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A Novel Technique for Muscle Onset Detection Using Surface EMG Signals without Removal of ECG Artifacts

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Abstract

Surface electromyogram (EMG) signal from trunk muscles is often contaminated by electrocardiogram (ECG) artifacts. This study presents a novel method for muscle activity onset detection by processing surface EMG against ECG artifacts. The method does not require removal of ECG artifacts from raw surface EMG signals. Instead, it applies the sample entropy (SampEn) analysis to highlight EMG activity and suppress ECG artifacts in the signal complexity domain. A SampEn threshold can then be determined for detection of muscle activity. The performance of the proposed method was examined with different SampEn analysis window lengths, using a series of combinations of “clean” experimental EMG and ECG recordings over a wide range of signal to noise ratios (SNRs) from –10 dB to 10 dB. For all the examined SNRs, the window length of 128 ms yielded the best performance among all the tested lengths. Compared with the conventional amplitude thresholding and integrated profile methods, the SampEn analysis based method achieved significantly better performance, demonstrated as the shortest average latency or error among the three methods ($p < 0.001$ for any of the examined SNRs except 10 dB).

INTRODUCTION

The onset (and offset) detection of muscle activity using surface electromyography (EMG) is often required in many fields such as motor control of human movement, posture or gait analysis, and myoelectric control of prosthetic and orthotic devices. The muscle activity onset detection can be implemented by different approaches. For example, if there is no requirement of computerized or automatic processing, visual inspection of the EMG signal relying on expert interventions can be used. Another frequently employed method is based on EMG amplitude thresholding which is characterized with simple and fast implementation [1] [2]. The main limitation of the amplitude thresholding method is that the amplitude measurement is sensitive to different types of noise [2]. If the surface EMG signal has low signal-to-noise ratios (SNRs), the onset detection performance may be compromised. To

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overcome this difficulty, more complicated statistical methods have been developed to differentiate EMG from background noise [3–7]. Other signal processing techniques such as wavelet matching analysis [8] [9] and Teager-Kaiser energy (TKE) operation [10] have also been used to improve the muscle onset detection performance in the case of low SNRs.

It is noted that most of the previous efforts for improving muscle activity onset detection performance are against Gaussian noise in the EMG recording. The electrocardiographic (ECG) artifact is another common category of noise that may contaminate surface EMG recording, especially when the EMG signal is recorded from trunk muscles near or over the heart [11]. Trunk muscle EMG is very suitable and often used for investigation of the activity of abdominal and back muscles, their fatigue development, and pathological alterations induced by neural or muscular disorders [22][23]. For example, accurate detection of trunk muscle activity is crucial in studying anticipatory postural adjustment for performing different types of human movement [24]. The ECG contamination can hamper EMG analysis and cause misinterpretations of the results. For example, ECG artifacts can severely affect the amplitude of surface EMG signal, making it a challenging task to accurately determine the muscle activity onset using conventional amplitude thresholding methods or those more complicated methods against Gaussian noise. Thus, it is important to develop techniques to overcome the influence of the ECG artifact for muscle activity onset detection, which is essential in many applications.

The objective of this study was to develop a novel method to detect the onset of muscle activity using surface EMG signals contaminated by ECG artifacts. The method is based on the sample entropy (SampEn) analysis of the EMG signal, which is an effective tool for measuring the signal complexity [12] [13]. Without the need to remove ECG artifacts from raw surface EMG signal in the time domain, the SampEn analysis can highlight bursts of surface EMG and suppress ECG contamination in the form of repetitive QRS complexes in the nonlinear dynamic domain, thus facilitating the muscle activity onset detection. The performance of the proposed method with different SampEn analysis window lengths was examined for muscle activity onset detection using a series of signal combinations of experimental surface EMG and ECG recordings over a wide range of SNRs. The SampEn based approach was also compared with the methods relying on conventional EMG amplitude and interference profile measurements to demonstrate its advantage for reliable muscle onset detection in the presence of ECG artifacts.

METHODS

A. SampEn

Entropy is a concept developed in the field of nonlinear dynamic analysis, which statistically measures the complexity of a dynamic system. Different algorithms have been proposed to estimate the entropy of a time series generated from a dynamic system. Among them, the two popular ones are the approximate entropy (ApEn) [12] and the sample entropy (SampEn) [13], with the latter being considered as a refinement of the former to reduce the bias caused by self-matching. The SampEn has the advantage of relative consistency in various situations and independence of recording length. Thus it is regarded as a robust complexity measure for analyzing short and noisy physiological time series [12] [13] [20].

The calculation of SampEn for a scalar time series $x(t)$, $t = 1, 2, \dots, n$, involves two probabilities defined for an m -dimensional space and an $(m+1)$ -dimensional space, respectively. First, in the delayed m -dimensional space a set of vectors are constructed from the original time series:

$$\mathbf{x}(p) = [x(p+k)]_{k=0}^{m-1}, p=1, 2, \dots, n-m+1.$$

The probability $B^m(r)$ that two vectors match for m points is then computed by counting the average number of vector pairs, without self-matching allowed. The match of two vectors is defined as their distance lower than a tolerance r . Similarly, the other probability $A^{m+1}(r)$ can also be computed for $m+1$ points. The SampEn is defined as follows:

$$\text{SampEn}(x, m, r) = -\ln[A^{m+1}(r)/B^m(r)].$$

The tolerance r is a critical parameter in calculating SampEn. Both the local and global tolerance schemes can be used.

B. Surface EMG onset detection using SampEn analysis

EMG and ECG signals can be viewed as being derived from two dynamic systems, demonstrating different complexity characteristics [13] [20] [21]. Thus it is feasible to discriminate between EMG activity and ECG artifact in the signal complexity domain. The muscle activity onset detection using the SampEn analysis includes three steps:

1. A sliding window was used to segment the processed signal into a series of analysis windows. The window length was chosen to be 128 ms and the window increment was 8 ms. We also evaluated the performance with different window length of 32 ms, 64 ms, 96 ms, and 160 ms, respectively.
2. The SampEn was continuously calculated on each analysis window, thus producing a curve of signal complexity. The SampEn curve can highlight the muscle activity in a way that it shows relatively high values during bursts of EMG and is insensitive to repetitive QRS complexes of ECG artifacts.
3. An appropriate threshold Th was determined for the SampEn curve. The onset timing of muscle activity was detected when the SampEn of the surface EMG signal exceeded the preset threshold.

Three parameters were involved in the above signal processing procedures, namely the dimension m , the tolerance r and the threshold Th . In this study, we empirically set $m = 2$ and r to be 0.25 times standard deviation (SD) of the processed signal. Such settings were also used in previous studies [12–14][20][21]. A uniform global tolerance r was applied to all analysis windows to evaluate signal complexity changes across windows. After assessment of different threshold as described in [14], we set Th to be 0.5 in this study for reliable detection of muscle activity.

C. Testing dataset description

To quantitatively evaluate the performance of the proposed method, a series of combinations of experimental surface EMG and ECG signals were constructed where the precise onset time was known *a priori*. Sixteen surface electrodes, arranged in a 2×8 formation, were used to record surface EMG signals free of ECG contamination, from the flexor digitorum superficialis muscle of a 30 year old male subject when he was asked to perform repetitions of hand grasping. The surface electrode was 10 mm in diameter, with an inner recording surface 5 mm in diameter. The reference electrode was located near the elbow. Each channel of surface EMG was recorded with respect to the reference electrode and with a feedback subtraction of the mean of all the recording channels. Each repetition of muscle contraction was held for at least 3 seconds. A rest period for approximately 5 seconds was allowed between two consecutive repetitions to avoid muscular fatigue. Similarly, the ECG signal was measured over the right pectoralis major muscle of the subject during muscle relaxation. Both EMG and ECG signals were recorded via a Refa EMG system (TMS International B.V., Netherlands). The signals were sampled at 2000 Hz with a bandpass filter setting at 20–500 Hz. The study was approved by the Institutional Review Board of Northwestern University (Chicago, USA).

Ten segments of recorded EMG bursts were first selected to form EMG dataset. The time durations of these EMG segments varied from 1.5 to 2.5 seconds. Meanwhile, 20 segments of typical ECG signal, each with time duration of 5 seconds, were identified to form ECG dataset. Then the 10 EMG segments were added with each of the 20 ECG segments (starting from 2 seconds along the 5 seconds period in total) respectively, thus generating 200 segments of EMG-ECG combined signals. Moreover, the ECG noise segments were scaled over a range of magnitudes to derive combined signals with different SNRs of −10, −8, −5, −2, 0, 2, 5, 8 and 10 dB, respectively. The SNR used in this study was defined as

$$\text{SNR} = 10 \cdot \lg(P_s/P_n),$$

where P_s and P_n represent the mean power of EMG signal and ECG noise, respectively. These EMG-ECG combined signals were used to examine the onset detection performance when different amounts of ECG contamination were present in surface EMG recordings.

D. Performance Evaluation

The onset detection performance can be estimated by the latency τ defined as the absolute difference between the detected onset time t_d and true onset time t_0 :

$$\tau = |t_d - t_0|.$$

For performance comparison, the proposed method was compared with two previously developed algorithms. One was slightly modified from a standard amplitude thresholding method (denoted as AMP method). A moving average procedure with a sliding window was performed on the rectified surface EMG to suppress ECG artifacts. The same sliding window as used for calculating SampEn was applied. The onset time was determined when

the averaged signal amplitude exceeded a predefined threshold. After testing different threshold values, the threshold was set as 5 times standard deviation of the baseline amplitude for best onset detection performance with the dataset used in this study.

The other algorithm used an integrated profile of the signal (denoted as IP method). The IP method was first introduced by Santello and McDonagh [15], and thereafter used by Allison [16] to detect EMG onset under the presence of ECG contamination. The method is briefly introduced below. Given a surface EMG time series $s(t)$, $t = 1, 2, \dots, L$, a continuous integration of all the rectified samples was performed to calculate the IP of the signal:

$$IP(t) = \sum_{i=0}^t |s(i)|, t = 1, 2, \dots, L.$$

It is obvious that at the final point L the IP reaches its maximum value $IP(L)$. Assume that another linear function $R(t)$ is used to create a reference line going to the same final value $IP(L)$:

$$R(t) = IP(L) \cdot t/L, t = 1, 2, \dots, L.$$

This function $R(t)$ represents the integral of a signal with equal distribution. Consequently, the onset time can be determined as the time point t_d at which $R(t)$ and $IP(t)$ yield the maximal difference:

$$t_d = \arg \max_t [R(t) - IP(t)].$$

The principle of the IP method is shown in Fig. 1.

Under the presence of ECG contamination, it is likely the onset detector would be triggered by an ECG complex far away from the true muscle activation using the AMP and IP methods. To exclude such effect, a searching range was limited within 500 ms before and after the true onset time (e.g. from 1.5 to 2.5 seconds for each testing signal). Such an approach, termed as target window or physiological window, was also used in other studies [5] [16]. A target window represents *a priori* knowledge of muscle activation expected to occur and can be based on both statistical and physiological justifications. It has been reported that initiating the onset detection algorithm at the specific target window helps to reduce the possibility of detecting false onsets [15]. The use of specific searching range and target window is not necessary for the SampEn analysis based method. For statistical analysis, a repeated-measure one-way ANOVA was employed in this study to compare the performance of different methods.

RESULTS

The effect of window length on SampEn analysis was first examined to determine the optimal window length for muscle activity onset detection against ECG contamination. The SampEn curves derived from an EMG-ECG combined signal at a SNR of -5 dB are illustrated in Fig. 2, when the window length was increased from 32 ms to 160 ms at 32 ms

increment. The rectified moving average signals using the same window lengths are also shown in the figure for comparison. It was observed that the SampEn shows an instantaneous increase at the onset time of muscle activation (2 s), whereas it only exhibits mild fluctuations along baseline as response to repetitive QRS complexes of the ECG contamination. With larger window length, the capability of SampEn to suppress ECG contamination in surface EMG signal can be enhanced. When a 32 ms window was used, there were clear peaks in the SampEn curve corresponding to the ECG QRS complexes. Such peaks can be effectively suppressed when the window length increased. By contrast, the capability of the signal moving average for suppressing ECG contamination is rather limited for any examined window length.

Fig. 3 shows the onset detection performance when the SampEn analysis with different window lengths was used. It demonstrates that the onset detection performance varies with the window length. The increase of window length from 32 ms to 128 ms led to consistent improvement in onset detection performance (decreased latency), especially in the case of low SNRs (e.g., -10 dB). Further increase of the window length to 160 ms slightly compromised the onset detection performance. For all the examined SNRs, the window length of 128 ms yielded the best performance demonstrated as the shortest average latency. Therefore, the window length of 128 ms was used in the following SampEn analysis for onset detection.

Fig. 4 compares the onset detection performance of three different methods, where for each method the mean latencies were averaged across all the testing signals. This was performed for each of the SNR levels. It was observed that under the presence of ECG contamination, the standard AMP method achieved the worst performance regardless of the SNR level ($p < 0.001$). When the SNR was relatively high (e.g., 10 dB), the IP method was able to achieve comparable performance with the SampEn analysis based method ($p = 0.055$). The onset detection performance of the AMP and IP methods was dramatically degraded when the SNR was decreased. By contrast, with the mean latencies no more than 20 ms, the SampEn analysis based method achieved the best performance among all the three methods ($p < 0.001$ for any of the examined SNRs except 10 dB). Moreover, the evaluation of onset detection performance over a wide range of SNRs from -10 dB to 10 dB showed that the performance of the SampEn-based method was relatively less sensitive with respect to varying levels of ECG contamination in surface EMG signals, compared with AMP and IP methods.

DISCUSSIONS

Surface EMG is very often contaminated by ECG artifacts when recorded from a location over or near the heart. Compared with considerable efforts toward overcoming the Gaussian noise in surface EMG for muscle activity onset detection, ECG artifacts are rarely addressed. To overcome the influence of ECG artifacts on muscle activity onset detection, one approach is to remove the ECG artifacts from raw EMG signals before further processing. While a range of ECG artifact removal methods [17–19] can reduce or suppress ECG artifacts in the surface EMG signal, they have several limitations compared with SampEn analysis for onset detection. Using high pass filtering as an example: when the

ECG artifact is substantial in the EMG signal, high pass filtering may not sufficiently reduce the ECG artifacts. Increasing the cutoff frequency of the high pass filter may reduce more ECG artifacts, but it may also significantly reduce the useful EMG signals. It is unclear how the removed EMG components may influence the onset detection. Other ECG artifact removal methods with less distortion of the EMG signals would require *a priori* information about the ECG waveform (such as ECG template subtraction) or extra channels' recording (such as adaptive filtering and independent component analysis based methods).

In this study, a novel approach for muscle activity onset detection was presented based on the SampEn analysis, without removal of ECG artifacts from surface EMG. Entropy is a measure to quantify the complexity and randomness of a dynamic system. Surface EMG can be viewed as a specific dynamic process that is different from the ECG signal. It follows that EMG activity can be differentiated from such ECG spikes by measuring their signal complexity. Mathematically the SampEn is computed by counting the number of "similar" vector pairs whose distances are just lower than a preset tolerance. As a result, the SampEn is not sensitive to instant large variations (e.g., ECG spikes). Taking this advantage, the SampEn analysis can highlight bursts of surface EMG signals while suppressing ECG spikes, thus facilitating muscle activity onset detection. Compared with the approach of removing ECG artifacts from raw surface EMG, the SampEn analysis based method is characterized with several features. It does not require extra channel recording or *a priori* information about the ECG template. Compared with the IP method, the onset detection is less sensitive to changes in ECG waveforms or reduced SNR levels. In this study, all the processing was performed offline. However, the sliding window approach for calculating the SampEn is potentially suitable for real time implementation while we acknowledge the complexity of the SampEn calculation (approximately 50 ms processing time for a 128-ms window using a laptop computer with a 2.67-GHz Intel Core i5 CPU and a 4-GB RAM).

When implementing the SampEn analysis for onset detection, the SampEn was calculated from a specific window. A sliding window with certain length was used along the processed signal to produce the SampEn curve. We found that increasing the window length would facilitate suppression of the ECG artifacts in the SampEn domain. On the other hand, because of increased ambiguity induced from relatively long window lengths, the time resolution for onset detection would be decreased. In this study, a 128 ms window length was used to maintain a reasonable signal processing delay and a relatively high time resolution for the onset detection. With such a window length the muscle activity can be clearly differentiated from ECG spikes with a smoothing SampEn curve. It is worth noting that in our previous study a 32 ms window length was used in suppressing involuntary motor unit action potential spikes [14]. The different choice in window length was due to the fact that the QRS complex (50–80 ms) of ECG artifact is much longer than spurious EMG spikes (10–30 ms). In addition to analysis window length, another parameter for the proposed method is the window increment/step, which determines the temporal resolution of the onset detection. Theoretically the smallest window increment (individual sampling point) depends on the signal sampling rate. Although higher temporal resolution can be achieved with smaller window increment, it also imposes an increasing computational burden. Thus, in

practical application, the window increment should be determined as a tradeoff between onset detection resolution and computational efficiency.

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Fig. 1.

Illustration of the IP method for onset detection using a surface EMG signal combined with ECG contamination at a SNR of 0 dB (i.e. semi-synthetic signal, the top panel). The IP of the signal is plotted along with its corresponding reference line (the middle panel). The onset can be determined as the timing that generates the maximum difference between EMG IP and reference line (the bottom panel).

Fig. 2.

(a) A surface EMG signal with ECG artifacts at a SNR of -5 dB and (b–f) its corresponding SampEn curves and average rectified amplitude curves. The signal was processed with different sliding window lengths from 32 ms to 160 ms at 32 ms increment. The true EMG onset time is exactly 2 seconds in each subplot.

Fig. 3.

Effect of sliding window length used for SampEn analysis on the onset detection performance using combinations of EMG and ECG signals at different SNRs (-10, 0, 10 dB). The onset detection performance was evaluated by the mean latency derived from all 200 signal segments. The error bars indicate standard deviations. The results under the condition of 32 ms window length and -10 dB SNR was not included in the figure due to the relatively large latencies induced by unsuppressed ECG contamination.

Fig. 4. Comparison of onset detection performance using three different methods. The mean latency was averaged across 200 surface EMG-ECG signal segments at each SNR. The error bars indicate standard deviations.