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Application of singular spectrum-based change-point analysis to EMG-onset detection

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ABSTRACT

While many approaches have been proposed to identify the signal onset in EMG recordings, there is no standardized method for performing this task. Here, we propose to use a change-point detection procedure based on singular spectrum analysis to determine the onset of EMG signals. This method is suitable for automated real-time implementation, can be applied directly to the raw signal, and does not require any prior knowledge of the EMG signal's properties. The algorithm proposed by Moskvina and Zhigljavsky (2003) was applied to EMG segments recorded from wrist and trunk muscles. Wrist EMG data was collected from 9 Parkinson's disease patients with and without tremor, while trunk EMG data was collected from 13 healthy able-bodied individuals. Along with the change-point detection analysis, two threshold-based onset detection methods were applied, as well as visual estimates of the EMG onset by trained practitioners. In the case of wrist EMG data without tremor, the change-point analysis showed comparable or superior frequency and quality of detection results, as compared to other automatic detection methods. In the case of wrist EMG data with tremor and trunk EMG data, performance suffered because other changes occurring in these signals caused larger changes in the detection statistic than the changes caused by the initial muscle activation, suggesting that additional criteria are needed to identify the onset from the detection statistic other than its magnitude alone. Once this issue is resolved, change-point detection should provide an effective EMG-onset detection method suitable for automated real-time implementation.

1. Introduction

Detecting the onset of muscle contraction from an electromyographic (EMG) signal is an important task in several types of applications. It is a marker for the start of active control of the muscle (Stylianou et al., 2003; Staude et al., 2001), and as such is useful when measuring performance in reaction time experiments with external stimulus (Staude et al., 2001; Van Boxtel et al., 1993), or for alignment of movement-related potentials in the electroencephalogram (EEG) in neurology and psychophysiological applications (Van Boxtel et al., 1993). The detection of EMG-onset also has an important role to play in the context of EMG-controlled neuroprostheses (Parker et al., 2004). Current approaches for EMG-onset detection can be divided into two categories: visual (Hodges et al., 2001; Urquhart et al., 2005) and algorithm-based detection (Staude et al., 2001; Morey-Klapsing et al., 2004). The visual method is subjective, dependent on the experience of the person performing the EMG-onset detection (Micera et al., 2001), and cannot be automated. To overcome these shortcomings, numerous onset detection algorithms have been proposed, but there is no standardized method for EMG-onset detection (Hodges and Bui, 1996).

A change-point detection problem is one in which the goal is to identify abrupt changes in the statistical properties of a signal, which occur at unknown instants (Brodsky and Darkhovsky, 2000; Basseville and Nikiforov, 1993). These changes are of interest because they are indicative of qualitative transitions in the data generation mechanism (DGM) underlying the signal. In the case of an EMG signal, the onset of muscle activity would constitute such a transition, and the goal of the present study is therefore to apply change-point analysis techniques to the EMG-onset detection problem. In particular, we use a change-point detection technique based on singular spectrum analysis (SSA). The approach that we are investigating is non-parametric, fast, requires no prior knowledge of the properties of the EMG signal, and therefore can be automated and applied in real-time to raw EMG recordings.

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These features make it particularly attractive for EMG-controlled prosthetic and neuroprosthetic applications. Previous applications of change-point detection algorithms to biological data include the segmentation of EEG data (Wendling et al., 1997; Brodsky et al., 1999; Kaplan et al., 2005) and the analysis of subthalamic nuclei (STN) recordings in patients with Parkinson's disease (Cassidy et al., 2002).

Because of the lack of a standardized methodology for identifying EMG-onset, we compare the results of our proposed algorithm with several other methods. The first of these methods consists of visual onset detection by several experts in EMG analysis; this approach is taken as the gold standard for the purposes of this study. The other methods are algorithm-based: Hodges and Bui's method (Hodges and Bui, 1996) (an example of a threshold-based approach) and Donoho's wavelet-based denoising (Donoho, 1995) followed by the Hodges and Bui algorithm.

2. Theory

In this section we outline the SSA-based change-point detection algorithm, which was developed by Moskvina and Zhigljavsky (2003). SSA functions by applying singular value decomposition (SVD) to a "trajectory" matrix. This decomposition computes the eigenvectors of the lag-covariance matrix (i.e., the trajectory matrix multiplied by its transpose), and indicates which ones best reflect underlying structure in the data and which ones reflect mostly noise. The SSA-based change-point algorithm applies SSA to a windowed portion of the signal, and describes the structure of the windowed portion of the signal as an L-dimensional subspace ($L \geqslant 1$). If the signal structure does not change further along the signal, then the vectors of the trajectory matrix further along will stay close to this subspace. However, if the structure changes further along, it will not be well described by the computed subspace, and the distance between this subspace and the new trajectory vectors will increase. This increase will signal the change.

To describe the algorithm mathematically, let $x_1, x_2, \ldots, x_N$ be a time series, where N is large. Choose a window width m and the lag parameter M, such that $M \leqslant m/2$. For our implementation we have used $M = m/2$ and used even window size m. Set $K = m - M + 1$. Then for each $n = 0, 1, \ldots, N - m - M$, take an interval of the time series $[n + 1, n + m]$ and define the $M \times K$ trajectory matrix X_n as follows:

$$X_n = \begin{bmatrix} x_{n+1} & x_{n+2} & \cdots & x_{n+K} \\ x_{n+2} & x_{n+3} & \cdots & x_{n+K+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n+M} & x_{n+M+1} & \cdots & x_{n+m} \end{bmatrix}.$$

This procedure is Takens' embedding (Takens, 1981) of the time series between $n + 1$ and $n + m$.

For each $n = 0,1, \ldots, N - m - M$:

(1) Compute the lag-covariance matrix $R_n = X_n * X_n^T$. R_n has the size $M \times M$.
(2) Determine the M eigenvalues and eigenvectors of R_n and sort the eigenvalues in decreasing order. Eigenvectors will have the size $M \times 1$.
(3) Compute the sum of the eigenvalues and the percentage of this sum that each eigenvalue contributes. The greater this percentage, the larger is the contribution of the eigenvector corresponding to the eigenvalue to the structure of the data.
(4) Select the number of eigenvectors to use for change-point detection. For change-point analysis, it was found that it works best to select a group of eigenvectors that represent most of the signal. The number of eigenvectors in this group is defined as L, and the choice of L remains fixed for all the X_n computed from the signal.
(5) Pick two test interval parameters, p and q (both greater than 0), and define a test matrix T on an interval $[n + p + 1, n + q + M - 1]$:

$$T_n = \begin{bmatrix} x_{n+p+1} & x_{n+p+2} & x_{n+p+3} & \cdots & x_{n+q} \\ x_{n+p+2} & x_{n+p+3} & x_{n+p+4} & \cdots & x_{n+q+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{n+p+M} & x_{n+p+M+1} & x_{n+p+M+1} & \cdots & x_{n+q+M-1} \end{bmatrix}.$$

The only requirement is that the interval defined by the choice of p and q creates a test matrix that includes at least one column of signal values different from the trajectory matrix columns. Test matrix has the size $M \times (q - p)$. We have used the choices $p = K = m - M + 1$ and $q = m + 1$ in our implementation, so that the test interval includes $M - 1$ points from those used to construct the trajectory matrix and M new points to construct M test vectors.
(6) Compute the detection statistic $D_n(T_n)$, which is the sum of squared Euclidean distances between the vectors of the test matrix T and L chosen eigenvectors of the lag-covariance matrix R_n:

$$D_n = \sum_{j=p+1}^{q} \left(\left(T_j^{(n)}\right)^T T_j^{(n)} - \left(T_j^{(n)}\right)^T U U^T T_j^{(n)} \right),$$

where $T_j^{(n)}$ are the vectors constituting the test matrix T_n, and U is a matrix consisting of the L eigenvectors of R_n. The increase of the value of this statistic signals that the change has occurred.
(7) To find more precise locations of change-points, a cumulative sum (CUSUM) statistic is helpful. The CUSUM statistic is computed for $n = 0 \ldots N - m - M$ (Moskvina and Zhigljavsky, 2003; Moskvina, 2001) as follows:

$$W_0 = S_0,$$
$$W_{n+1} = \max\left[0, W_n + S_{n+1} - S_n - 1/\left(3\sqrt{M(q-p)}\right)\right].$$

Here, $S_n = D_n/v_n$. v_n is an estimator of the normalized sum of squared distances D_n at time intervals at which the hypothesis of no change can be accepted. v_n is effectively a variance of noise in the signal (Moskvina and Zhigljavsky, 2003). It was recommended by the original authors of the algorithm to use $v_n = D_k(X_k)$, where k is the largest value of $j < n$, so that the hypothesis of no change could be accepted in the interval $[j + 1, j + m]$ (Moskvina, 2001). This, however, is somewhat ambiguous, since we do not know precisely the part of the signal where the changes start occurring. We can only expect that there should be no change at the very start of the signal. In the current study, we therefore use $v_n = D_n(X_n)$ for $n < m/2$ and $v_n = D_{m/2}(X_{m/2})$ for $n > m/2$. This assumes that there is no change for $n < m/2$ (for the first half of the first window), since points that are used for the very first test matrix begin at $m/2 + 1$ (because of our choice of $p = m - M + 1$ and $M = m/2$), and thus may start contributing to the change of D_n statistic. This is a reasonable assumption for the application of EMG-onset detection since there is always at least a short rest period before the movement-related EMG event occurs. The term $1/(3\sqrt{M^*(q-p)})$ is a small non-negative constant used to shift the CUSUM statistic downwards in case of the null hypothesis of no change occurring; its form has to do with the statistical distribution properties of the squared distances functions (Moskvina, 2001; Moskvina and Zhigljavsky, 2003).

The change-point estimate is found by first comparing W_n to a threshold, then finding the first point at which W_n has a non-zero value before reaching this threshold. In the current application, however, it is likely that there will be multiple changes detected in the signal. One possible way to decide which changes are most important is based on the relative height of peaks corresponding to the changes in the detection statistics. Our hypothesis here is that the largest change in the EMG signal detected by the SSA-based change-point detection algorithm will correspond closely to the movement onset. Therefore, in what follows, a threshold is not used; rather, the onset is defined as the first point with a non-zero value before the CUSUM statistic reaches its maximum.

3. Methods

3.1. Data acquisition

The proposed change-point detection algorithm was tested using existing EMG data from two different previous experiments. The first consisted of a wrist extension task, whereas the second involved recording trunk muscle activity during sitting.

3.1.1. Wrist extension experiments

These experiments were conducted at the Toronto Western Hospital, according to the experimental protocol described in Paradiso et al. (2003). Nine individuals with Parkinson's disease participated in wrist extension experiments during which EMG was recorded from the extensor carpi radialis and flexor carpi radialis muscles, using round disposable surface electrodes, placed approximately 3 cm apart over the skin overlying these muscles. The ground electrode was placed on the bone, to the side of the wrist. Skin was prepared with alcohol wipes prior to electrodes placement. SynAmp amplifiers (NeuroScan Laboratories, USA) were used to amplify the raw EMG signals. The sampling rate of the data acquisition system was 1 kHz. The EMG signals were band-pass filtered between 30 and 500 Hz.

Participants were seated in an armchair in front of a computer monitor. The EMG activity was first recorded at rest for 1–2 min. Participants were then asked to perform wrist extension tasks followed by passive wrist flexions (i.e., the hand dropped due to gravity after the extension was completed) with one arm/hand. They were asked to perform two types of tasks:

- *Internally triggered task* (i.e., a participant decided when to initiate a movement) where participants had to perform wrist extensions every 5–10 s. The sequence of movements was self-paced and typically lasted between 10 and 15 min.
- *Externally triggered task* where participants had to perform wrist extensions when prompted by a computer program. The externally triggered tasks were recorded until about 40 wrist extensions were performed.

Both externally and internally triggered tasks were first performed by the participants after the overnight withdrawal of dopamine medication, then the usual dose of medication was administered and both tasks were performed again (Paradiso et al., 2003). The experimental procedures used in this study were approved by the local ethics committee.

The EMG recordings obtained during these experiments were segmented into 6 s long intervals (6000 points), each of which contained an EMG event. The actual onset of EMG activity occurred between 3000 and 4000 ms in all segments. All extracted wrist EMG segments were manually checked to ensure that there was no loss of EMG signal, and that there was an increased activity due to movement.

3.1.2. Trunk muscles involved in sitting

Thirteen healthy, able-bodied male subjects participated in a perturbed sitting study (Masani et al., 2009; Thrasher et al., accepted for publication). They were asked to sit on a special apparatus and to wear a harness. External perturbations were applied manually in different directions by a researcher using a rope attached to the harness in series with a force transducer. There were eight perturbation directions, at increments of 45 degrees.

There were a total of 40 perturbations for each subject (5 sets of 8 directions each). Perturbations in different directions were given in random order within each set, so that the subject was not pulled consecutively in the same direction to prevent fatigue and anticipation. During each perturbation, surface EMG measurements were recorded using disposable silver–silver chloride surface EMG electrodes with a diameter of 10 mm and a distance of 18 mm between them. Each electrode was connected to a preamplifier before connecting to a Bortec AMT-8 EMG system. The EMG signals were sampled at 2 kHz and band-pass filtered between 10 and 1000 Hz. Two EMG systems were used during the experiments for a total of 16 channels of EMG recording. Surface electrodes were placed bilaterally on the skin above the following muscles: rectus abdominis (RA) – 3 cm lateral to umbilicus, aligned vertically; external obliques (EO) – 15 cm lateral to umbilicus, aligned 45 degrees to the vertical, internal obliques (IO) – midway between ASIS and symphasis pubis, above the inguinal ligament, aligned 45 degrees to the vertical; thoracic erector spinae (T9) – 5 cm lateral to the T9 spinous process, aligned vertically; lumbar erector spinae (L3) – 3 cm lateral to L3 spinous process, aligned vertically; latissimus dorsi (LD) – lateral to T9 spinous process, over the muscle belly; sternocleidomastoid (SM) – 1/3 the distance from the sternal notch to the mastoid process at the distal end overlying the muscle belly; and splenius capitis (SC) – over the C4–C5 level, aligned vertically. The reference ground was placed over the clavicle. Illustrations of this setup can be found in Masani et al. (2009). The experimental procedures used in this study were approved by the local ethics committee.

The datasets collected from these experiments were subdivided into 4 s long segments (8000 points). The muscle activation event occurred about 1–1.5 s after the start of many but not all of the segments. No additional segmentation was required for these signals.

The change-point detection method did not require any additional processing of the signals prior to the application of the method.

3.2. Implementation of EMG-onset detection methods

The SSA-based change-point algorithm was implemented with the parameters described in the Section 2 set to the following values: $m = 100$, $M = 50$, $p = m - M + 1 = 51$, and $q = m + 1 = 101$. The window length $m = 100$ was a reasonable choice since the main frequencies of the EMG signal were in the range of 30–500 Hz, so their corresponding periods were at least twice shorter than the chosen window length and thus were not affected by windowing. The value of L, the number of eigenvectors retained after the decomposition, was chosen on a case-by-case basis for each data segment, as follows: the trajectory matrix X_0 (corresponding to the first window in the segment) was constructed and SSA-decomposed. L was defined as the number of eigenvectors with eigenvalues greater than 5% of the total sum of eigenvalues of the matrix $X_0X_0^T$, and was then kept constant for the whole data segment. In practice, this process resulted in values of L ranging from 1 to 8.

The onset detection methods used for comparison were: (1) visual detection by three specialists in EMG processing, (2) Hodges and Bui algorithm, and (3) Donoho's wavelet-based denoising followed by Hodges and Bui algorithm.

Before visual detection and application of the Hodges and Bui algorithm application, the signals were band-pass filtered between 30 and 200 Hz and then rectified. Kaiser window FIR filters were used, and applied in a zero-phase filtering manner, to ensure that there was no phase shift in the filtered signals. The Hodges and Bui algorithm was implemented using a 50 ms sliding window. This window was moved along the rectified EMG signal one sample at a time and the mean of values within this window was computed. If the mean of the values of the signal in this window exceeded the threshold, then the first point of the window was called the onset of movement (Hodges and Bui, 1996). To compute the threshold for the onset detection for externally triggered wrist movements, the section of the signal 500 ms prior to the trigger event was subdivided into five 100 ms portions. For each of these portions a mean was computed and the median of five mean values was taken as the mean used in the threshold computation. The standard deviation of the 100 ms portion with the median mean value was also used in this threshold calculation. The threshold was then defined as the mean plus three standard deviations calculated above. The 50 ms window started from right after each trigger event and was advanced by one sample for 2 s (2000 samples) until the movement onset was found. For internally triggered wrist movements and trunk muscles a similar approach to the threshold computation was used, except that in the trunk EMG segments the region which was further subdivided for threshold computation was between 500 and 1000 ms from the segment's start and in the internally triggered signals it was the region between 2500 to 3000 ms of the 6000 ms segment (same as in externally triggered EMG signals). The 50 ms window started sliding from the beginning of the EMG segment and was advanced by one sample until a movement onset was found. In all cases, after the onsets were determined, they were visually checked to make sure that the calculated locations made sense.

For the wavelet-based method, the raw EMG signals were full-wave rectified. The denoising procedure described in Donoho (1995) was then applied, using the first 500 ms of each EMG data segment to estimate the amount of noise in the signal and using a Haar wavelet (Boggess and Narcowich, 2001) with 14 levels of decomposition. After the denoising, the Hodges and Bui method was applied to the denoised signals in the same manner as described above to obtain the EMG-onset estimates. After the onsets were determined, they were visually inspected to make sure that the calculated locations made sense.

4. Results

4.1. Sample onset detection in wrist and trunk muscle EMG

A typical onset detection in the wrist muscle EMG is shown in Fig. 1. Both detection statistics show low values for the portion of the signal when there is no change and a large increase in their

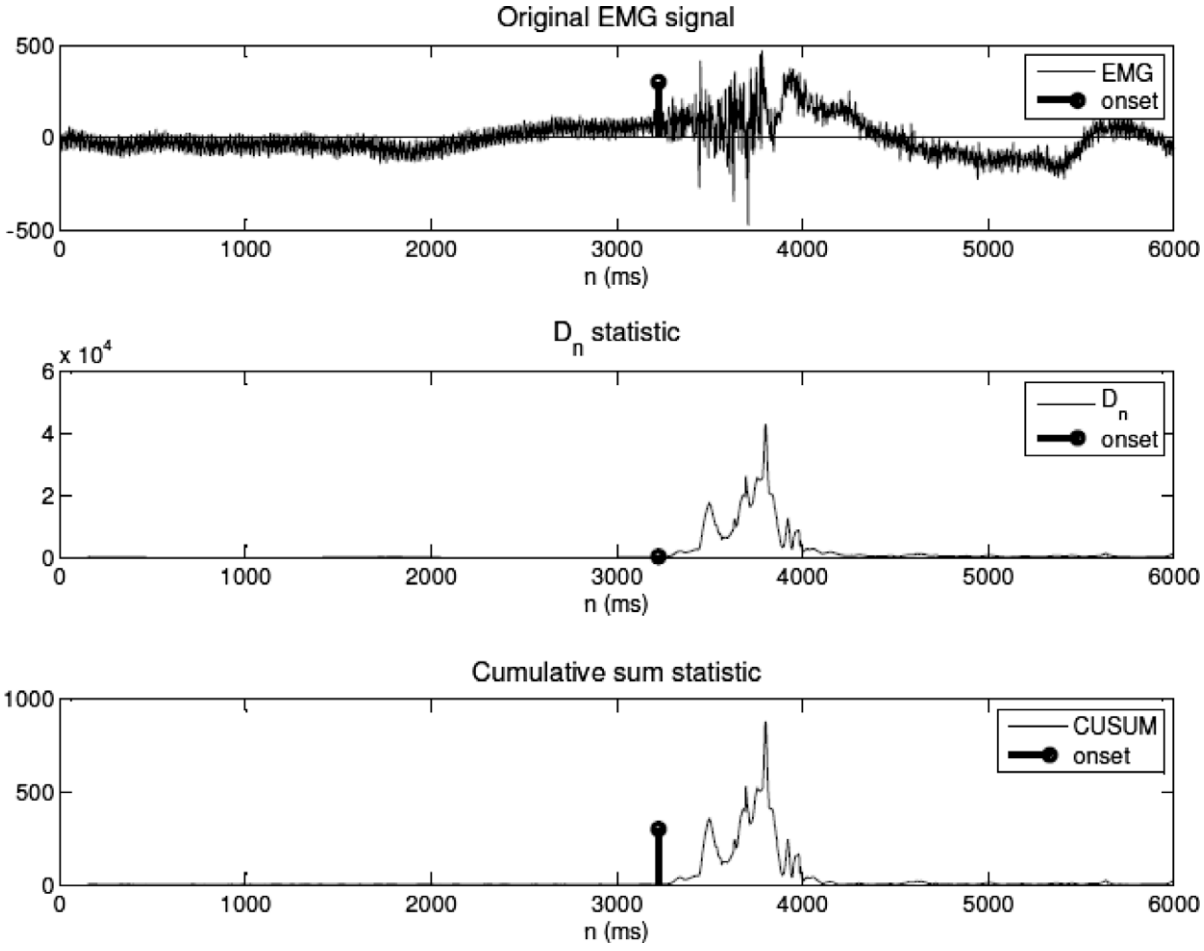

Fig. 1. Sample detection results for wrist muscle EMG. (a) Original EMG signal, (b) and (c) change detection statistics. Circle marker shows the computed EMG-onset.

values when a change occurs due to muscle activation. After the increased muscle activity is over, the detection statistics fall off to the low values again. The onset shown in the plots is computed from the CUSUM statistic. The time of the peak value of this statistic for each EMG segment is taken and the first location where the statistic is equal to zero preceding the peak time is searched for. This is the value defined as onset. The detection of onsets in most of the analyzed wrist EMG segments was reasonably clean, because wrist EMG has a fairly good signal to noise ratio (SNR). Although the changes in the baseline fluctuation are not ignored, which can be seen in the small peaks of the detection statistics, overall they are significantly smaller than the change due to muscle activity increase.

A sample onset detection in a trunk muscle signal is shown in Fig. 2. The change-point analysis statistics computed from the trunk muscles EMG produce many more peaks than the corresponding statistics from wrist muscles. This is due to the much noisier nature of the recordings from the trunk muscles, which have a lower SNR. As a result, misdetections of onsets by the change-point analysis become more common, as do cases in which change-point analysis cannot detect relevant onset at all.

4.2. Frequency of onset detection by different methods

4.2.1. Wrist EMG

The frequency of onset detection was assessed for every EMG experiment by counting the number of detected onsets in the vicinity of the expected muscle activation time out of the total number of segments in which detection was attempted. For the wrist EMG signals the expected onset location was between 3000 and 4000 ms. In some cases there was some EMG activity greater than the baseline level but smaller than the main muscle activation event, leading to onset detection between 2800 and 3000 ms. Such detections were also counted as successful. The histogram of calculated onset detection frequencies for wrist muscles based on 48 datasets are presented in Fig. 3. Frequency of the onset detection did not provide an indication of correctness or precision of the estimates, but rather showed how often the detection could not be achieved.

Overall, the frequency of detection for the change-point method was comparable and often higher than the detection frequency of the threshold-based methods. In most cases the frequency of onset detection exceeded 87.5%. It is, however, notable that all the instances in Fig. 3 when change-point detection method performed worse than others relate to the recordings from the same participant (coded AAA4) for whose files the onset detection frequency was 14–48%. This is because this participant had tremor, and thus the regular wrist muscles EMG was contaminated by tremor-related spikes. This case illustrates the fact that the change-point detection algorithm will detect any change in the underlying process, not only EMG-onset, such that the presence of tremor or other interfering events will hamper performance. Fig. 4 shows a sample onset detection in the EMG with tremor.

The top plot in Fig. 4 shows the raw signal, where the muscle activation is between 3000 and 4000 ms, and other peaks are due to tremor. When the signal is filtered from 30 to 200 Hz (second plot), these peaks are removed, thus in this case the direct application of Hodges & Bui algorithm yields the best results. Denoising

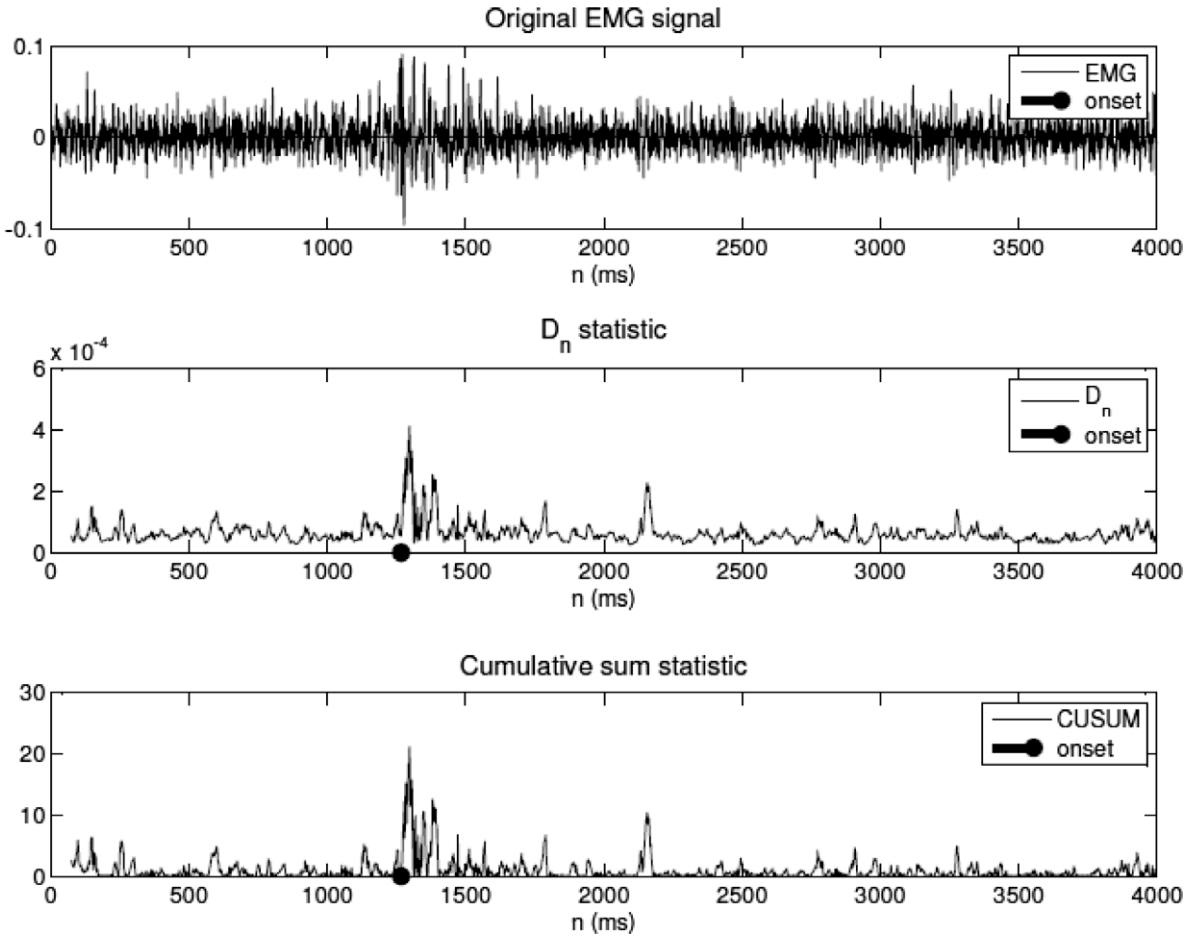

Fig. 2. Sample detection results for trunk muscles EMG. (a) Original EMG signal, (b) and (c) change detection statistics. Circle marker shows the computed EMG-onset.

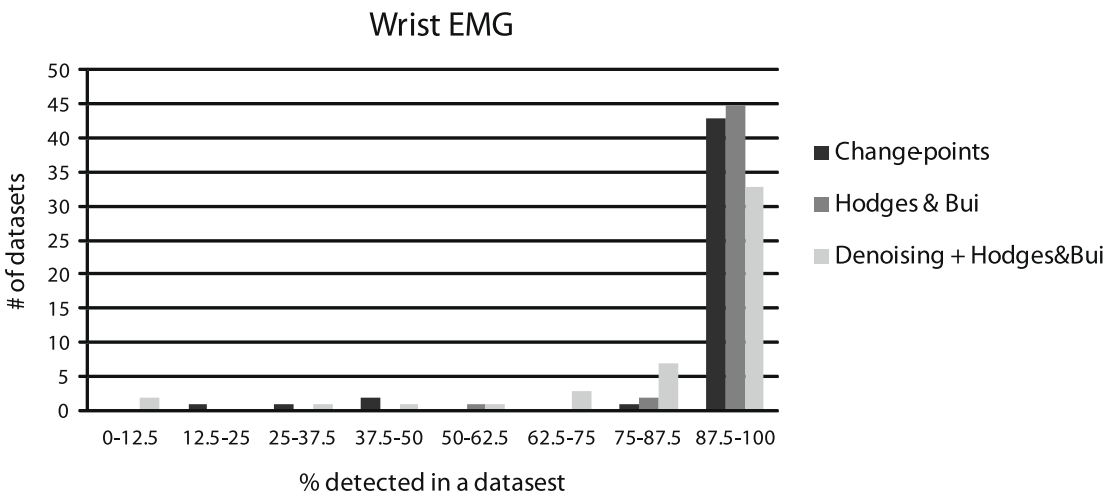

Fig. 3. Histogram of % successful onset detection in wrist EMG for different computer methods.

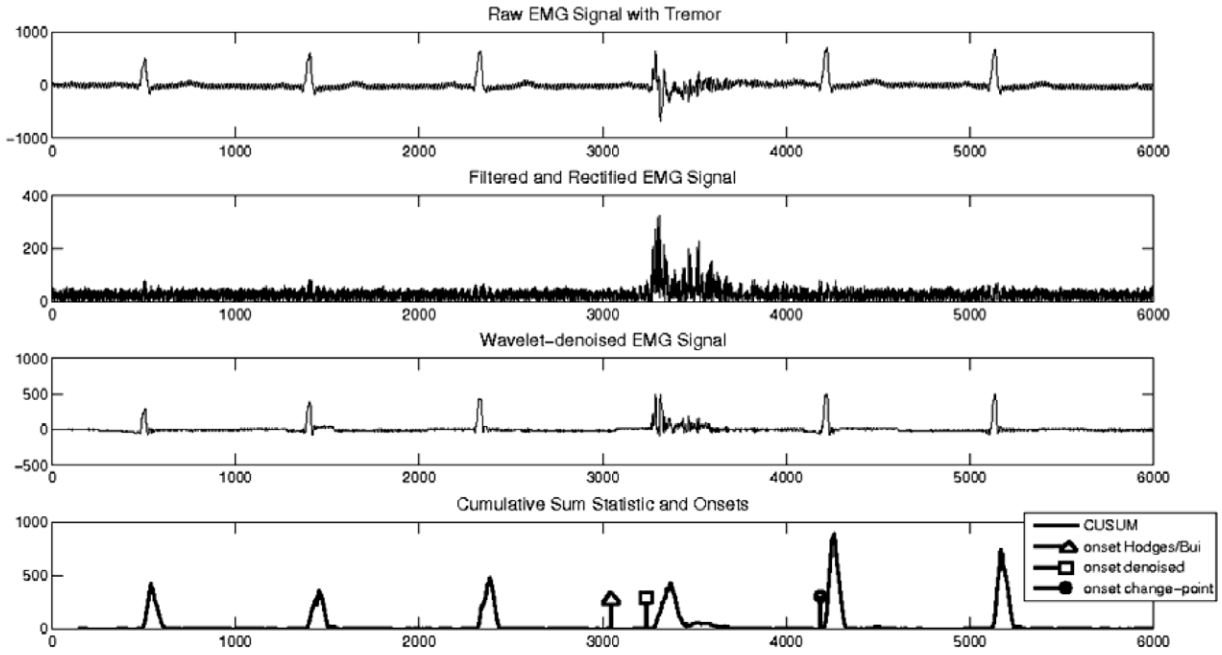

Fig. 4. Detection of onset in EMG signal contaminated by tremor.

(third plot) does not eliminate the tremor-related peaks, but Hodges & Bui algorithm applied to a denoised signal still makes an estimate in the expected time range (at least between 3000 and 4000 ms). The change-point algorithm detects all the changes promptly, both those due to tremor and due to movement onset, but the criterion that the change due to movement is the largest of these changes frequently fails. To maximize the detection of EMG onsets in the signal with tremor, filtering may thus be unavoidable. Alternatively, criteria more sophisticated than choosing the change event with the largest amplitude may have to be investigated.

4.2.2. Trunk muscles

Computing the frequency of onset detection for the trunk muscles EMG is more challenging since not all the trunk muscles were contracted during the perturbed sitting, hence they did not necessarily produce movement-related activations. Therefore, the frequency of onset detection was found only among the signals for which the presence of the muscle activation event was confirmed with the assistance of visual detection experts. Because of a large number of trunk muscle recordings (520 data files), the onset detection frequency was only evaluated for 16 representative data files collected from two experimental subjects for which EMG-onset were visually estimated. The results are shown in the histogram in Fig. 5.

It is notable that although the onset detection for change-point analysis was reasonably consistent for Subject 1 recordings, the frequencies of detection for Subject 2 were rather low. The nature of the problem was similar to the tremor case described in the previous section: there were multiple changes in the signal segments, sometimes due to multiple muscle activations, sometimes due to some additional events, and the change-point detection statistic increase corresponding to the EMG-onset was in many cases smaller than such an increase due to other activity. For example, in a noisy signal, extreme spikes due to outlier values generate peaks in detection statistics, which can be bigger than the other changes

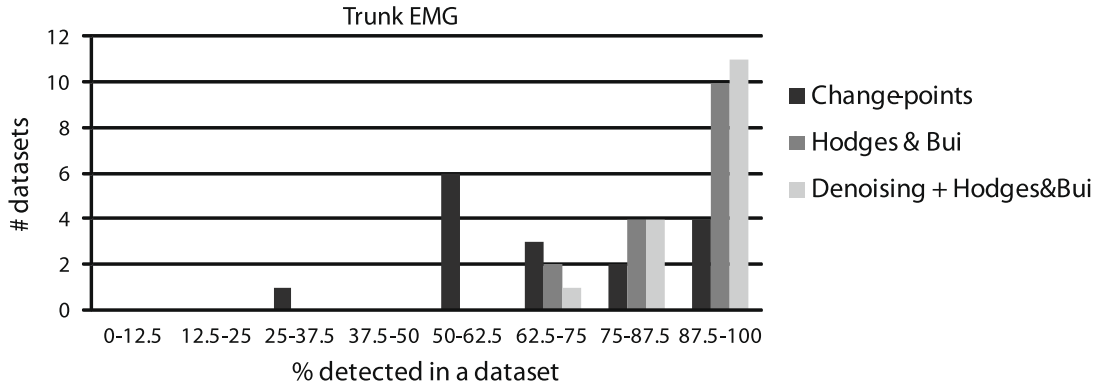

Fig. 5. Histogram of % successful onset detection in trunk EMG for different computer methods.

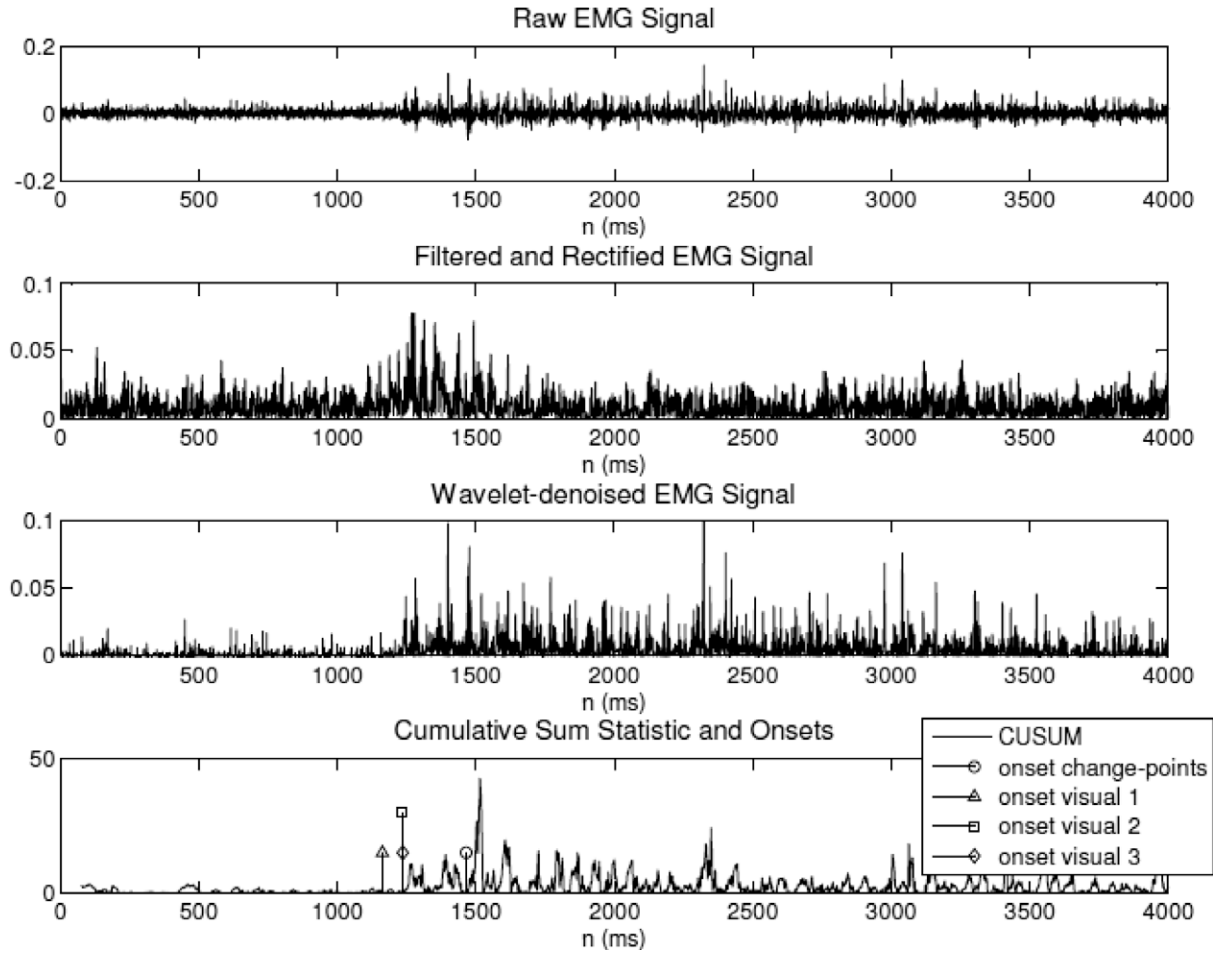

Fig. 6. An example of onset misdetection by the change-point analysis algorithm in trunk EMG.

in the signal structure (Moskvina and Zhigljavsky, 2003). An example of when a misdetection of onset occurred is shown in Fig. 6.

In this case one can observe the increased activity of the muscle around 1500 ms from the start of the data segment; this is evident in all the shown plots – on the raw, filtered and denoised signals. In fact, the CUSUM statistic also shows its first large peak around this time as well. This is a location selected by visual estimators as the EMG-onset. However, one can also observe a larger activity around 2000 ms from the start of the segment (again reasonably visible on raw, filtered and denoised signals). This activity corresponds to the largest peak on the CUSUM statistic plot and it is thus selected as the EMG-onset by the change-point detection algorithm, which disagrees with the visual estimates.

4.3. Quality of onset detection by different methods

4.3.1. Wrist muscles

For the datasets for which visual estimates of EMG-onset were collected it was possible to assess the quality of the computer methods' onset calculations. This was done to ensure that the change-point detection method is at least as accurate as the other tested computer methods for the purpose of EMG-onset detection.

The visual estimates of onsets of wrist muscle activities were made by 3 evaluators, trained in EMG signal processing, for 9 datasets recorded from different individuals. In these datasets, the segments for which at least one of the computer methods was not successful were removed from the quality calculation. This allowed making sure that the quality of the computer methods is assessed over the same segments.

To evaluate the quality of the estimates two methods were used. The first one is to compute the average absolute differences between the three visual estimates and each of the computer estimates in all used segments. The average absolute differences within the same dataset can then be compared to determine if they are significantly bigger or smaller depending on the chosen computer method. A Lilliefors test for normality was applied, and in many cases the test showed that distributions of these differences were not normal, thus regular parametric methods such as ANOVA could not be applied. Therefore, to perform the analysis of distributions of average absolute differences, the Kruskal–Wallis non-parametric test was applied with a 5% significance level (Wackerly et al., 2002). The Kruskal–Wallis test was followed by a multiple comparisons test, which provided information on whether the sets of average absolute differences for computer methods were significantly different from each other pairwise. The summary of computer detection quality measurements as average absolute differences between visual and computer estimates is shown in Table 1.

The median ranks in Table 1 show whether the average absolute differences in visual and computer estimates are significantly different for different computer methods (the non-parametric statistical methods use the rank of a given measurement in the ordered list of measured values instead of the actual value of the measurement, such that we can only make conclusions about the median of the set of values, not the mean; therefore, the outputs of the Kruskal–Wallis and multiple comparison tests are median ranks of average absolute differences). Smaller median ranks correspond to smaller detection error relative to visual estimates. It is notable that in two recordings analyzed in this way (AAA1 and AAA9) the change-point detection method was superior to other methods, for six files it was not statistically different from other methods, and for one file (AAA3), it was statistically inferior to one computer method and comparable to the other one.

Table 1
Quality of onset detection assessed by median ranks of average absolute differences between visual estimates and computer methods in wrist EMG signals. The description column shows the coded participant ID (i.e., AAA1). All the recordings whose results are presented in this table were externally triggered and were recorded off medication (OFFMED) or on medication (ON). Kruskal–Wallis test was used with significance level of 5%.

Description	Number of points	Median ranks ± standard error		
		Change-point analysis	Hodges and Bui	Denoising + Hodges and Bui
AAA1 OFFMED	42	50.4 ± 5.7	69.8 ± 5.7	74.7 ± 5.7
AAA2 OFFMED	32	44.4 ± 4.9	67.5 ± 4.9	33.6 ± 4.9
AAA3 OFFMED	43	69.1 ± 5.7	46.6 ± 5.7	79.3 ± 5.7
AAA4 OFFMED	11	16.0 ± 2.9	11.5 ± 2.9	23.5 ± 2.9
AAA5 ONMED	42	70.0 ± 5.6	56.8 ± 5.6	63.8 ± 5.6
AAA6 OFFMED	40	59.9 ± 5.5	49.5 ± 5.5	72.1 ± 5.5
AAA7 OFFMED	38	55.6 ± 5.4	48.0 ± 5.4	68.8 ± 5.4
AAA8 OFFMED	20	34.9 ± 3.9	31.4 ± 3.9	25.2 ± 3.9
AAA9 OFFMED	37	37.4 ± 5.3	68.0 ± 5.3	62.6 ± 5.3

The second way to compute the detection quality is to compute how well the visual detection estimates correlate with the results produced by the computer tests. This is achieved by evaluating the Spearman rank coefficient, which is a non-parametric method to test for correlation between two ranked variables (Wackerly et al., 2002). To apply the method, the mean value of three visual estimates for each processed segment was computed. Then the Spearman rank coefficient was evaluated between these means estimates and the sets of estimates for each of the computer algorithms. A large Spearman coefficient indicates closer correlation between the two series. The Spearman's rank correlation statistical test computation was also used to obtain p-values, where a smaller p-value indicates that it is more likely that the correlation between the two tested sets is non-zero. The results of Spearman coefficients calculations are presented in Table 2.

Overall, according to Table 2, the Spearman rank coefficient is showing a similar assessment of detection quality than the average absolute differences comparison. For AAA1 and AAA9, the correlations for the change-points analysis are the highest of the computer methods. For AAA2, AAA3, AAA4 and AAA7, the change-point analysis method has the second highest correlation coefficient and for AAA8 the lowest. These quality evaluations are consistent with the median ranks in Table 1, although the mean rank differences among the computer methods for most files were not significant. For AAA6 and AAA5, the Spearman coefficient results and mean rank results disagree, but a perfect match was not expected since correlation and relative size of discrepancies between visual and computer onsets are two fairly different quantities. However, because there are no error bounds on the Spearman coefficients, the median ranks comparison is a more reliable method to assess the detection quality

4.4. Trunk muscles

The quality of onset detection in trunk EMG signals was assessed by the same methods as those used in wrist EMG: computation of average absolute differences between visual and computer estimates and correlation between visual and computer estimates. The visual estimates of onsets of trunk muscle activities

Table 2
Quality of onset detection assessed by spearman rank coefficients between visual estimates and computer methods in wrist EMG signals. The description column shows the coded participant ID (i.e., AAA1). All the recordings whose results are presented in this table were externally triggered and were recorded off medication (OFFMED) or on medication (ON).

Description	Change-point analysis		Hodges and Bui		Denoising + Hodges and Bui	
	Spearman coefficient	p-Value	Spearman coefficient	p-Value	Spearman coefficient	p-Value
AAA1 OFFMED	0.7198	<<0.001	0.6250	<<0.001	0.2212	0.154
AAA2 OFFMED	0.9592	<<0.001	0.9465	<<0.001	0.9709	<<0.001
AAA3 OFFMED	0.7005	<<0.001	0.9092	<<0.001	0.5700	<<0.001
AAA4 OFFMED	0.7062	0.0152	0.8242	0.00181	−0.1149	0.7365
AAA5 ONMED	0.7586	<<0.001	0.7512	<<0.001	0.6733	<<0.001
AAA6 OFFMED	0.8957	<<0.001	0.8875	<<0.001	0.6204	<<0.001
AAA7 OFFMED	0.9505	<<0.001	0.9800	<<0.001	0.8995	<<0.001
AAA8 OFFMED	0.7424	1.78e−4	0.8605	<<0.001	0.8060	<<0.001
AAA9 OFFMED	0.7698	<<0.001	−0.2262	0.1782	0.3067	0.0648

Table 3
Quality of onset detection assessed by median ranks of average absolute differences between visual estimates and computer methods in trunk EMG signals. Kruskal–Wallis test was used with significance level of 5%.

Name	Number of points	Median ranks ± standard error		
		Change-point analysis	Hodges and Bui	Denoising + Hodges and Bui
Subject 1	43	87.5 ± 5.7	53.6 ± 5.7	53.9 ± 5.7
Subject 2	64	96.0 ± 6.9	98.2 ± 6.9	95.3 ± 6.9

Table 4
Quality of onset detection assessed by spearman rank coefficients between visual estimates and computer methods in trunk EMG signals.

Name	Change-point analysis		Hodges and Bui		Denoising + Hodges and Bui	
	Spearman coefficient	*p*-Value	Spearman coefficient	*p*-Value	Spearman coefficient	*p*-Value
Subject 1	0.6238	<<0.001	0.6377	<<0.001	0.7009	<<0.001
Subject 2	0.7841	<<0.001	0.8674	<<0.001	0.9011	<<0.001

were made by 3 evaluators, experts in EMG signal processing, in 16 datasets recorded from two individuals. In these datasets, the segments for which at least one of the computer methods was not successful were removed from the quality calculation. Each particular dataset had only 16 EMG segments, and not all of these contained a movement-related activation of muscle. In addition, not all computer methods succeeded for all segments. Therefore, all EMG segments from 8 datasets for each experiment subject for which there were three visual and three computer onset estimates were combined for the statistical analysis. Thus, there were a total of 42 EMG segments for Subject 1 and 64 segments for Subject 2 that were used for the quality calculations. The results for median ranks comparison and Spearman coefficients are presented in Tables 3 and 4.

The median ranks for the change-point method for Subject 1 are significantly larger than those for other computer methods, which mean that it was less accurate than other methods. For Subject 2, the differences in accuracies of computer methods are not statistically significant, thus the change-point method is not inferior to other ones. Results of Spearman rank coefficients are less conclusive since estimated coefficients are rather close to each other for all computer methods.

5. Discussion

We investigated the application of an SSA-based change-point detection algorithm to the problem of EMG-onset detection. Change-point analysis is designed to detect changes in a signal's statistical properties, which is exactly the situation that is encountered in the EMG-onset detection task. Part of the motivation for our study was that there is currently no accepted gold-standard method for performing this onset detection, which is not to say that are no existing methods. Indeed, multiple algorithms have been proposed, two of which were used as comparison points in this paper. What sets the change-point-based algorithm investigated here apart from other techniques is that it can be applied directly to the raw signal (without any filtering or rectifying), does not require very intensive computations, and does not require *a priori* knowledge of the signal's properties. These features make it suitable for application in real-time, and therefore attractive for situations in which this is a requirement, for example EMG-controlled prostheses or neuroprostheses. Another advantage is that the SSA-based change-point detection procedure automatically "denoises" the signal, which is important because EMG signals are frequently complex. For example, signals recorded in the trunk study, which represent the superposition of activity of many muscles in the area, have a rather high baseline activity, so the EMG events due to perturbation do not exceed the baseline by easily detectable amounts. The denoising ability of the change-point based algorithm may therefore be very useful. This effect is achieved during the subspace decomposition step, when eigenvectors that represent noise can be eliminated from the computation of detection statistics. Fluctuations of the baseline level do not strongly affect the detection. Another advantage of the technique is that it can work with fairly short signal segments. This is valuable because frequently the pieces of signal that correspond to a movement phenomena are short, and might not contain enough points for more advanced computational techniques.

In terms of performance, it was shown in this study that for wrist EMG muscles, the onsets obtained from the maximum of the detection statistic in the change-point analysis yielded detection frequencies and accuracies comparable to the threshold-based methods (with or without denoising). For the trunk muscle, more visual estimates are needed to be able to better judge the accuracy and detection frequency of the change-point method, but for one of the two individuals for which the visual estimates were obtained, accuracy and detection frequency were comparable with other methods.

The main drawback of change-point detection when applied to EMG processing was its inability to recognize the onset among the multiple changes present in the signal, which may or may not be related to muscle activation. Many changes may be detected in a single data segment, and it is therefore easiest to determine the onset when one change is significantly bigger than the others – in this case this dominant change corresponds to the increase of muscle activity. This was the case in most of the wrist muscle EMG segments. However, in the wrist EMG with tremor and in trunk EMG there were many changes causing similar increases of the detection statistics. The largest change did not correspond to the EMG-onset in many cases, so our hypothesis regarding this relationship did not hold. For example, in the EMG with tremor, the peaks of the detection statistic due to tremor were comparable in height and frequently higher than those due to increased muscle activity, as shown in Fig. 4. In the case of tremor, one could filter the signal for the purpose of removing the tremor peaks, but part of the appeal of the change-point analysis approach is its ability to process raw signals. In the trunk muscle EMG signals there were either multiple small activations of muscle in a sequence, or multiple activations at different times of the recording. In these cases, the earliest observed significant change, which corresponded to the EMG-onset detected by the visual estimators, was in many cases not the largest of the changes detected by the change-point analysis algorithm. An example of this is shown in Fig. 4. Unfortunately, the change-point detection does not allow us to classify the changes by origin; it only finds locations in time where changes happened. There is therefore a need for better ways to identify the onset from the change-point detection statistics. These could include a threshold for the increase of the statistic from the baseline level, or perhaps finding a region of the statistic where several significant changes occur in succession. Another possibility is to check for how long the CUSUM statistic stays above zero or above some threshold for different peaks. In the wrist EMG the duration of the common muscle activation due to movement was about 500–600 ms (see Figs. 1 and 4) while spikes due to tremor lasted for about 100–200 ms (Fig. 4); using temporal information of this type may provide a better way to determine from the detection statistic which changes actually correspond to the movement onset and which do not. It is likely that if the onset is identified using

more sophisticated methods such as these, rather than simply using the maximum of the detection statistic, then the performance of the algorithm could be improved. In other words, by incorporating some additional logic into the algorithm, it could be customized to a given situation.

A noteworthy limitation to our study is that the visual onset estimation, which we used as our gold standard, is of course not perfect. We used real recorded EMG signals for this study, not simulated ones, such that the true onsets were not known before the application of the detection methods. Visual estimates are subjective and dependent on the estimators' experience. In addition, an EMG segment may contain features that could be interpreted differently by different observers, and therefore affect the onset detection. For example, a small activity increase (compared to the baseline) may precede the main increase, casting doubt on which one corresponds to the actual movement onset. The lack of precise knowledge regarding the true onset time of course makes it more difficult to compare the different detection methods.

We also did not investigate the effects of the change-point algorithm's parameters in detail, rather opting to choose the parameters based on relatively basic criteria (Vaisman, 2008). Setting the window size equal to 100 was believed to be a sufficient (and perhaps superfluous) approximation of the order of the EMG signal, without interfering with the 30–500 Hz frequencies of the EMG. The other parameters were in large part chosen to depend on the value of the window size (as outlined in the Section 2 of the article). Note that a larger window size and lag parameter will create the need for larger matrices and slow down the algorithm. Precisely optimizing this parameter to obtain both speed and accuracy will be particularly relevant in real-time applications. Another parameter to consider is the number of eigenvectors used for the calculation of the detection statistics. In the present implementation, this number changed for every data segment to include all eigenvectors whose eigenvalues exceed 5% of the total sum of eigenvalues. Instead it may be useful to investigate keeping this number of eigenvectors fixed at some reasonable value, say 5–10, to ensure that at least a set number were used to compute detection statistics for all segments. Tuning of other parameters can also be investigated. For example, by increasing the window length m to values larger than twice the lag parameter M, some small changes could be smoothed out, highlighting the larger ones. However, when there are many changes due to a sequence of small activations of muscles, as happens in trunk muscles, smoothing out small changes might not be useful.

6. Conclusion

In this article we investigated the use of a singular spectrum analysis (SSA) based change-point detection algorithm to detect an onset of EMG. The advantage of this method is that it can be fully automated, applied in real-time in prosthetic and neuroprosthetic applications, and does not require prior knowledge of the properties of the EMG signal. The only information required is a segment of the signal before the onset of EMG, since the algorithm functions by detecting a change. The analysis presented in this paper suggests that the SSA-based change-point detection algorithm applied using a simple "maximum change event" detection algorithm not only has similar detection capabilities to Hodges and Bui's method (Hodges and Bui, 1996) and Donoho's wavelet-based denoising (Donoho, 1995) method followed by the Hodges and Bui algorithm, but additionally has significant benefits in terms of automated real-time implementation. Furthermore, since the "maximum change event" detection algorithm is a simplistic way of applying the SSA-based change-point detection algorithm and since simple logic could be incorporated into the algorithm to weed out unwanted events such as tremors, we believe that the proposed EMG-onset detection algorithm has great potential for real-time applications involving prostheses and neuroprostheses.

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