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Two stage EMG onset detection method

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Detection of the moment when a muscle begins to activate on the basis of EMG signal is important task for a number of biomechanical studies. In order to provide high accuracy of EMG onset detection, we developed novel method, that give results similar to that obtained by an expert. By means of this method, EMG is processed in two stages. The first stage gives rough estimation of EMG onset, whereas the second stage performs local, precise searching. The method was applied to support signal processing in biomechanical study concerning effect of body position on EMG activity and peak muscle torque stabilizing spinal column under static conditions.

Key words: EMG signal processing, real EMG recordings, expectation-maximization, kernel density estimation, event detection

1. Introduction

Detection of changes in noised signals is classical problem of signal processing. It is commonly solved task connected with various problems such as fault detection, diagnosis, prediction of natural catastrophic events (e.g. tsunami, earthquake), and monitoring in biomedicine [1]. In this work authors focus their attention on one of the field of biomedical signal analysis i.e. onset detection of EMG signals. These signals reflect electrical behaviour of muscles stimulating neuromuscular system and are recorded from the skin over the muscles. Analysis of these signals properties are used in research concerned with clinical diagnosis, [7] (e.g. diagnosis of neuromuscular, neurological and psychomotor disorders), rehabilitation, sport science, and engineering (e.g. control of neuro-prosthesis, grasp recognition, human-machine interaction and biofeedback system) [16, 10, 18].

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In general, there are two main approaches for EMG onset detection i.e.: visual inspection and algorithm-based approach. The first one is subjective and strongly depends on experience of an expert. This means that obtained results are not reproducible and are heavily biased by personal skills. Furthermore, analysis and processing of EMG signal is performed manually in most cases, [14]. This means that visual approach is very time consuming and, in practice, can be employed only for small datasets.

On the other hand, many researchers propose and use algorithms which help to overcome drawbacks of visual inspection methods: it's subjective character, operator dependency, and large time consumption. Many different methods to EMG onset detection was proposed. They have different properties, computational complexity and exactness. For example, real-time system demands fast algorithms having low computational complexity. If EMG signals can be processed off-line, more sophisticated algorithms offering greater accuracy are preferred. Exact estimations of EMG onset detection is crucial in the task of electromechanical delay calculation and other task related to analysis of human motor system [16].

EMG signals activity detection is challenging problem due to lack of exact mathematical definition of the „EMG onset". Typical problems are related to background noise presented during EMG signal recording. As it was stated by many researchers, signal to noise ratio (SNR) significantly affects accuracy of onset detection [12]. In [13] authors shows that high SNR reveals performance degradation of EMG onset detection algorithms. This problem may be exposed strongly when people with neuromuscular disorders are examined, but it occurs even for healthy ones. Another reason is power hum that may interfere with EMG signal during measurements.

Another problem making EMG signals detection challenging is connected with long ramps, meaning slowly increasing muscle activity [12]. It is clear that abrupt change in analyzed signals are easier to detect than slowly progressing changes in signal behavior. Moreover, neighboring motor units introduce their own signal patterns into measured signal. Those patterns typically look like real muscle activation patterns having very low amplitude and many algorithms fail to recognize them as noise.

Estimation of onset EMG involves two quality criteria common to all estimation procedures: bias and variance of estimate. It must be mentioned that exact estimation of onset EMG is required mostly in scientific and engineering research, where hypotheses concerning biomechanical phenomena are investigated and statistical inference takes place. Other applications, such as recognition of human arm movements, only make use of rough onset EMG estimations. Real-time applications prefer rough results returned immediately instead of exact results retuned too late. For those applications, simple approaches performs well enough, e.g. analysis of differences between amplitude variances evaluated over shifting window of a fixed length. However, there are many task where precise solution is very important. In sport science a problem of determining electromechanical delay (EMD) plays crucial role in biomechanical analysis. EMD is the difference between onset EMG and onset of the force moment, [5]. It is quite easy to detect regions of activity in force moment signal, because it is measured very accurately and signal-to-noise ratio is very high. However, in order to calculate EMD, precise algorithm to detect EMG onset is needed. Electromechanical delay is stated to take values between 30 and 100 ms [4], while length of single muscle's EMG recordings varies from about 1 s up to about 15 s. For statistical analysis, accuracy of onset EMG detection should allow to distinguish between at least 15 levels of EMD values. Thus, we demand biases of onset EMG estimates not to be greater than 2 ms, which is requirement very hard to satisfy.

2. Review of EMG onset detection methods

In [19, 18] authors propose general structure of EMG onset and offset detection algorithm. As it was noticed, in mentioned works most of methods contains the following processing stages:

- signal conditioning,
- detection of an event,
- estimation of the exact change time.

The first one, signal conditioning, stands for signal preprocessing, but in most of algorithms it simply reduces to filtering process. The filter type is chosen individually but in most cases low-pass filter, such as Butterworth, are applied. They are used in order to reduce high frequency noise. In more advanced methods whitening filters are also applied.

The second step is used to detect a moment of time when muscle goes from the relaxed state to contracted state. It must be stressed that methods must detect changes in EMG signals at the very beginning of activity burst. Therefore, the third step is introduced, which is the final decision step. After the second step we obtained information about the region when muscle activity has just arisen. The final step is about estimating onset EMG as accurately as possible on the basis of preprocessed signal and information generated during previous steps. Precise activation time calculation is based on result of event detection and the signal itself.

Before we describe methods of EMG onset detection, we introduce some notation:

$\{x(n)\}_{n=1}^{N}$ – recorded EMG signal,

τ_{on} – the time when onset is detected,

τ_0 – the time when change is detected,

σ – variance of the recorded EMG signal,

μ – mean value of the recorded EMG signal.

2.1. Single-threshold methods

One of the first method to detect onset of EMG was proposed by Komi and Cavanagh [4]. One purpose of the work was determination of electromechanical delay (EMD). As mentioned in the previous section, EMD is a delay between electrical activity and tension of muscle contraction. Since EMD takes quite small values, it is required to determine EMG onset detection precisely. Authors proposed method based on the threshold level. It is the most common and intuitive approach to determine not only EMG onset but also other signal's properties. Authors, analyzing results of experimental investigations, suggested sufficient threshold level for full wave rectified EMG on the level of 30 $[\mu V]$. This value is strongly related to noise generated by power hum and vibration in dynamometer. The main idea is very simple: estimate onset EMG after amplitude of the filtered signal exceeds the threshold. It is simple method but obtained results are not satisfactory and heavily depend on the choice of the threshold. In [22] authors propose to determine the threshold level as mean power of background noise. Unfortunately, it did not improve results meaningfully. Single-threshold methods do not allow user to set probability of detection and probability of false alarms independently.

Following the three-steps template introduced by [19], single-threshold method can be described in the following way

$$\tau_{on} = \min\{n : x(n) \geqslant h\}, \tag{1}$$

where h is the threshold which is compared with signal $x(n)$. It can be set to value 30 $[\mu V]$ (Komi's proposal).

There are different approaches to EMG onset detection utilizing the idea of single threshold but usually leading to more sophisticated calculations. Important group of methods is the finite moving average (FMA). They rest on fixed-size sliding window which is used to determine weighted sum of EMG signal amplitudes contained within window [18]. Usually raw EMG signal is rectified and low pass filtered (e.g. Butterworth filter). The rest part of the method is similar to describe above i.e. for processed signal weighted sum is determined and compared to specified threshold. If analyzed signal exceeds predefined value of the threshold, the time is detected as muscle activity region. Formal description of this method is given below:

$$\bar{x}(n) = \frac{1}{W} \sum_{m=n-W+1}^{n} x(m), \tag{2}$$

$$\mathcal{H}(\bar{x}(n)) = \frac{1}{\sigma}(\bar{x}(n) - \mu), \tag{3}$$

$$\tau_{on} = \min\{n : \mathcal{H}(\bar{x}(n)) \geqslant h\}, \tag{4}$$

where W is the length of the window, σ and μ are calculated over first M samples of background noise measurements.

2.2. Double-threshold methods

In order to overcome drawbacks of single-threshold detection methods mentioned in the previous subsection, a group of methods based on two thresholds were proposed [3]. As it was noticed by the author, single-threshold methods have only one degree of freedom. This limits possibility of controlling detection algorithm sensitivity and probability of false alarms occurrence [14]. Effectiveness of the single-threshold methods, measured by the number of false alarms, is reduced by low value of signal to noise ratio.

Double-threshold method proposed in [3] allows to decrease the number of false alarms and improves sensitivity of detection by increased number of degrees of freedom. The idea is as follows: for a given number of samples of EMG signal envelope a traditional single-threshold method is applied but signal onset is detected only when at least a predefined number (the second threshold) of consecutive samples exceed the first threshold. It is easy to see that proposed approach for EMG signal detection is defined by two parameters: the first threshold (from a traditional first-threshold method) and the second threshold (the number of consecutive samples exceeding the first threshold). Original approach proposed in [3] employs whitening procedure to guarantee independence of consecutive samples. The formal description of proposed algorithm is:

$$\widetilde{x}(n) = \mathcal{F}(x(n)), \tag{5}$$

$$\mathcal{H}(\widetilde{x}(n)) = \frac{1}{\sigma^2}(\widetilde{x}(n)^2 - \widetilde{x}(n)^2), \tag{6}$$

$$\tau_0 = \min\{n : \mathcal{H}(\widetilde{x}(n)) \geqslant h_1\}, \tag{7}$$

$$\tau_{on} = \tau_0 \quad \text{if} \quad m \geqslant h_2, \tag{8}$$

where $\mathcal{F}(x(n))$ is whitening filter, m is the length of active state and h_1, h_2 are thresholds. First threshold h_1 plays the same role as in single-threshold methods.

As it was shown by [3], two-threshold method gives better results than one elaborated by Komi and Cavanagh but it is computationally more expensive. Decrease of computational burden may be obtained by redesigning detection procedure in such a way that whitening stage is unnecessary. Note that whitening procedure reduce sensitivity of onset detection a little bit by lowering the signal to noise ratio [24]. The main drawback of such approaches is necessity of having repetitive samples of activity.

2.3. Statistically Optimal Decision methods

Methods presented in previous subsections do not assume any additional information about analyzed signals properties. In some situations statistical information is available and may be utilized by onset detection procedures, [9].

Let us assume that we have variable x which is a sample of random variable X. Statistical properties of random variable X are fully described by probability density function with vector of parameters θ.

General idea of methods is based on statistical hypotheses testing. Two hypotheses are proposed: the zero hypothesis is related to the rest state of the muscle (H_0) and alternative hypothesis connected with active state of the muscle (H_1). Before detection algorithm starts, it is assumed that the zero hypothesis H_0 holds true. In order to detect the status change from H_0 to H_1, the so called decision function is used:

$$\ln\frac{p(x(1),x(2),...,x(N)|H_1)}{p(x(1),x(2),...,x(N)|H_0)} > h \quad \text{if} \quad H_1 \quad \text{is} \quad \text{true}, \tag{9}$$

or

$$\ln\frac{p(x(1),x(2),...,x(N)|H_1)}{p(x(1),x(2),...,x(N)|H_0)} < h \quad \text{if} \quad H_0 \quad \text{is} \quad \text{true}, \tag{10}$$

where $p(\cdots|H_1)$ and $p(\cdots|H_1)$ are probability density function of H_0 and H_1 respectively, h stands for the threshold.

The Cumulative Sum (CUSUM) method can be used when exact values of probability density function parameters are known [1]. Formal description of CUSUM is given below:

$$S_n = \sum_{k=1}^{n} \ln\frac{p(x(k)|\theta_0)}{p(x(k)|\theta_1)}, \tag{11}$$

$$m_h = \min_{1\leqslant n\leqslant N} S_n, \tag{12}$$

$$\tau_{on} = \min\{n : S_n - m_h \geqslant h\}, \tag{13}$$

where m_h is adjusted threshold, h stands for threshold as it was in previous algorithms. The clue of this method is to compare cumulative sums S_n with the threshold $m_h + h$.

Cumulative sum method require information about the probability density function. However, in most real-life problems such information is not available. In [6] authors proposed solution that overcomes this problem. The method uses two sliding windows (for two parameters θ_0 and θ_1). As it was reported by authors, proposed method gives satisfactory results for e.g. EMG signals and even overcomes limitation of original approach, since its assumptions are usually met in practice.

2.4. Singular Spectrum Analysis method

Typical drawbacks of above methods that base upon statistical properties of processed signal are necessity of probability density functions reconstruction or mutually dependent algorithm parameters. One of the method that overcomes aforementioned problems is based on singular spectrum analysis (SSA) and was applied to EMG onset detection in [23]. SSA is non-parametric, fast and requires no prior knowledge about the properties of the EMG signal. Author suggest to use the method in applications requiring real-time processing, such as control of prosthesis and neuro-prosthesis.

The clue of the SSA method is applying principal component analysis to the so called trajectory matrix. This matrix is obtained from the original time sequence e.g. measured EMG signals. The basic version of this approach consists of following steps:

$$K = N - W + 1, \tag{14}$$

$$X(n) = [x(n), x(n+1), ..., x(n+W-1)]^T,$$
$$n = 1, 2, ..., K, \tag{15}$$

$$\mathbf{X}(n) = \begin{bmatrix} x(n+1) & x(n+2) & ... & x(n+K) \\ x(n+2) & x(n+3) & ... & x(n+K+1) \\ \vdots & \vdots & \ddots & \vdots \\ x(n+W) & x(n+W+1) & ... & x(n+N) \end{bmatrix}, \tag{16}$$

$$R(n) = \mathbf{X}(n)\mathbf{X}(n)^T, \tag{17}$$

where W is the window length.

After the matrix $R(n)$ is computed, eigenvalues and eigenvectors of $R(n)$ are determined. As a results of decomposition process one obtains a representation of matrix $\mathbf{X}(n)$ as a sum of rank-one bi-orthogonal matrices. The last step of the process of EMG onset detection is to solve optimization task to find the time of muscle activity. More detailed description of this method can be found in [15]. In [23] author proposed to include to SSA the CUSUM procedure, which finds onset EMG in the signal under analysis more precisely.

3. EMG onset detection in two stages

Precise assessment of EMG onset is required in studies of motor control and performance. Some studies involve also the so called Electromechanical Delay (EMD) parameter [21, 20], which is the difference between the EMG onset and the force moment onset. Since noise in force moment signal is negligible, precision of EMG estimation depends mainly on the EMG onset algorithm accuracy.

Precise determination of onset EMG in real, not artificial, signals is challenging task due to irregular background activity, smooth gradual transitions, noise artefacts and noise-related spikes, gradual increase of amplitude and frequency, random variations in the background noise, usually introduced by electrode movement over the skin, activation patterns superimposed on the background noise from neighboring muscle units.

For these reasons we proposed new EMG onset detection method. We aim at developing algorithm useful in scientific studies, where signals may be processed off-line. Thus the accuracy of estimate is considered more important than computational and memory requirements. We assume that input EMG signal contains pre-contraction, contraction and post-contraction parts.

The idea behind the method is to search for EMG onset in two stages. On the first stage algorithm performs global view on the signal and finds approximately region of interest. During the second step it continues searching, but limits itself to area close to previous approximation. Its goal is to detect EMG onset with high accuracy.

Detailed description of two stage detection method is given below.

Algorithm is fed up by the sequence of numbers $\{(x_n)\}_{n=1}^{N}$ representing absolute values of EMG signal.

The first stage

Step 1 Extract local maxima from the sequence $\{(x_n)\}_{n=1}^{N}$, by determining a set of indices $l_1 < l_2 < \cdots < l_M$ $(M < N)$, for which the following condition holds:

$$x_{l_m-1} \leqslant x_{l_m} \ \wedge \ x_{l_m} \geqslant x_{l_m+1}.$$

Step 2 Split samples belonging to the sequence $x_{l_1}, x_{l_2}, \ldots, x_{l_M}$ into two groups: background noise group and activity region group. Use the Expectation-Maximization (EM) clustering method. Store results of clustering in the set:

$$\{(x_{l_1}, d_1), (x_{l_2}, d_2), \ldots, (x_{l_M}, d_M)\},$$

where

$$d_m = \begin{cases} 1 & \text{for activity region} \\ 0 & \text{for background noise} \end{cases}$$

Step 3 Derive Probability Density Function (PDF) for the background noise group:

$$\{q_k\}_{k=1}^{K} \quad \text{such that} \quad d_{q_k} = 0.$$

Use kernel density estimation procedure with Gaussian kernel, resulting in PDF function $f_0(q_k)$.

Step 4 Derive PDF for activity region group:

$$\{p_k\}_{k=1}^{M-K} \quad \text{such that} \quad d_{p_k} = 1.$$

Use kernel density estimation procedure with Gaussian kernel, resulting in PDF function $f_1(p_k)$.

Step 5 Interpolate both PDF functions $f_0(q_k)$ and $f_1(p_k)$ over the whole time domain $n = 1, 2, \ldots, N$, obtaining PDF functions $f_0(n)$ and $f_0(n)$ (linear interpolation may be applied).

Step 6 Select candidates for activity regions as areas between intersection of both PDF functions $f_0(n)$ and $f_1(n)$. The beginning points are the points, where value of the function $f_1(n)$ goes up and at the same time value of the function $f_0(n)$ goes down. The end points are characterized by similar relation: value of the function $f_1(n)$ goes down whereas value of the function $f_0(n)$ goes up. Take the first sample of the largest region as a first, rough approximation of the EMG onset.

The second stage

Step 7 Find accurate estimate of the EMG onset by analyzing neighborhood of the sample found at the first stage. Seek for such a sequence of samples x_n, which represents the most rapid variations of the EMG signal or use any of simple onset EMG detection method described in literature.

Step 2 relies on Expectation-Maximization clustering algorithm, [2]. It must be noted, that it is the only clustering method that splits properly samples of EMG signal. This is mainly due to non-symmetrical and non-smooth distribution of groups among samples. The choice of non-parametric density estimation method is not so crucial, many other methods may be considered, such as orthonormal kernel estimators, Parzen estimators and so on. The same comment should be given to the step 5: any interpolation method should also perform well.

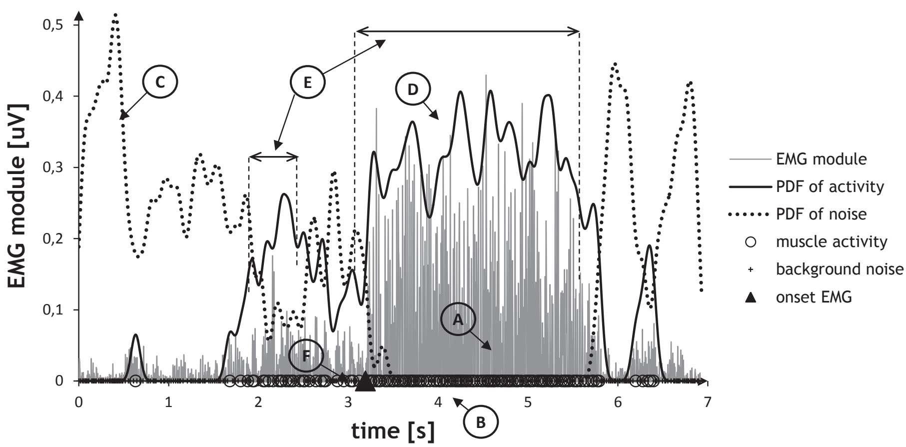

Figure 1. Illustration of EMG detection algorithm.

Illustration of the method is given in Fig. 1. **A** points to absolute value of input EMG signal, **B** indicates local maxima, where background noise samples are marked by crosses and muscle activity samples are marked by circles. **C** and **D** stand for PDF functions of the background noise and bursts of activity, respectively. **E** indicates potential regions of activity. **F** is EMG onset estimate obtained after the first stage. Precise estimate lies very close to that point in the given picture, so it is pointless to show it.

4. Experimental study

Existing onset detection methods were tested mainly on simulated EMG signals. We were able to test the algorithm on a large set of real EMG signal recordings.

4.1. Materials and methods

Thirteen female students of the University School of Physical Education in Wrocław participated in the study. The methods of measuring muscle torques and surface electromyography (sEMG) were used under static conditions. The torques were measured on a multifunctional chair in the lying and sitting positions. The surface EMG electrodes were placed on the right and left hand sides of m. rectus abdominis (RA) and m. erector spinae (ES). The action potential of the muscles was recorded using solid gel Ag/AgCl surface electrodes (NORAXON Inc. USA) placed in a bipolar configuration on muscle bellies along muscle fibres. The electrode set included 6 pairs of active electrodes and 1 reference electrode, which was placed on the skin at an electrically passive location (anterior superior iliac spine). An 8-channel electromyographic device „Octopus" (Bortec Electronics Inc., Calgary, Alberta, Canada) was used, and signals were sampled at a frequency of 1 kHz. The raw EMG signal were recorded in a personal computer by using the „BioWare" software. Files with „tbd" extension were exported to the MATLAB environment, which was then used to process EMG signals.

4.2. Results

1404 EMG signals were visually inspected and correct onset times were marked manually. Then all signals passed through the two-stage onset detection method. Results of the algorithm were compared to results of visual inspection. In order to assess mean value and standard deviation of estimates given by the algorithm, probability density function of onset estimation errors was evaluated empirically, see Fig. 2. Error is considered as the difference between result of visual inspection and result returned by the algorithm. Table 7 depicts bias (mean value) and standard deviation of estimates. It

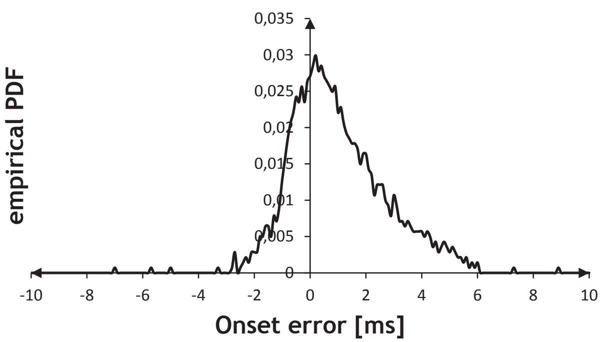

Figure 2. PDFs of onset estimation errors

must be noticed, that the best algorithm – *AGLRramp* – reported in [18], for real EMG recordings had the same mean value but greater standard deviation (3.6 ms).

4.3. Discussion

It can easily be seen on Fig. 2, that onset estimates has small bias (0.4 ms), and are accurate (relatively small standard deviation). We also observe assymetry in PDFs shape. The right hand tail of the function is longer, meaning that the algorithm more often gives delayed detections than premature ones. Six estimates happened to fall far away from the true value, but signals used to generate those estimates were considered damaged.

As mentioned previously, computational efforts are significant. It took about 15 minutes to process all 1404 EMG recordings on PC equipped with 2.16 GHz processor. The most demanding part of the method is Expectation-Maximization clustering.

Important advantage of the method is that it does not need signal filtering to perform properly. Filtering procedures shift the signal and it is not easy to guess the shift length, [8]. All methods, that utilize filtering procedures, affect location of EMG onset. Two-stage method does not need any threshold parameters, simplifying its usage.

5. Conclusions

In this study we proposed a novel method of EMG onset detection. Two-level approach was motivated by observations made on real EMG recordings. It was intended to allow an expert to focus on the main matter of research, letting computer do the boring job. Our results confirmed that algorithm gives satisfactory results in the form of precise EMG onsets estimates.

Authors applied two-stage algorithm in practical biomechanical study and reported results in [20] The objective of the study was an assessment of EMG activity of abdominal and spinal muscles during the measurements of muscle torques in the sitting position, as well as in the lying position. Based on results of investigations, authors concluded that in order to assess the effects of abdominal muscles training, measurements of the trunk flexors torque should be performed in the lying position. The goal of the study [21] was to evaluate the symmetry of action potential and electromechanical delay (EMD) in *rectus abdominis* (RA) and *erector spinae* (ES) during generation of maximal muscle torque.

Table 7. Assessment of two-stage method estimates

Total number of EMG recordings	*mean value*	*standard deviation*
1404	0.4 ms	2.9 ms

Visual inspection is time consuming and gives non reproducible results. Typical way to assess onset detection estimation error is to compare calculated onset with the one determined visually. The question arises: does this definition of error make any sense? Not only two experts give slightly different estimations, but also a single expert would have problems with the same signal, while guessing the same values, when asked in two different times. However, most researchers assume that in large dataset such differences do not significant influence on bias and variance assessment.

An expert performing lots of visual inspection of EMG signal may observe, that burst of activity is associated with increased both signal amplitude and frequency. This observation was utilized in works [11, 17]. The Teager-Kaiser (TK) operator was proposed to enhance those areas of EMG signal, where amplitude and frequency increase considerable faster. In future works we should combine the proposed two-stage method with TK operator. Original EMG signal should be transferred through TK operator and results should be input to the two-stage onset detection method. It would allow to keep good quality of estimates for lower values of signal-to-noise ratio.

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