RESEARCH

Review and Performance Comparison of EMG Onset Detection Methods Towards Real-Time Control of Robotic Exoskeletons

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Abstract

Background: Electromyography (EMG) is a classical technique used to records electrical activity associated with muscle contraction and is widely applied in biomechanics, biomedical engineering, neuroscience and rehabilitation robotics. Determining muscle activation onset timing, which can be used to infer movement intention and trigger prostheses and robotic exoskeletons, is still a big challenge. The first aim of this paper was to perform a review of the state-of-the-art of EMG onset detection methods. The second aim was to compare the performance of the most commonly used methods on experimental EMG data.

Methods: A total of 158 papers published until March 2022 were included in the review. The papers were analyzed in terms of application domain, pre-processing method and EMG onset detection method. The three most commonly used methods (Single (ST), Double (DT) and Adaptive Threshold (AT)) were applied offline to experimental intramuscular (iEMG) and surface EMG (sEMG) signals obtained during contractions of ankle and knee joint muscles.

Results: DT required more processing time, which led to increased average onset timing detection. Regarding the three methods, ST, DT and AT, muscle onset was detected earlier from iEMG (by 0.16s, 0.02s and 0.17s, respectively) signals compared to concurrently recorded sEMG signals. AT achieved an error detection rate of only 7.3 %, proving to be a reliable option for the automatic detection of muscle activity onset timing in an offline analysis.

Conclusions: This study organized and classified the existing EMG onset detection methods to create consensus towards a possible standardized method for EMG onset detection, which would also allow more reproducibility across studies. Two of the most commonly used methods (ST and AT) proved to be accurate and fast in terms of EMG onset detection time, especially when applied to iEMG data. These are very important results towards movement intention identification. In that sense, this opens the window to further explore these methods in real-time applications.

Keywords: Electromyography; EMG onset; Movement detection; Real-time; Robotic Exoskeletons

Background

Electromyography (EMG) has been used as interface tool for human-robot interaction and rehabilitation systems[1]. In fact, EMG is a relevant biological signal to inform on the motion onset of the user and can be applied in different applications such as the control of robotic devices in rehabilitation, kinesiology, biomechanics and motor control during several movements of the upper and lower extremities [2, 3, 4, 5, 6, 7].

Muscle activation can be defined as the degree to which a muscle is excited, encompassing both the number of activated muscle fibers and the rate of their discharge [8]. Therefore, muscle activation onset, which is commonly estimated from EMG, is a physiological variable related to the beginning of contraction of a given muscle. As there is a latency between the onset time and the final movement that involves action on tendons and bones, there is a time window after detecting movement intention that allows actuation and control of wearable robots such as an exoskeleton. Therefore, accurate and fast detection of muscle on-

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set time can potentially be used to identify movement intention [9, 2] and assist the user in real time.

The first method applied to detect muscle onset was the offline visual inspection by a trained user [10]. Although it is a subjective approach, visual inspection can be considered to provide accurate EMG onset detection values [10, 11]. On the other hand, visual inspection lacks reproducibility and can hardly be used in real-time applications [10]. In this context, computerized methods started to be developed and applied, and are currently the main solution to detect EMG onset in robotics and neurofeedback fields.

Due to the stochastic nature of the EMG signal, detecting onset of muscle activation is a challenging task, especially when EMG signals are weak [12]. Furthermore, despite the extensive literature devoted to detection of muscle contraction episodes, there is not a gold standard approach yet [13] and there is a degree of disparity across studies with regard to the algorithms definitions and parameters applied to identify onset of muscle contraction.

This leads to similar EMG onset detection methods with different nomenclatures, making it difficult to identify the most appropriated method for a specific application [11, 10, 13].

Given the lack of agreement on a standardized method for online EMG onset detection and its importance towards intuitive and natural EMG-based control systems, it is timely to explore methods for automatic EMG onset detection in this review and to compare the performance of some of the most commonly used ones towards online applications. Therefore, the first goal of this study was to review the state-of-the-art on EMG onset detection algorithms, applied either on intramuscular (iEMG) or surface EMG (sEMG) data. This can boost the development of novel algorithms and finally create consensus towards a possible standardized method for EMG onset detection, which would also allow more reproducibility across studies. The standardization trend is already being carried out in the literature. A recent example is the CEDE project, an international initiative which aims to guide decision-making in recording, analysis, and interpretation of EMG data. Results of the project encompass definitions for terms used in the EMG literature, basic principles for recording and analyzing EMG and electrode selection [8, 14].

The second goal of this study was to evaluate the performance of the most commonly used onset methods (three threshold-based algorithms - single (ST), double (DT) and adaptive threshold (AT)) to determine muscle onset. This allowed us to to evaluate the potential of these methods for the real-time control of wearable robots (e.g. robotic exoskeletons).

Literature Review

This review was based on the papers retrieved from the Scopus database using the following query strings:

TITLE-ABS-KEY ((emg OR electromyograph*) AND (onset AND detection))

and

TITLE((emg OR electromyograph*) AND (onset OR muscle OR movement) AND (detection OR activation)).

The first search returned a total of 245 papers and the second search 171, for a total of 416 possible publications. This research considered papers published until March 2022.

We applied the following exclusion criteria for our review:

- papers aiming at detecting muscle fatigue;
- use of additional sensors (i.e. inertial measurement unit).

A total of 156 full-text journal articles were selected for analysis. The papers were analysed in terms of their application domain, EMG source type, pre-processing method and EMG onset detection method.

In the application domain, papers were classified as follows: Robotics, Clinical, Research, and Others. Specifically, papers that used EMG onset detection in the robotics domain (e.g., to control a robotic device) were classified as Robotics. Papers that centered their goal on applying EMG onset techniques for clinical purposes or in the clinical setting were defined as Clinical. Research papers were those that proposed and/or tested a new technique of EMG onset detection. Remaining papers were classified as Others.

Pre-processing methods used to improve EMG quality before the application of the onset method itself were also analyzed in detail.

Literature Review Results

Figure 1 presents the number of research papers on EMG onset detection methods along the years. After analyzing all papers selected, the pre-processing and EMG onset detection methods were classified and defined according to the methods used and their relevance in terms of papers in the literature that applied each of them.

Pre-processing Methods

Pre-processing methods, used to improve EMG quality towards the extraction of meaningful information, usually add more computational time, which means a delay in real-time implementations. The pre-processing

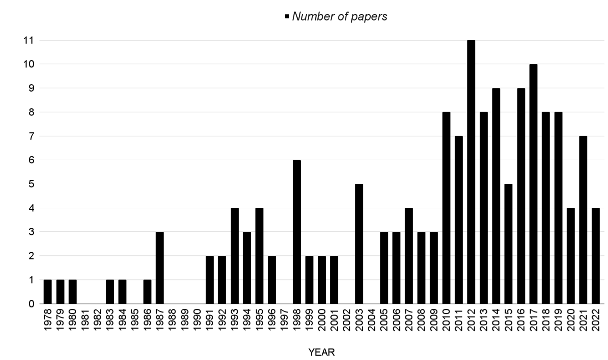

Figure 1 Trend of research on EMG onset detection.

methods evaluated in this review were classified in the following categories: Envelope method, Teager-Kaiser Energy Operator (TKEO), Wavelet Transform, and, for those that did not fit in none of these categories, the "Others" category. Different pre-processing methods were applied 90 times in the papers reviewed. Calculating the EMG envelope was the method most frequently used, followed by the TKEO method.

SIGNAL ENVELOPE

According to the CEDE project, EMG envelope is a smooth curve that tracks changes in the amplitude of an EMG signal over time[8]. Calculating the EMG envelope is a pre-processing method that can be obtained in several ways, as shown in Figure 2.

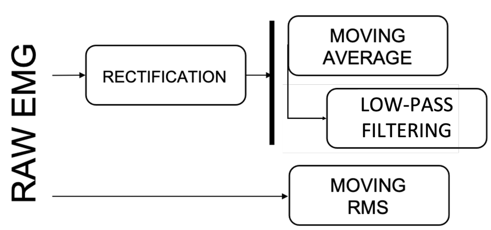

Figure 2 Methods to calculate the signal envelope from the raw EMG signal.

To obtain the EMG envelope from raw signals, two main options are available: 1) low-pass filtering of the rectified signal; 2) root-mean-square (RMS) on raw EMG signal.

Low-pass filtering of the rectified signal: Another way to acquire the EMG envelope is to use a discrete version of traditional low-pass filters such as Butterworth or Chebyshev. These filters can be considered as Infinite Impulse Response (IIR) filters [15]. This method was applied in: [16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26], with the Butterworth being the most predominant filter used.

Moving Average (MA): According to the CEDE project, MA is defined as a method to smooth EMG data, that acts as a low-pass filter, reducing random fluctuations in the rectified or squared EMG signal [8].

According to the literature review, this method was first used in the context of EMG onset detection by Maple-Horvart and Gilbey in 1992 [27]. After that, MA was applied to calculate EMG envelopes for EMG onset detection in several other papers: [28, 29, 30, 31, 32, 33, 34, 13, 35, 36, 37, 38, 39, 40, 41].

The MA is calculated with a series of averages from successive segments, with or without overlapping windows. The consequence of its use is the attenuation of rapid variations through local averaging, but retention of slow variations [28], smoothing the signal and acquiring its envelope.

RMS on raw EMG signal: This method ([42, 28, 43, 33, 44, 45, 46, 47, 48, 49, 50, 51]) computes the RMS value of the signal within a window that "moves" across the EMG signal.

The RMS value measures the square root of the signal's power, thus it has a clear physical meaning. For this reason, the RMS value is normally used for several applications [42]. EMG envelopes can be calculated from the RMS according to Equation 1.

$$X_{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \qquad (1)$$

Where x_i is the EMG value in the i^{th} sample and N the number of samples.

TEAGER-KAISER ENERGY OPERATOR (TKEO)

The TKE operator method ([52, 53, 17, 53, 54, 55, 56, 57, 58, 48, 59, 60, 25, 38, 39, 61, 62, 63, 64, 40, 65, 66, 67]) was first proposed by Teager in 1982 [68, 69, 70]. Teager performed experiments, from which results suggested that the production of speech involved nonlinear processes. As a result, Teager derived the TKE operator in the discrete-time domain to compute the energy of a sound. This method has been extended to cover other continuous signals such as EMG [53].

The discrete TKE operator ψ is defined in the time domain as:

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

Where n is the sequence index and x the raw EMG signal. Considering a signal defined by equation 3:

$$x(n) = Acos[\omega_0(n) + \theta] \quad (3)$$

Where A is the amplitude, $\omega_0(n)$ is the angular frequency, and θ is the initial phase, the energy operator can be rewritten as defined in Equation 4:

$$\psi_d[x(n)] \approx A^2 sin^2(\omega_0) \quad (4)$$

Equation 4 shows that the TKEO is proportional to the instantaneous amplitude (A) and frequency (ω_0) of the input signal. Therefore, TKEO is usually applied on EMG signals to extract motor unit activity by making the action potential spikes sharper and narrower, enhancing the muscle activation points [53].

Several studies have demonstrated that pre-processing using TKEO can improve the EMG onset detection with respect to different pre-processing methods [71, 17, 57, 52, 53].

WAVELET TRANSFORM (WT)
Pre-processing of raw EMG using the wavelet transform was applied in the following papers: [72, 73, 74, 52, 75, 76, 32, 77, 48, 59, 62, 64, 78, 67].

The WT is one of many time-frequency representations used in signal processing. These transforms deconstruct a time domain signal into a sum of signals of different scales and time shifts, to produce a time-frequency representation of a time domain signal [8].

OTHER PRE-PROCESSING METHODS
The other pre-processing methods found in the literature were the Hilbert filter [79, 9, 80, 81], the Kalman filter [82], the Morphological Close Operator (MCO)[38, 55], the Morphological Open Operator (MOO)[38], the Multi Objective Optimization Genetic Algorithm (MOOGA)[83], the Adaptative Linear Energy Detector (ALED)[84], the use of an statistical criterion based on the amplitude distribution of EMG signal[85], the Constant False Alarm Rate (CFAR) method[86] and the Empirical Mode Decomposition (EMD)[81].

EMG Onset Detection
EMG onset detection methods are those that, when applied to the EMG signal (raw or pre-processed signal), allow the identification of the beginning of muscle activation. Onset of muscle activation can be detected using mainly the following methods: Visual, Threshold based and Statistical methods. EMG onset detection methods that do not fit the previous techniques were classified as "Other EMG onset Detection Methods".

Figure 3 shows the number of papers that applied each of these categories, in the context of the application domains previously described. The most remarkable application field is the "Research" domain. EMG onset detection has been applied in this field more than in all the other fields together, indicating that still there's a lack of standard on the EMG onset detection.

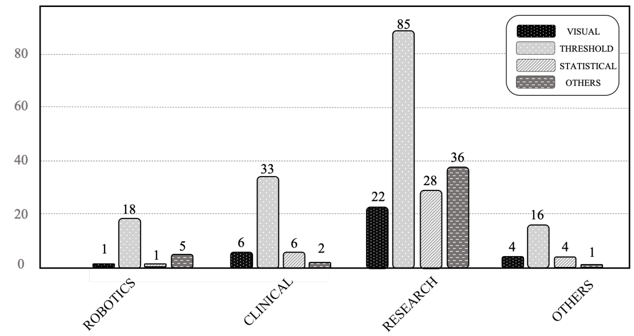

Figure 3 Application domain findings.

VISUAL METHOD
Visual inspection entails subjectivity and needs to be performed by an expert. There are no criteria on the visual inspection technique, although it is usually employed to detect the earliest rise in EMG activity above the steady-state (*i.e.*, basal activity) [87, 88, 89, 90, 50, 91, 92, 93].

Despite being a subjective technique, visual inspection can be used to validate automatic EMG onset detection methods, serving as a gold-standard on the development of computerized algorithms of EMG onset detection methods. Visual EMG onset detection has been widely referred in the literature: [94, 11, 73, 52, 95, 17, 96, 32, 33, 97, 98, 49, 21, 57, 99, 36, 24, 43, 60, 25, 100, 60, 26, 101].

THRESHOLD METHODS
Threshold-based methods are the most common EMG onset detection methods found in the literature, appearing 253 times in all revised papers. It this method, one attributes a threshold to discriminate between baseline activity and muscle activation. Nonetheless, there is lack of agreement among researchers on a standardized threshold method for EMG onset detection[46].

Cavanagh et al. were the first to propose the use of a threshold method [102]: authors investigated the dependence of electromechanical delay in the human elbow flexor group upon selected initial conditions at the time of muscle activation. Most common strategies followed to set threshold values are based on the baseline amplitude characteristics of the EMG signal, such as the mean or standard deviation. Some researchers name this strategy as the Shewhart protocol [16, 30, 103, 104].

Some of the signal characteristics that can be considered for the threshold selection are the following:

- Standard Deviation (SD);
- Period of time;
- % Maximum Voluntary Contraction (MVC);
- % Maximum EMG Amplitud Peak.

The threshold method can be classified in three different methods: Single Threshold (ST), Double Threshold (DT) and Adaptive Threshold (AT).

Single Threshold (ST) ST method is the most predominant EMG onset detection method found in the literature: [105, 102, 106, 107, 108, 109, 110, 94, 111, 112, 11, 113, 85, 114, 29, 115, 30, 2, 116, 16, 31, 74, 117, 118, 52, 82, 53, 119, 81, 95, 80, 46, 17, 32, 120, 121, 45, 122, 77, 123, 124, 125, 98, 126, 55, 13, 18, 19, 56, 127, 128, 22, 23, 57, 47, 24, 37, 35, 36, 43, 129, 83, 48, 59, 60, 38, 39, 41, 40, 130, 63, 131, 132, 133, 66, 51, 67, 134].

ST compares the raw signal amplitude with a previously selected threshold. The onset is detected when the EMG amplitude is bigger than the threshold.

This method can be considered the most intuitive and standard computer-based method of time-locating the onset of muscle contraction activity [2].

ST can be useful in overcoming some of the problems related to visual inspection. However, results of applying ST strongly depend on the choice of the threshold [135], which can lead to false positives in noisy signals, in theses cases, the signal envelope could be used to smooth the signal and improve the detection.

Double Threshold (DT): The DT method was applied in the following studies: [136, 137, 138, 139, 94, 140, 141, 142, 143, 144, 10, 2, 116, 73, 82, 145, 81, 120, 121, 124, 33, 122, 34, 146, 19, 42, 55, 20, 21, 147, 128, 148, 149, 24, 99, 129, 150, 151, 86, 152, 65, 93, 51].

To overcome some of the ST problems, Lidierth et al. introduced the DT method in 1986 [136]. This method adds a second threshold to determine the muscle activation onset time, with the final goal of avoiding false positives and enhance EMG onset detection precision. A common strategy when applying DT method is to define an amplitude threshold, similar to what is done in ST. If the signal amplitude is higher than this threshold for a certain amount of time or samples (second threshold), then muscle activation is detected with DT. Due to the stochastic characteristics of the EMG signal, it is normally necessary to use a pre-processing method to acquire the signal envelope and make it possible to apply the second threshold.

Adaptive Threshold (AT) The AT method can be applied directly to the raw EMG signal. AT method segments the signal using the signal-to-noise (SNR) [61] or the energy value [84] to adapt the threshold of muscle activation by windows. As the SNR is the relative power of wanted EMG to unwanted signal components that are contained in the overall signal [8], this threshold method can be considered as an improvement of ST method, as it adapts its threshold value according to the EMG window being analyzed, which might enable a more precise EMG onset detection over time. AT was applied in the following works: [153, 11, 119, 154, 96, 122, 155, 54, 52, 156, 55, 84, 157].

STATISTICAL METHODS

The onset of muscle activation can be detected by evaluating the statistical properties of the EMG signal before and after a possible change in model parameters [116]. Two main statistical approaches can be identified in the literature: the Approximated Generalized Likelihood Ratio (AGLR) and the Cumulative Sum (CUSUM).

Approximated Generalized Likelihood Ratio (AGLR)
The AGLR method was applied in the following publications: [158, 159, 160, 72, 10, 116, 52, 82, 17, 122, 77, 57, 37, 99, 129, 58, 92, 93, 161, 67].

Sometimes also referred to as "Maximum Likelihood Estimator", this method was first proposed as a change detection algorithm, with its first use in the context of muscle activity detection being presented in Hogan et al., in 1980 [158]. In short, the AGLR algorithm calculates an estimate of muscle activity as a function of the mean and variance of the activity level [122].

By using a log-likehood ratio test $g(k)$ [66], the AGLR method detects if there is muscle contraction or not.

The log-likelihood ratio test is defined by the following equation:

$$g(k) = ln\left(\prod_{k=1}^{r}\frac{p1(Y_n|H_1)}{p0(Y_n|H_0)}\right) \quad (5)$$

Where ln represents the natural logarithm, $Y(n)$ represents the series of EMG samples, k the index of the product, r is the total length of the series, $p1$ and $p0$ represent the probability density function corresponding the alternative hypothesis H_1 (i.e., there are changes in the statistical properties of the EMG sequence) and the null hypothesis H_0 (i.e., there are no changes in the statistical properties of the EMG sequence), respectively.

If the log-likelihood $g(k)$ value is smaller than a predefined threshold, it indicates that the muscle is relaxed, whereas EMG onset is detected if $g(k)$ value exceeds the threshold.

Cumulative Sum (CUSUM): This method was used by:[109, 94, 72, 67]. CUSUM was first proposed by Ellaway in 1978 [162] with applications on the analysis of histograms.

The first study to propose the use of CUSUM to detect EMG onset was Chanaud et al, in 1991 [109], which used this method to determine how the different regions of the biceps femoris activated in a cat during a broad range of limb movements.

The CUSUM method works as follows [162]: a reference level (k), dependent on the task to be performed and selection in a previous training phase, is subtracted from each of the series of points on the signal $(x1, x2, ..., xi, ..., Xn)$. The result of these subtractions, showed in equation 6, is a new series of points (Si) which are formed by adding up these differences consecutively.

$$\begin{aligned} S1 &= (x1 - k) \\ S2 &= (x1 - k) + (x2 - k) \end{aligned} \tag{6}$$

The CUSUM chart is defined as the sequential plot of the values of Si, expressed by the Equation 7:

$$Si = \sum (xi - k) \tag{7}$$

The CUSUM technique has a smoothing action on the data [162] and the EMG onset detection is determined by a previous threshold, which can be previously defined by a training phase (see [72] for more details).

Other Statistical Methods : Other statistical methods were also used in the following papers [61, 49, 163, 164, 148, 146, 60, 25, 75, 50, 161]

OTHER EMG ONSET DETECTION METHODS
Other methods could be classified as: Energy-based methods [84, 34, 91], Entropy-based methods [25, 38, 126, 12, 147], Mathematical/numerical techniques [16, 165, 166, 55, 9, 78], Neural Networks [167, 33, 65], Computer Vision [128], Slope/discontinuities detectors [76, 62, 51] and External stimulation [168, 169].

Experimental Protocol

The second goal of this study was to compare the performance of the three most commonly used methods for EMG onset detection, having in mind their potential for online control of robotic exoskeletons for gait assistance or rehabilitation. As shown in Figure 3, threshold methods are the most commonly used methods in all domains (robotics, clinical and research). For this reason, ST, DT and AT were tested on real data (iEMG and sEMG signals) obtained during motor tasks involving knee and ankle joints.

Participants

Three healthy subjects participated in this study. All procedures were approved by a local ethical committee ("Ethical Committee of Clinical Research with Medicines of the Hospital Complex of Toledo"), as well as by the Spanish Agency of Medicines and Medical Devices (AEMPS) - record 721/19/EC. All subjects volunteered to participate in the study, were informed about the procedures and possible adverse effects, and signed the informed consent to participate.

Data Collection

EMG data were recorded with an EMG amplifier (Quattrocento, OT Bioelettronica, Torino, Italy) using a sampling frequency of 10,240 Hz. Surface and intramuscular EMG recorded from Tibialis Anterior (TA) and Vastus Lateralis (VL) were selected for analysis. EMG data were recorded while participants performed ankle flexion/extension and knee flexion/extension movements. More information on the protocol can be found in [170]. For sEMG recordings, bipolar electrodes (Ag-AgCl, Ambu Neuroline 720, Ambu, Ballerup, Denmark) were used. For iEMG recordings, intramuscular thin wire electrodes (Fi-Wi2, Spes Medica, Genova, Italy) were used.

Data Processing

EMG onset was automatically detected offline using each of the three threshold methods (ST, DT and AT) on the EMG data recorded from each muscle and participant. Threshold values were calculated individually for each subject and task, and were based on the SD of the baseline, visually accessed.

Threshold values were defined between 1 and 3 times (see Table 1)the SD of the EMG baseline, according to a training phase performed with each subject.

To perform the DT method, it is essential to use the EMG envelope pre-processing method due to the variation of the EMG amplitude over time (our second threshold). The envelope of the signal was calculated using a Butterworth low-pass filter of second-order with a cut-off filter of 6 Hz [15].

The time used to determinate muscle activation using DT method was of 2.50 ms, i.e., EMG envelope needed to stay above the first threshold for at least 2.5 ms in order for muscle activation to be detected.

Table 1 Values of EMG onset threshold used in the experiments. Values were based on the standard deviation of each subject and task.

Method	Task	S01	S02	S03
ST	Ankle	2 SD	2 SD	1 SD
	Knee	2 SD	1.5 SD	2 SD
DT	Ankle	1 SD	2.5 SD	1 SD
	Knee	3 SD	2.5 SD	3 SD
AT	Ankle	2 SD	2 SD	1.5 SD
	Knee	2 SD	2.5 SD	1 SD

The windows used in AT had a duration of 1/N of the total recording, where N is the number of movement cycles performed by the subject. To analyze the performance of each method, the number of false EMG onset detection events, the detection time and the processing time of each method were compared. Furthermore, the difference between onset timing calculated by each threshold method and the visual method (which was used as reference) was calculated for each cycle, task and subject. The average difference was calculated for each method and subject. For this step, the first and last cycle of movement in both knee and ankle task performance were not taken into account, to exclude possible transients in the signal. EMG onset detection times were also analyzed.

Results

The processing times needed by the computer (2,7 GHz Intel Core i7 processor) to compute the three threshold methods are shown in Table 2.

Table 2 Average processing time spent per cycle, that means, for each EMG onset detection, for ST, DT and AT methods.

Method	Processing time/ cycle [ms]
ST	1.250 ±0.23
DT	14.302 ±4.65
AT	1.905 ±0.14

This result reports the average processing time required to compute the time took to detect muscle onset activation for each cycle of movement uusing the ST, DT and AT methods.

DT method required more processing time (almost 10 times more) than the other two methods. The lengthy process required by DT to calculate EMG oset is due to the use of a pre-processing method (EMG envelope).

Regarding the detection of false positives, ST and DT methods obtained one false positive in a total of 124 cycles, which corresponds to 0.8% of detection error. The AT obtained 9 false positives, which corresponds to a 7.3% error of detection. Table 3 represents the average time differences that each automatic method needed to detect muscle activation compared to the visual method.

Table 3 Comparison of the average detection times between ST, DT and AT methods regarding the reference EMG onset detection (defined by visual inspection) in both sEMG and iEMG recordings and it's standard deviation.

Method	Subject 01 [ms]	Subject 02 [ms]	Subject 03 [ms]
ST	245.92 ±116.81	332.10 ±249.13	424.42 ±261.03
DT	210.31 ±180.10	502.47 ±245.90	574.57 ±192.89
AT	233.08 ±132.52	336.67 ±306.40	347.63 ±63.21

Considering the global performance of each threshold method, higher time precision was achieved using AT, which detected the onset of muscle activation, on average, 0.30 seconds after the visual method. ST and DT detected activation onset, on average, 0.33 seconds and 0.43 seconds after the visual method, respectively. Figure 4 shows an example of the detection timing for each of the threshold methods assessed, which were applied on iEMG data from TA during one cycle.

EMG is very selective (at least judging from the recording that clearly shows individual action potentials). If both iEMG and sEMG are considered in the experimental evaluation, it is relevant to discuss whether the iEMG was always detected at the level of individual motor units (as it seems in this example). If so, the comparison with the surface EMG is not easy to make (also in terms of algorithms

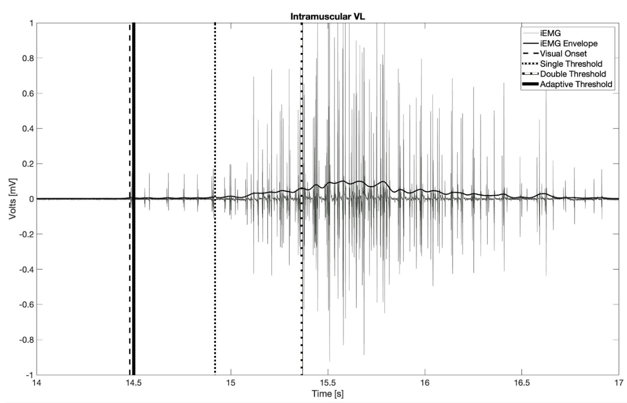

Figure 4 Example of EMG onset detection with the four methods in the TA from an intramuscular EMG recording.

Although the iEMG presented in Figure 4 is very selective, the iEMG signal was not always detected at the level of individual motor units, making a signal decomposition into individual motor unit action potentials not a viable option.

Table 4 presents differences in terms of detection times when applying each of the threshold methods on sEMG and iEMG recordings. Positive values mean that detection time in iEMG data happened before when compared to the corresponding sEMG data.

Muscle activation was detected before in the intramuscular signal in all subjects and methods, with the exception of the DT method in subject 02. On average,

Table 4 Comparison of the average EMG onset detection times between intramuscular and surface EMG for ST, DT and AT methods and it's standard deviation

Method	Subject 01 [ms]	Subject 02 [ms]	Subject 03 [ms]
ST	115.15 ±297.19	233.67 ±152.21	163.11 ±261.77
DT	46.86 ±524.71	-7.35 ±68.01	26.93 ±83.99
AT	157.92 ±364.06	293.94 ±323.81	21.31 ±297.51

ST, DT and AT methods detected muscle activation 0.17, 0.02 and 0.16 seconds before in iEMG than in sEMG recordings respectively.

Discussion

EMG has been increasingly applied in research as part of intuitive and natural control in Human–Robot Interaction (HRI) systems for restoration of human movement and control of external devices from neural activity. One key component of these systems is the detection of movement intention (i.e., the onset of muscle activity). Given the lack of agreement on a standardized method for online EMG onset detection, it is timely to explore methods for automatic detection. Review papers published so far have not performed an extensive classification and definition of the available methods. Therefore, the first goal of this study was to review the state-of-the-art on EMG onset detection algorithms. This can boost the development of novel algorithms and finally create consensus towards a possible standardized method, which would also allow more reproducibility across studies.

A total of 158 papers published until March 2022 were analyzed in terms of application domain (Robotics, Clinical, Research and Others), pre-processing methods and EMG onset detection methods.

Regarding the application domain, EMG onset detection has been applied in the "Research" field more than in all the other domains together (i.e., Robotics, Clinical and others). This result indicates that most author needs to perform a research of onset methods before applying to a real application, evidencing the lack of standard in the literature.

A total of 40% of all papers reviewed used a pre-processing method technique before applying one of the onset detection methods described in this review. Fast computational pre-processing methods are sometimes necessary to improve EMG quality towards the extraction of information. A basic estimation of the EMG envelope (average activation of the EMG signal), is the most frequently applied pre-processing algorithm across the reviewed papers.

Threshold-based methods were found to be the most commonly used methods for EMG onset detection, in all application domains. Implementation of threshold methods is straightforward and can explain its extensively use.

Surface EMG signal is susceptible to muscle cross-talk (EMG signals from muscles other than the muscle of interest [14, 8]), in addition to motion artefacts, and environmental conditions (mostly owing to the skin interface) [171], which might considerably degrade the controllability of the wearable robot. Even so, most of the threshold methods are applied with sEMG recordings and not with iEMG.

Direct measure of iEMG provides signals with higher SNR ratio and less muscle cross-talk, therefore more robust and selective signal for control purposes [170]. Considering some of the advantages and opportunities of using iEMG recordings towards intuitive EMG-based control systems, the second goal of this study was to evaluate the performance of the most commonly used threshold methods (single (ST), double (DT) and adaptive threshold (AT)) to determine muscle onset in real EMG data (sEMG and iEMG). This allowed us to evaluate the potential of these methods for the real-time control of wearable robots (e.g. robotic exoskeletons).

Results showed that DT required more processing time, which led to increased average onset timing detection compared to the other two methods. On the other hand, ST and AD proved to be accurate and fast in terms of EMG onset detection time, especially when applied on iEMG data. In that sense, this opens the window to further explore these methods in real-time applications such as the intuitive control of exoskeletons.

The ST was the faster threshold method in both surface and intramuscular results. This result was expected once ST doesn't require complex computational processing nor the use of pre-processing methods and signal treatment of any king to properly work. The DT method was the slower one, with a big difference regarding both ST and AT methods. The calculation of the envelope adds more processing time to the double threshold method, complicating its use in real-time applications. A possible solution is to optimize the envelope windows size, trading off performance and accuracy.

Comparing the EMG onset detection times of the three methods, the AT was the more precise one, which means that the average EMG onset detection using this method was closer from the gold standard compared to the other two methods. The DT was the less precise method, presenting a delay with respect to the visual detection of 0.43 seconds. The ST method calculates the threshold according to the entire EMG signal, which can lead to a less precise EMG onset detection time.

Another problem involving the simplicity of the ST method is the possibility to obtain false positives and false negatives, as there is only one condition of EMG onset detection. An example of this can be found in Solnik et al. [71], where they propose the use of TKEO pre-processing to improve accuracy on the EMG onset detection times regarding the ST method.

Results showed that the error of EMG onset detection using TKEO was significantly lower than the one using ST method. Lack of accuracy on the EMG onset detection, besides having false negative and positive detections can lead to misleading conclusions, and could compromise the results. Therefore, ST method should be considered to simpler applications, i.e, static rehabilitation tasks, where a fast response of the system is more important than its precision and false negatives and positives do not lead to security problems to the user.

The AT method calculates the threshold according to smaller windows of the whole signal, which can lead to more adapted threshold values, allowing a more precise muscle activation detection. This method is ideal for real-time applications that need more precision on the EMG onset detection time that the one single threshold can provide. Such real-time function is for example demonstrated in Zhang et. al [154], with a performance of an effective EMG-controlled meal assistance system. The results showed that the EMG onset could be adjusted automatically to avoid false alarms and worked well when the contraction power is not consistent in a real-time EMG-based control application.

DT method can be considered a more rigorous detecting method due to the use of two conditions of threshold (amplitude and time). With a high time threshold, there is, a large amount of time that the signal should maintain the first amplitude threshold, can lead to delay with respect to the real activation and a small-time threshold could lead to false positives. Nevertheless, a DT threshold method can be a robust solution to process offline EMG recordings. An example of this is showed in Silva et al., where they analyse EMG onset during the golf swing, by comparing ST and DT method [19].

Results showed that both methods achieved a similar EMG onset detection time, although in some cases occurred at different levels of maximum activity amplitude, indicating the reliability of the DT method when compared to the ST one, mainly in noisy EMG signals. These three threshold methods have been tested separately to analyse their individual performance. Intramuscular recordings resulted to be faster than the surface EMG in all methods except when using DT method for subject 2, there is, muscle activation is detected before with intramuscular recordings with surface recordings in almost all cases.

Early detection, with values under 50ms, can be critical for applications with real-time requirements and thus, intramuscular signals could be considered to be used as input for human-machine interfaces [9], for instance, as input information to the control of robotic exoskeletons, where timing is crucial for an efficient control strategy. The ST and AT methods showed to be faster than the DT method, once this last one need a pre-processing method to properly function. Despite the use of a pre-processing technique DT method was less precise on the EMG onset time of detection, which can lead to the control signal delays hindering its use in real-time applications.

In brief, ST method demonstrated to be the faster method but not so reliable in terms of detection, once it can lead to false positives and negatives, which can mislead the researcher to wrong conclusions. DT method was the slower one, due to the need of use a pre-processing method. Nevertheless, DT is a much more reliable method because of the use of two different thresholds to detect the onset of the muscle activation. AT is the most precise method, as its threshold adapts the signal thanks to the smaller windows of onset evaluation. AT can be a good solution where accuracy and fast processing times are needed.

The choice of what EMG onset processing method should vary according to the application's needs. A trade-off between processing speed, accuracy and quality should be take into account before defining which onset method best fits the application in question.

Conclusions

EMG can be used to infer movement intention and trigger exoskeletons and prostheses. However, determining the onset of muscle activation from EMG activity is not a trivial task. The first conclusion of this paper is that there is still no agreement on a standardized method for EMG onset detection (neither offline nor online), which hinders reproducibility across studies. Therefore, this study organized and classified the existing EMG onset detection methods in an attempt to bring additional interest to the field and create consensus towards a possible standardized method for EMG onset detection, which would also allow more reproducibility across studies. Despite the lack of standardized methods, the research interest has been growing along the years, with a soaring number of publications in the field.

A total of 158 papers published until March 2022 were analyzed in terms of application domain (Robotics, Clinical, Research and Others), pre-processing method and EMG onset detection method. Pre-processing methods are used to improve EMG quality towards the extraction of meaningful information, although this adds more computational time and might be a drawback towards real-time applications. EMG envelope, which represents the average activation of the EMG signal, was found to be the most used pre-processing method before applying algorithms aiming at detecting onset of muscle activity.

Threshold-based methods were found to be the most commonly used methods for EMG onset detection. The second goal of this study was to compare the performance of the most commonly used threshold methods (Single (ST), Double (DT) and Adaptive Threshold (AT)) in real EMG data. Results showed that DT required more processing time, which led to increased average onset timing detection compared to the other two methods. On the other hand, ST and AD proved to be accurate and fast in terms of EMG onset detection time, especially when applied on iEMG data.

These are very important features towards movement intention identification. In that sense, this opens the window to further explore these methods in real-time applications such as the intuitive control of exoskeletons.

Abbreviations
EMG: Electromyography; ST: Single Threshold; DT: Double Threshold; AT: Adaptive Threshold; iEMG: Intramuscular Electromyography; sEMG: Surface Electromyography; TKEO: Teager-Kaiser Energy Operator; RMS: Root-Mean-Square; IIR: Infinity Impulse Response; MA: Moving Average; WT: Wavelet Transform; MCO: Morphological Close Operator; MOO: Morphological Open Operator; MOOGA: Multi Objective Optimization Genetic Algorithm; ALED: Adaptive Linear Energy Detector; CFAR: Constant False Alarm Rate; EMD: Empirical Mode Decomposition; SD: Standard Deviation; MVC: Maximum Voluntary Contraction; AGLR: Approximated Generalized Likehood Ratio; CUSUM: Sumulative Sum; TA: Tibialis Anterior ; VL: Vastus Lateralis.

Ethics approval and consent to participate
Participants were informed about the procedures and possible discomfort associated with the experiments. After that, they signed an informed consent to participate. All procedures were conducted in accordance with the Declaration of Helsinki and approved by a local ethics committee, as well as by the Spanish Agency of Medicines and Medical Devices (AEMPS) - record 721/19/EC.

Consent for publication
Not applicable.

Availability of data and materials
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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Authors' contributions
CRC:main writing process for the manuscript. CRC, JMF, AJD-A, FOB and JCM: study design. CRC and JMF: data acquisition. CRC and JMF: data analysis. CRC, JMF, AJD-A, FOB and JCM: data interpretation. All authors: approval of final manuscript and agreement to be accountable for all aspects of the work while ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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