optimal parameters of the burst detector, leading to minimal detection errors, are identified by applying it to simulated EMG traces with known onset and offset times. Next, comparative simulations are performed with and without TKEO pre-processing. It is hypothesized that inclusion of the TKEO as pre-processor will reduce onset and offset errors. Additionally, the burst detector is applied to real muscle activity recorded from the arm and hand in a group of healthy adults who performed reach-to-grasp movements, to verify correct functioning of the burst detector by creating Muscle Onset and Offset Profiles (MOOPs) of the sub-maximal reach-to-grasp movements.

2. Materials and methods

Simulations for burst detection settings

The autonomous burst detector consisted of three major steps, see Fig. 1. In the first step, data is pre-

processed by the TKEO [5] to increase the SNR of the sEMG signal. Comparison between onset and offset errors with and without the TKEO decided whether this step needs to be included in the burst detector.
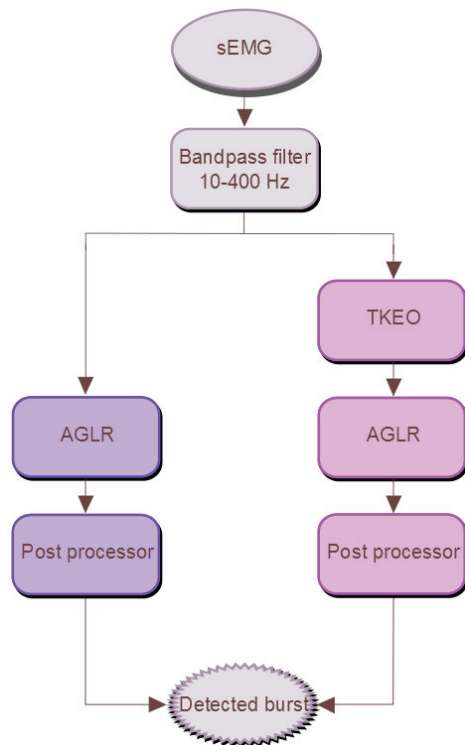

Fig. 1. The three major steps involved in sEMG burst detection without (left) and with (right) TKEO data pre-processing

Second, the AGLR [23] algorithm was used to estimate changes in the variance of the (pre-processed)

sEMG signal. As part of this procedure, optimal values for window length "L" and threshold "h" were determined based on simulations. Third, a rule-based postprocessor classified the detected changes in signal variance in muscle onset and offset times, in terms of "muscle contracted" or "muscle relaxed" based on a priori defined thresholds "Th_{on}" (15 µV) and "Th_{off}" (10 µV).

TKEO pre-processing

To be able to compare onset and offset errors with and without data pre-processing with the TKEO, the thresholds "Th_{on}" and "Th_{off}" need to be known in the TKEO domain. For this purpose 1000 traces of sEMG with amplitudes varying from 1 to 25 µV RMS, in steps of 1 µV, were generated (25000 traces in total). EMG was simulated as band pass filtered brown noise [15]. Each trace was band-pass filtered with a 2nd order, zero-phase-shift Butterworth band-pass filter with cut-off frequencies of 20 and 400 Hz in Matlab (R2011b, the Mathworks, Natick, MA) and converted into the TKEO domain. A second order polynomial was fitted through the data points in the least squared error sense and evaluated at 10 and 15 µV to obtain thresholds "Th_{on}" and "Th_{off}" in the TKEO domain.

AGLR settings

Simulations were used to optimize performance and robustness of the burst detector. Several parameters of the burst detector such as window lengths (L, Δ) and threshold values (h, Th_{on}, Th_{off}) of the burst detector need to be set, either heuristically, based on
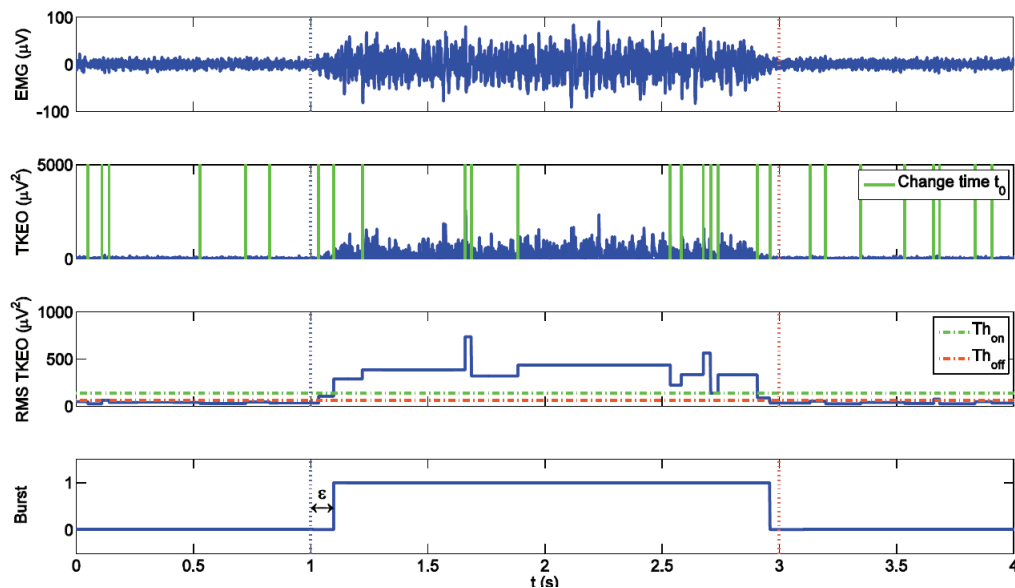

Fig. 2. Example of a synthesized EMG trace (upper panel) before transformation into the TKEO domain (second panel).
The RMS values between two alarm times (t_0) are thresholded (third panel)
which yielded the final detected burst (fourth panel) with onset detection error ε

simulations or based on a priori knowledge. To find optimal settings for the AGLR parameters "*L*" (length of detection window) and "*h*" (detection threshold), sEMG signals with known onset and offsets were synthesized. A burst of muscle activity was simulated as a ramp up from 0 to 25 μV_{RMS} at $1.0 < t < 1.2$ s, a block of constant activity with an RMS value of 25 μV at $1.2 < t < 3.8$ s and a ramp down from 25 to 0 μV at $3.8 < t < 4.0$ s, see also the upper panel of Fig. 2. Gaussian white noise with RMS values between "An" = 1 and "An" = 10 μV was added to create EMG signals with a SNR between 8.0 and 28 dB.

Onset and offset errors were calculated for synthesized EMG signals with different SNR and different values for *L* and *h*. For each combination of SNR, *L* and *h*, 50 EMG traces were analyzed. Onset and offset errors ε were defined as the difference between the exact and the detected onset and offset times: $\varepsilon = t_{exact} - t_{estimated}$, see also Fig. 2. The detection window length "*L*" of the AGLR algorithm should be bigger than the shortest event to be detected. Muscle contractions with duration shorter than the electromechanical delay were discarded, because they will not result in noticeable movement of the limb. Since the electromechanical delay for muscle contractions of arm muscles is around 80 ms [3], window length "*L*" should preferably exceed 80 ms. Window length "*L*" was varied between 30 and 500 ms in steps of 10 ms. Threshold "*h*" was varied between 5 and 150 in steps of 5. To find optimal parameter settings, onset and offset errors were averaged over the 50 repetitions and the 10 noise levels "An". Optimal parameter settings were defined as minimal detection errors for each combination of threshold "*h*" and window length "*L*". Parameter "Δ" which is used to determine the exact change time "t_0" from the estimated change time is chosen to be the same length as "*L*" [23].

Post processor

After the two steps of the AGLR algorithm, changes in signal energy have been identified. A knowledge based postprocessor is needed to decide whether a detected change time "t_0" is a true muscle onset or offset. Root mean squared (RMS) values of the TKEO signal between two consecutive change times were calculated. If the RMS of the TKEO signal between two change times exceeds a threshold "Th_{on}" the muscle is regarded as being contracted. When the RMS of the TKEO signal is below a threshold "Th_{off}" the muscle is regarded being relaxed. Finally, bursts of muscle activity with duration shorter than 100 ms are removed. Similarly, periods of muscle relaxation with duration shorter than 125 ms are removed [16].

When the TKEO data pre-processing was omitted, a highly similar postprocessor was used. The muscle is regarded as being contracted when the RMS of the (10–400 Hz bandpass filtered) EMG between two consecutive change times exceeds threshold "Th_{on}" and being relaxed when the RMS value is below "Th_{off}".

The automated burst detector consisting of the TKEO and AGLR algorithms and the postprocessor described above was applied to EMG signals recorded during the reach-to-grasp task performed by healthy adults, in order to create MOOPs.

Subjects

Twenty subjects were recruited from the local community. Inclusion criteria were an age over 40 years, no history of neurological disorders and no limitations in upper extremity range of motion due to pain or other disorders. Data of two subjects were excluded because of wrong execution of the movement task and technical failure during the measurement. Demographic data of the remaining 18 subjects are summarized in Table 1. All subjects provided written informed consent. The study was approved by the local medical ethics committee (NTR2638).

Table 1. Subject demographic data

	Subjects ($n = 18$)
Age (yrs)	60.4 ± 8.4
Gender	11 M / 7 F
Arm dominance	18 R / 0 L
M = male, F = female, R = right side, L = left side	

Reaching movements

Subjects performed reaching movements while seated on a chair with a sitting height of 50 cm in front of a custom designed table with a height of 75 cm. Before movements started, the subject's hand was placed on a white instrumented button containing 5 micro switches that represented the starting position, see Fig. 3. The signal of the starting button indicated that subjects released the button and started movement. Subjects reached for a cylindrical object with a diameter of 4.0 cm, a height of 9.8 cm and a weight of 0.14 kg. The object was placed on the tabletop, 35 cm in front of the starting button, see Fig. 3. Subjects were asked to transfer the cylindrical object towards the starting position at a self-selected speed, which required a forward reaching and grasping movement, followed by a reverse move-

ment towards the trunk. The object was returned to the target location by the researcher. Movement duration of each individual reaching movement was time-normalized, defined as the time between release of the start button (0%) and the time when maximal reaching distance, based on the position of MCP3 (100%), occurred. EMG signals were analyzed between – 100 and 200% of the movement duration. Application of the burst detector to an EMG signal yielded a binary signal which was zero when the muscle was relaxed and one when the muscle was contracted.
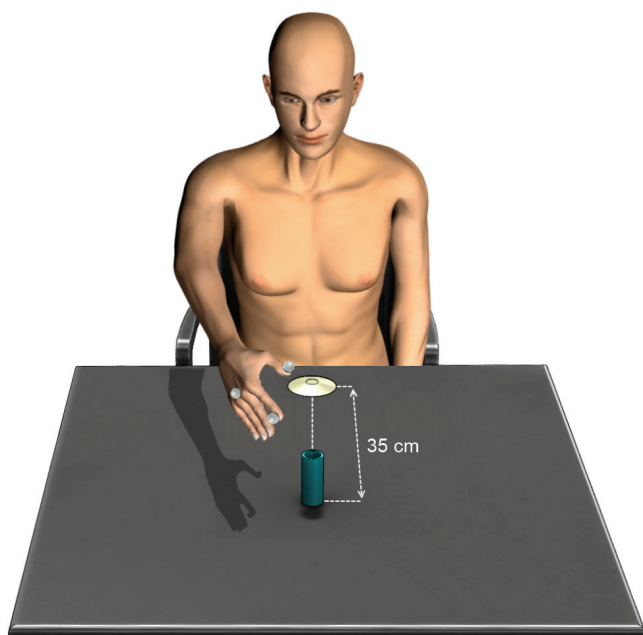

Fig. 3. Setup for the reach-to-grasp task where subjects reached for and grasped a blue cylindrical object

Kinematics

To be able to quantify the reach-to-grasp movements, 3D kinematics of the arm and hand were recorded with a 6-camera VICON motion analysis system (VICON MX + 6 MX13, VICON, Oxford Metrics, UK). Reflective, 9 mm spherical markers were placed on the tip of the thumb and index finger and on the third metacarpophalangeal (MCP3) joint to measure movement of the hand and the amount of hand opening (i.e., 3D Euclidean distance between the markers on the tip of the thumb and index finger), see Fig. 3. Positions of the markers were recorded with a frame rate of 100 Hz. Positional data of the markers were offline filtered with a first order, zero-phase-shift Butterworth filter with a cut-off frequency of 10 Hz, in Matlab (R2011b, the Mathworks, Natick, MA).

Electromyography

Bipolar surface electromyography (EMG) was recorded with rectangular 16×19 mm Ag/AgCl electrodes (Ambu, type BRS-50-K/12, Ambu BV, Schiphol Airport, the Netherlands). The inter electrode distance was 20 mm. Six muscles in the forearm and 1 thenar muscle were recorded: the abductor pollicis brevis (APB), abductor pollicis longus / extensor pollicis brevis (EPB), extensor digitorum communis (EDC), extensor carpi ulnaris (ECU), extensor carpi radialis (ECR), flexor carpi ulnaris (FCU) and flexor carpi radialis (FCR). Before application of the surface electrodes, the skin was shaved and prepared [2] with an abrasive gel (Nuprep, Weaver and Company, Aurora, CO). EMG signals were differentially amplified by a K-Lab amplifier (K-Lab, Haarlem, the Netherlands) with a gain of 18750, input impedance > 10 GΩ, common mode rejection ratio > 110 dB and input voltage noise < 2 µV. EMG signals were digitized by a 16 bits analog-to-digital converter with a sample rate of 2 kHz. To reduce noise and movement artifacts, EMG signals were online filtered with a 3rd order Butterworth high-pass filter with a cut-off frequency of 20 Hz and offline filtered with a 2nd order, zero-phase-shift Butterworth band-pass filter with cut-off frequencies of 20 and 400 Hz in Matlab (R2011b, the Mathworks, Natick, MA).

Subjects performed 10 repetitions of the movement task. The resulting binary output from the autonomous burst detector was averaged to obtain a group-mean MOOP. The resulting MOOP indicated in how many cases the muscle was contracted during the reaching movement.

To calculate differences in timing of muscle activation, the MOOP of each muscle was compared to the MOOP of the EDC, which was regarded as the prime mover during these reach-to-grasp tasks. For this purpose the time derivative of each MOOP was cross correlated with the time derivative of the MOOP of EDC. This cross correlation yielded a phase lead or lag, compared to the activation of EDC.

Statistics

For the simulations, onset and offset errors were compared by means of a repeated measures analysis of variance (ANOVA) with within-subjects factors "TKEO" (2 levels) and between-subjects factor noise amplitude "An" (10 levels). With Šidák adjustment for multiple post-hoc comparisons, effects were considered statistically significant for $p < 0.05$. Statistical tests were performed with IBM SPSS Statistics version 19 (International Business Machines Corp, New York, NY).

3. Results

Simulations

The RMS values of the synthesized EMG traces and their corresponding RMS values in the TKEO domain are displayed in Fig. 4. EMG with an RMS value below 10 µV (62.3 µV^2 in the TKEO domain) was regarded as noise. The muscle was regarded as being active when RMS EMG exceeds 15 µV (138.7 µV^2 in TKEO domain). An example of a synthesized EMG trace and the output of the burst detector is displayed in Fig. 2.

Onset and offset errors

Both onset and offset errors increased with increasing noise amplitudes, see Fig. 5. Onset errors differed significantly ($p < 0.001$) after inclusion of the
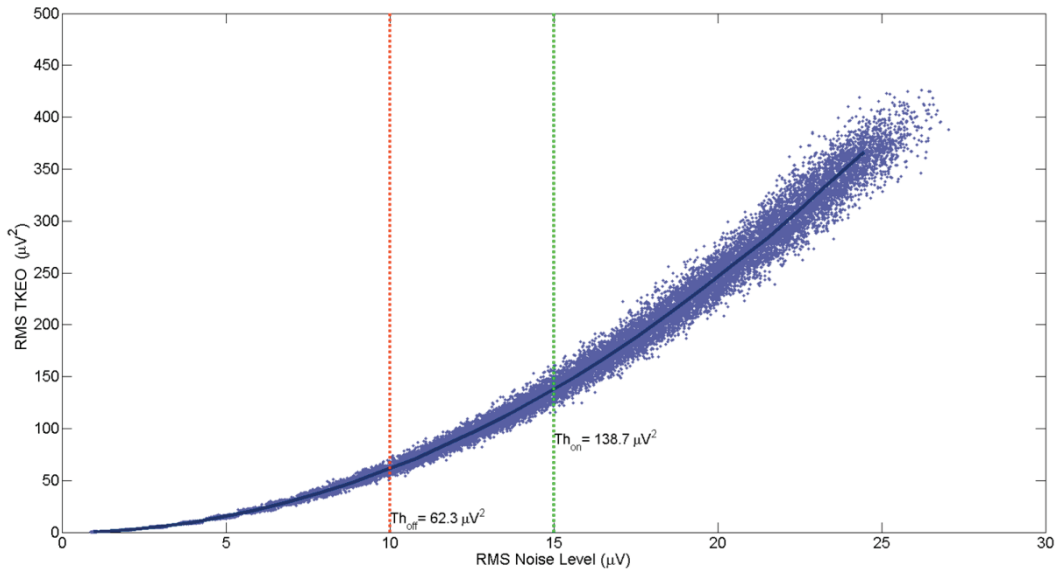

Fig. 4. Relation between the RMS value of synthesized EMG traces and the corresponding RMS values in the TKEO domain. The green and red lines represent threshold values for muscle onset (Th$_{on}$) and offset (Th$_{off}$) respectively
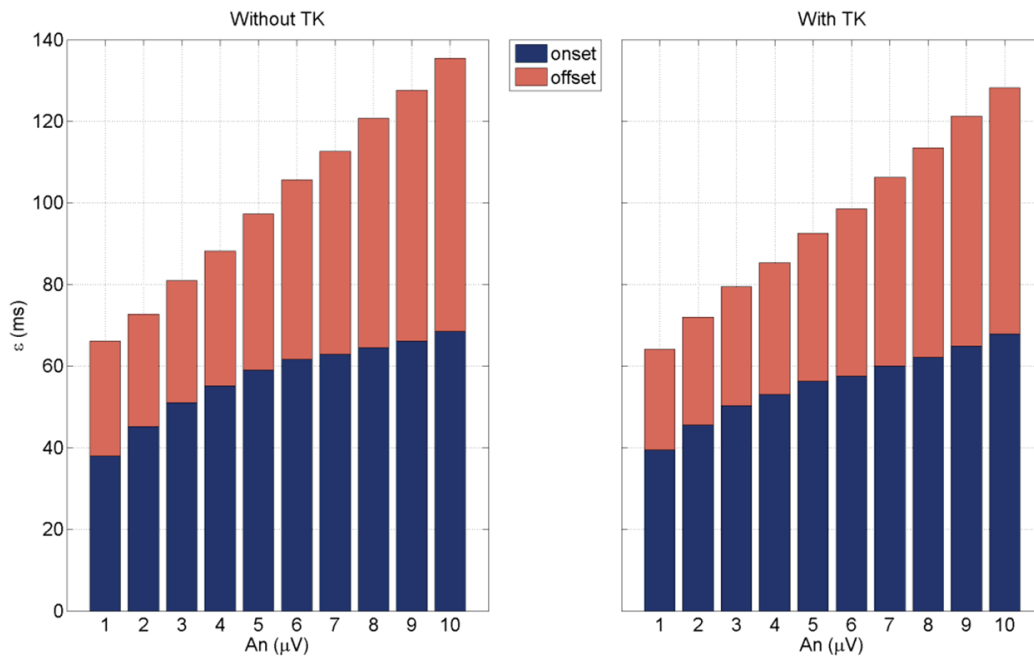

Fig. 5. Onset and offset errors in ms without Teager-Kaiser data pre-processing (left) and with Teager–Kaiser data pre-processing (right)

TKEO algorithm. Changes in onset errors were also dependent on noise level (TKEO*An, $p < 0.001$), leading to smaller onset errors after applying TKEO for $3 \leq An \leq 10$ µV and slightly bigger onset errors after applying TKEO for $An = 1$ and 2 µV.

Mean onset and offset detection errors in ms for each combination of threshold "*h*" and window length "*L*" are shown in Figs. 6 and 7, respectively. Combinations of "*h*" and "*L*" where the detection ratio differed from 100%, either because more than 1 burst of EMG was detected (type I error) or no burst at all was detected (type II error), are indicated by white color, see Fig. 7.
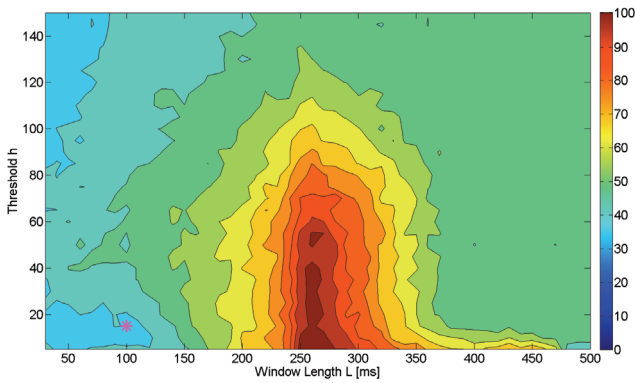
The minimal value of the total detection error, i.e., the sum of onset and offset errors, was achieved with a threshold "*h*" of 15 and a window length "*L*" of 100 ms. These values are highlighted in Figs. 6 and 7 by purple asterisks. These values were used when the burst detector was applied to real EMG activity.
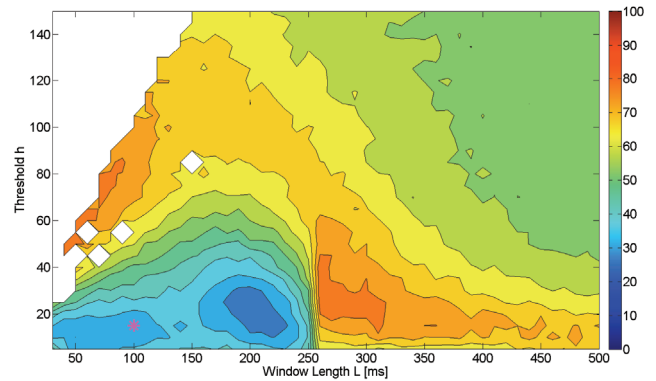

Fig. 7. Mean offset detection errors in ms
depending on threshold "*h*" and window length "*L*"

Reaching movements

Maximal hand opening during reaching movements was on average 12.8 cm. Maximal hand opening occurred when the distance between the MCP3 and the target was on average 11.1 cm which corresponds to 68.4% of the reaching phase, see also Fig. 8.

Fig. 6. Mean onset detection errors in ms
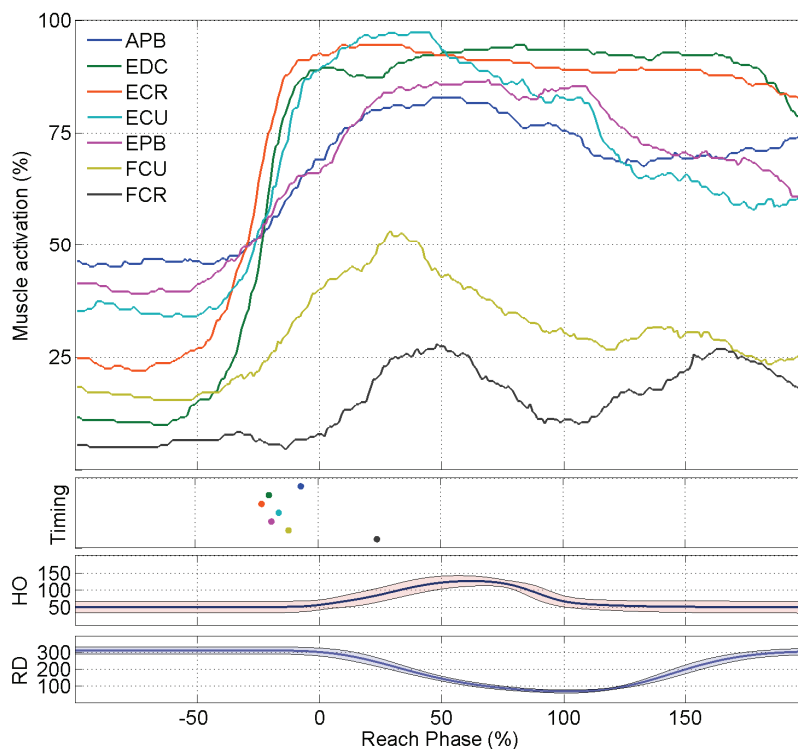depending on threshold "*h*" and window length "*L*"

Fig. 8. Group mean Muscle On- and Offset Profile (MOOP) and timing with respect to EDR onset (top and second panel)
as well as hand opening (HO in mm) and reaching distance (RD in mm) in the bottom two panels (mean +/–1 standard deviation)

Figure 8 displays the MOOP of the reaching task. Based on timing and amplitude of the MOOP, muscle activation during the reach-to-grasp task can be divided into three groups. The first group containing EDC, ECR, and ECU, has the most pronounced muscle activation characterized by almost no muscle activation before movement onset, high activation during movement and a high slope just before movement onset (Reach Phase = 0%). Muscle activation of ECR and ECU was almost simultaneous with EDC (lag = –3% and 4%, respectively).

The second group contains the thumb extensor and abductor muscles APB and EPB. Before movement onset, these muscles are activated in around 50% of the cases. Maximum increase of the MOOP of these muscles occurred almost simultaneously with EDC, with lags of 13% and 1% of the movement time respectively.

The third group is formed by the flexors FCU and FCR. Muscle activation of these muscles remained below 55% during the entire movement. Low values around 15% and 10% are observed before movement onset. With respect to EDC, muscle activation of FCU and FCR is delayed with 8% and 44% of the movement time.

4. Discussion

The present study shows that inclusion of the TKEO in an AGLR-based burst detector, leads to decreased muscle onset and offset detection errors in simulated EMG traces. The burst detector consists of the TKEO [5] to enhance signal quality, the AGLR [23] algorithm to detect changes in signal variance and a cascaded knowledge based postprocessor that classifies the detected change times as muscle onset and offsets. AGLR parameters were optimized for minimal onset and offset detection errors by applying the burst detector to simulated EMG traces with known onset and offset times. The resulting burst detector is able to autonomously create MOOPs of 7 muscles of the forearm and hand involved in reaching for and grasping of objects in a sample of 18 healthy adults.

A study applying TKEO to EMG recordings of the vastus lateralis muscle in 17 healthy subjects showed that adding TKEO to onset detection with a threshold based algorithm [20] resulted in smaller onset errors regardless of the SNR of the EMG. In a subsequent study [21], similar results were observed when EMG bursts were identified by visual inspection and by

means of the AGLR algorithm. This is in line with the present simulation results, in terms of reduction of detection errors. In the present study, onset errors were smaller after application of the TKEO when the background noise level exceeded 2 µV (SNR < 18.4 dB), and slightly bigger when noise levels were below 2 µV. The magnitude of onset errors was comparable to those reported by Solnik et al., ranging from 40–66 ms [20, 21]. Remarkably, Solnik used EMG signals constructed from EMG recordings during rest and during near-maximal contractions, i.e., the ramp-up EMG signal during initiation of muscle activation was removed from the data. However, the slow ramp-up signal (125 µV·s^{-1}) included in the EMG recordings in the present study corresponds better with real-life functional movements at a sub-maximal level. Adding the finding that TKEO is mainly beneficial when noise in EMG exceeds 2 µV as found in the present study, which is very likely to occur in such context, TKEO presents a useful tool as data preconditioning to reduce onset and offset errors in autonomous burst detection.

An additional advantage of the TKEO, particularly for application with smaller muscles, regards its tendency to increase the SNR in EMG signals, since both signal amplitude and frequency content increase during muscle contraction. Due to its non-linear behavior it is particularly sensitive to high frequency content, which primarily originates from superficial muscles directly below the sEMG electrodes. Higher frequency EMG signals that originate from neighboring muscles are attenuated by the surrounding tissue acting like a low pass filter [2], [11]. In other words, only low-frequency cross talk signals arrive at the electrode, for which TKEO is less sensitive. Therefore, the use of TKEO leads to spatial filtering that suppresses cross talk [13] which is likely to occur in EMG measured at the forearm where small muscles lie close to each other.

Furthermore, TKEO requires only three samples to estimate the signal energy at each sample time, resulting in low computational demands, which even enables semi real time applications such as EMG driven (training) devices. Even though absolute improvements in onset detection were rather small, these advantages warrant application of TKEO as data preconditioning for autonomous burst detection during real life, sub-maximal arm-hand movements.

To confirm correct functioning of the burst detector in realistic conditions, the burst detector was applied to real sEMG signals that were obtained from a sub-maximal reach-to-grasp task performed by healthy adults. During this task, maximal hand opening oc-

curred between 60 and 70% of the reaching phase, which is in accordance with previous studies addressing kinematics of reaching for and grasping of a cylindrical object [17], [19], [25]. Furthermore, Sangole et al. [19] observed that hand shaping started simultaneously with the arm transport or reaching phase. Similar results were seen in this study, both in kinematic and EMG data. The autonomously extracted MOOP showed that hand opening started with finger extension, shortly followed by thumb abduction/extension and by contraction of the wrist flexors, approximately halfway through the reaching phase.

Application of the burst detector in other groups of muscles is possible, but might require adjustment of thresholds "Th$_{on}$" and "Th$_{off}$". The application of the autonomous burst detector will be explored further in future work, where firstly kinematics and MOOPs will be compared between both healthy adults and stroke patients. Subsequently, this information can be used to develop control algorithms for an EMG driven electrical stimulator that can be used to support hand opening and closing in conjunction with a robotic arm training device.

5. Conclusions

The present study demonstrated a beneficial effect of the TKEO as data pre-processor in an autonomous burst detector that can be used to create onset and offset profiles from surface EMG. Simulations yielded parameter settings with minimal onset and offset errors, combining AGLR based burst detection with TKEO for data preconditioning. Using an additional knowledge-based postprocessor, the burst detector was able to autonomously create MOOPs from muscles in the forearm and hand that are in accordance with muscle activation profiles described in literature. The burst detector can be used to objectively compare MOOPs that are obtained from different movement tasks or different groups of subjects, such as healthy adults and people with neurological disorders. Burst detectors that can operate autonomously and in real time, can be used to control biomedical (training) devices such as for example, EMG controlled prostheses.

Acknowledgments

Conflict of interest

The authors declare that they have no conflict of interest.

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