Automatic ECG artifact removal in the real-time SEMG recording system

Yong Hu, Jerry Kwok,Jessica Tse
Department of Orthopaedics and Traumatology
The University of Hong Kong
Hong Kong, China
Email: yhud@hku.hk

Abstract—The contaminated electrocardiography (ECG) is a big problem in the surface electromyography (SEMG) signal detection and analysis. The objective of the current study is to propose and validate an algorithm for the automated feature cognition and identification for eliminating ECG artifact from the raw SEMG signals. The utilization of Independent Component Analysis (ICA) method is to decompose the raw SEMG signals into individual independent source components. After that, some of the independent source components with the characteristics of ECG artifact were detected by the automated identification algorithm and thereafter eliminated. The sensitivity and specificity of the algorithm for distinguishing ECG source components from independent source components are 100% and 99% respectively. The automated identification algorithm exhibits the prominent performance of recognition for ECG artifact and can be considered reliable and effective.

Keywords—surface electromyography; electrocardiography; low back muscle; independent component analysis

I. INTRODUCTION

The real-time surface electromyography (SEMG) analysis system has been widely sued for low back pain (LBP) assessment. To record SEMG signals over low back region, it is easily influenced by the electrocardiography (ECG) signals induced by the cardiac muscle activities [1-4]. The raw SEMG signals from the trunk muscles were contorted by the ECG artifact in terms of two major parameters: amplitude and frequency [5]. Therefore, it cannot completely reflect the myoelectric activities of muscles, thereby contributing to the inaccurate results [5, 6].

The electrodes simultaneously collected the EMG and ECG signals from low back region. This would cause a problem of the mixture of the amplitude and frequency of these two signals. Many previous studies [7-11] proposed different ways to eliminate ECG artifact from the raw SEMG signals. One of the common methods for removing ECG artifact from the raw SEMG signals is the spectral filtering technique that removes all the components in the raw SEMG signals within a specific range of frequency corresponding to the ECG artifact frequency range. However, this method may eliminate some EMG components falling within the selected frequency range.

Independent Component Analysis (ICA) method for the ECG-artifact removal from the raw SEMG signals was suggested in scientific literatures [12-15]. It is able to decompose the linear mixture of EMG and ECG signals into distinct independent source components statistically based on limited information about the original source of the signals. ICA method is different from the spectral filtering technique as ICA method eliminates ECG artifacts on the basis of the source of the signals rather than the given frequency range. After the ICA process, the independent components should be classified as ECG artifact by visual inspection [16]. Another method to identifying ECG artifact is an automated recognition method, proposed by Joseph et. al. (2010) [17]. However, this method was not implemented in a online system and not validated. Therefore, this paper compiled and developed in C Sharp code to implement in a real-time SEMG system. In addition, the performance of this automatic ECG cancelation method was evaluated in terms of its specificity and sensitivity by using the real data collected from subjects in the course of the flexion-extension motion.

II. METHODS

A. SEMG test

The real-time SEMG topographic system encompasses four main components: 1) a 3×7 electrode-array, 2) a signal amplifier, 3) an analogue to digital converter and 4) SEMG topographic analysis. SEMG data were collected from the lumbar region using a 7x3 electrode-array applied evenly in the lumbar region from L2-5 (Fig. 1). It consists of twenty-one surface electrodes (Ag–AgCl disc electrodes with diameter of 1.5 cm) which are evenly placed on the skin surface layer of the low back region from the second (L2) lumbar vertebrae to the fifth (L5) lumbar vertebrae. Two electrodes used as ground potential were located on the upper left and right corners of the low back region respectively. Three reference electrodes were attached along the spine from L2 to L5. The diameter of each SEMG electrode was 1.5 cm. In order to keep the impedance between skin and electrode contact below 10kΩ, the skin surface layer in the lumbar region was cleaned with alcohol before attaching the 3×7 electrode-array on the skin, and conductive gel was inserted in the interface between each electrode and the pre-cleaned skin surface. The signal amplifier is utilized to amplify SEMG signals 2000 times. Subsequently, the analogue to digital converter (NI data acquisition card, DAQ6063, National Instruments Inc., Austin, Texas, USA) is employed to convert the original analogue format of SEMG signal into its corresponding digital format. Meanwhile, SEMG signals are filtered with a band width of 15

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Hz and 950 Hz and acquired at the sampling frequency of 2 kHz and.

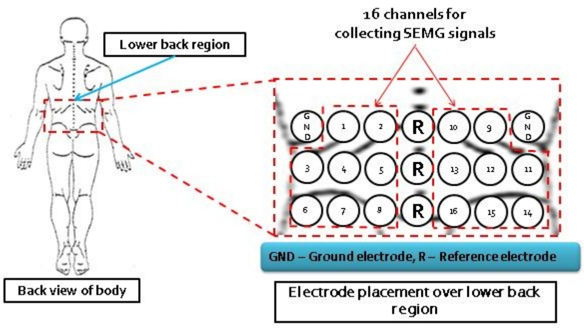


Fig. 1. Placement of the 3×7 electrode-array

B. *Automatic ECG cancelation method*

The unprocessed SEMG signals (Fig. 3a) collected from low back muscles are a superposition of EMG signals and ECG artifact induced by myoelectric activities of trunk muscle and cardiac muscle. The algorithm of ICA was introduced to decompose the unprocessed SEMG signals into individual independent source components (Fig. 3b). The assumptions and requirements of ICA were suggested in many previous studies associated with the mathematics of ICA [13].

The entire process of the automated ECG artifact removal is illustrated by the following matrix.

$$a = X \cdot u \xRightarrow{\text{Step A}} u = X^{-1}a \xRightarrow{\text{Step B}} w = X \cdot u_{clean} \quad (1)$$

where X is a mixing matrix, a is a matrix of the raw SEMG signals, u is a matrix of independent source components, u_{clean} is a matrix of the processed independent source components after the removal of ECG signals and w is a matrix of the cleaned SEMG signals.

In the step A, the ICA separation process is to transform the unprocessed SEMG signals into distinct independent source components. After independent source components were determined, some of the components containing the feature of ECG-artifact were recognized. In the step B, the cleaned SEMG signal (Fig. 3c) was reconstructed after removing the ECG-artifact components from the independent source components. The ICA method is employed for separating the raw SEMG signals into independent components by utilizing the MATLAB package (FastICA) [18].

The overall procedure of the automated feature recognition method for ECG-artifact removal was illustrated in Fig. 2.

After the ECG-artifact separation, the automated ECG artifact recognition algorithm is employed to distinguish between ECG and EMG source components on the basis of the two major distinctive ECG artifact features - the spike-like and periodic waveform. The recognition algorithm involves three steps as follows.

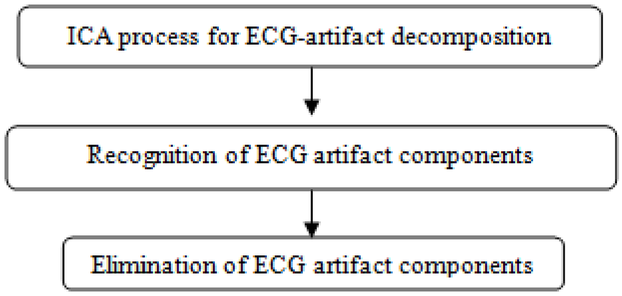


Fig. 2. Flow chart of the automated feature recognition method for ECG-artifact removal

First of all, to highlight the major morphological features of the independent source components, the Hilbert transform algorithm and median filter [19] is utilized as an effective and reliable envelope extraction method for transforming the original independent components into the corresponding waveform envelope. After the process of the Hilbert transform algorithm and median filter, these unique features of ECG-artifact components were amplified.

To find out peaks existing in each waveform envelope, the following steps are employed [17]:

i. Each waveform envelope is defined as a signal $g(n)$.

ii. The peak value g_{peak} is determined from the signal $g(n)$. A threshold level is referred to as a fraction of the peak value,

$$\text{Threshold} = 0.6 \times g_{peak} \quad (2)$$

iii. The signal $g(n)$ is converted into binary format according to the following algorithm.

$$\begin{cases} g_{binary}(n) = 1, & g(n) \geq \text{Threshold} \\ g_{binary}(n) = 0, & g(n) < \mathit{Threshold} \end{cases} \quad (3)$$

iv. The rate of change of signal $g_{change}(n)$ is calculated as follows:

$$g(n) = g_{binary}(n) - g_{binary}(n-1), \qquad n = 2,3,4,5, \ldots\ldots, N \quad (4)$$

(Where N is the sample size)

v. When the rate of change of signal $g_{change}(n)$ is equal to one, the corresponding index of n is recorded in the set M which shows the peak-appearing sequence, as described below:

$$\mathbf{M} = \{n \mid g_{change}(n) = 1\} \quad (5)$$

Subsequently, a recognition algorithm for the unique characteristics of ECG artifact examines whether the set **M** belongs to the distinct features of ECG artifacts according to three main criteria: number of peaks, peak-to-peak interval and variance of peak-to-peak intervals, as illustrated as follows.

i. On the basis of the fundamental physiology, the normal range of the human heart rate is around between 60 to 100 beats per minute (BPM) [20]. Hence, the range of the number of human heart beats during the specific period of time can be calculated from the range of the normal human heart rate. Joseph et. al. (2010) [17] stated that a broader heart rate ranges between 40 and 200 BPM is used as the reference range so that most of the components with the pattern of the ECG artifact can be identified. The following algorithm identifies whether the number of signal $g(n)$ falls within the reference range.

$$(40\,\mathrm{BPM}/60\mathrm{s}) \cdot t \leq |\mathbf{M}| \leq (200\mathrm{BPM}/60\mathrm{s}) \cdot t \quad (6)$$

(where $|\mathbf{M}|$ means the number of peaks in the set $\mathbf{M}$, that is the number of peaks recorded, and t indicates the duration of the signal g(n) (in second))

ii. To examine the peak-appearing periodicity, the following algorithm of peak-to-peak interval is to identify whether the peak-to-peak interval in the signal $g(n)$ is in the reference range of peak-to-peak interval between 0.3s and 1.5s.

$$0.3\mathrm{s} \leq \mathbf{M}(n+1) - \mathbf{M}(n) \leq 1.5s, \qquad n = 1, 2, 3, \ldots \ldots, N \quad (7)$$

(where $\mathbf{M}$(n) is the peak-appearing time of the *n* th recorded peak. N is the number of peaks measured. 1.5 s is the mean peak-to-peak interval value with the heart rate of 40 BPM and 0.3 s is the mean peak-to-peak interval value with the heart rate of 200 BPM.)

iii. To find out the consistency of the peak-appearing periodicity, variance of peak-to-peak intervals is to examine whether the distance between each adjacent peak-to-peak interval in the signal $g(n)$ exceeds the reference range [17].

$$[g(n+2) - g(n+1)] - [g(n+1) - g(n)] \leq R \cdot (1.5s), n = 1, 2, 3, \ldots \ldots, N \quad (8)$$

(where 1.5s is the upper limit of the peak-to-peak interval value. A scaling factor R is equal to 0.5.)

Provided that the set **g** complies with all of the above three criteria, the corresponding signal $g(n)$ is regarded as an ECG artifact.

C. Validation

A total of 20 healthy male subjects were enlisted to engage in a clinical test (mean age = 32 ± 6.5 years). The clinical test was approved by the ethics committee and consent forms were signed by all subjects prior to the clinical test.

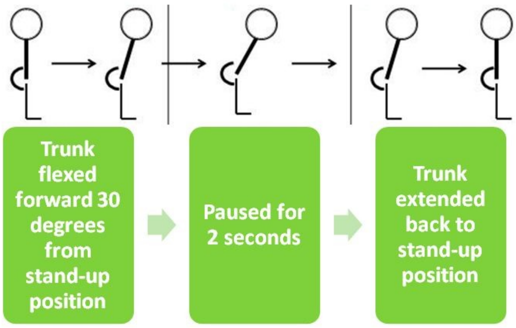


Fig. 3. Procedure of trunk-bending motion

In order to assess the performance of ECG artifact recognition algorithm, the results of the ECG artifact recognition by the algorithm were compared with those by using visual inspection. Three observers, professionals in clinical electrophysiology, were responsible for discriminating ECG artifacts from independent source components. To measure the sensitivity and specificity of the algorithm, the following algorithm was employed.

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (9)$$

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}} \quad (10)$$

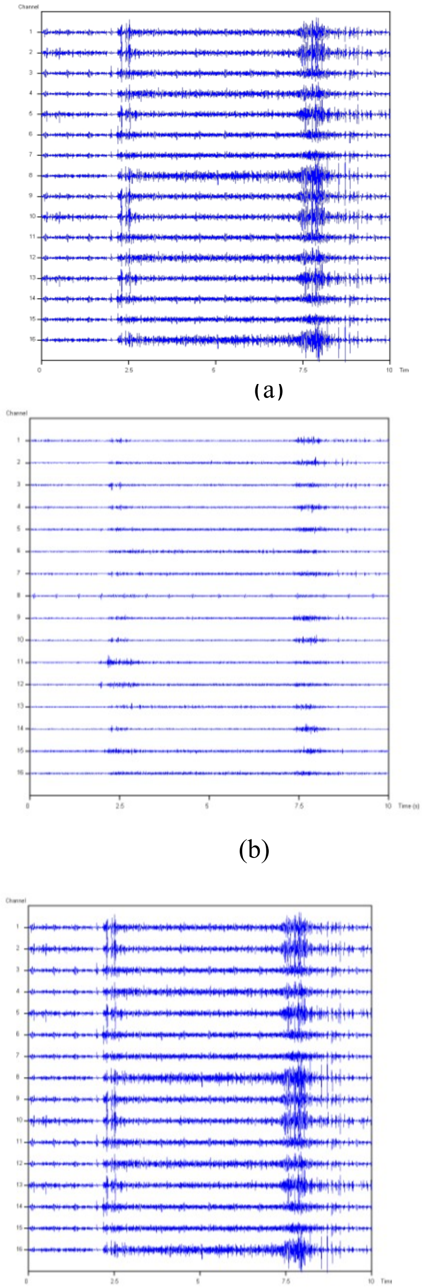
The parameters in the above algorithm were defined as follows:

1) True Positive: the number of ECG artifact components recognized by the algorithm and at least one of the observers.
2) False Positive: the number of ECG artifact components recognized by the algorithm but not by any of the observers.
3) True Negative: the number of non-ECG artifact components recognized by the algorithm and all of the observers.
4) False Negative: the number of non-ECG artifact components recognized by the algorithm but not by all of the observers.

III. RESULTS

As shown in Fig. 4, independent source components comprising ECG artifact were completely detached from the EMG components in raw SEMG signals from low back muscles through the process of independent source component (ICA) on the basis of our assumption that ECG artifacts bear no relation to EMG signals in terms of anatomy and physiology.

Following the process of ICA, the automated ECG identification algorithm, as suggested by Joseph et. al. 2010 [17], was introduced to recognize the source components corresponded to ECG artifact. This algorithm involves several steps as follows. Firstly, the underlying ECG components in the raw SEMG signals were significantly highlighted by the Hilbert transform. In order to recognize peak appearing in each waveform envelope, the algorithm of threshold and binary transformation was employed. To our knowledge, a threshold level was set to 0.6 the peak value of the amplitude. After the corresponding peaks were identified, a recognition algorithm was used to finds out whether the features of corresponding peaks fulfill the characteristics of ECG artifacts.



(a)

(b)

(c)

Fig. 4. (a) The real unprocessed SEMG signals contaminated with ECG artifact. (b) Independent source components decomposed via the process of ICA (c) cleaned SEMG signals after eliminating ECG components from independent source components

To evaluate the recognition performance of this algorithm, the two parameters – the specificity and sensitivity of the system were utilized. In the SEMG measurements, a total of 320 unprocessed SEMG signals were collected from subjects during the flexion-extension motion. The ICA method separated ECG artifact from EMG signals. A total of 16 source components were classified as ECG artifacts by observers whereas the remaining components (304) were regarded as EMG source components. Compared with the results of manual classification, the automated ECG identification algorithm successfully identified ECG-artifact components with a sensitivity of 100% and specificity of 99% (True Positive = 16, False Positive = 2, True Negative = 304, False Negative = 0), as shown in Table 1.

TABLE 1
RECOGNITION PERFORMANCE OF THE AUTOMATED ECG IDENTIFICATION ALGORITHM

Test Outcome	Condition	
	Condition Postive	Condition Negative
Test outcome positive	16	0
Test outcome negative	2	304
	Sensitivity = 100%	Specificity = 99%

IV. DISCUSSION

The reliability and efficacy of the proposed automated feature recognition method for ECG-artifact removal from SEMG signals in the system was validated by the results of this study. This method involves two major steps: 1) an ICA process and 2) an automated ECG artifact recognition algorithm. First of all, the ICA process decomposed the raw SEMG signals collected from subjects into ECG and EMG components. Secondly, some of the independent source components corresponding to ECG artifact were identified and then automatically eliminated by the automated ECG artifact recognition algorithm.

There are two major methods for identifying ECG artifact components: 1) the manual recognition and 2) the automated ECG artifact recognition algorithm. In the manual recognition, ECG components were recognized by visual inspection. The automated ECG artifact recognition algorithm is able to overcome the disadvantages of visual inspection. Before the utilization of the automated recognition algorithm, the Hilbert transform algorithm and median filter [19] is used as an effective and reliable envelope extraction method for converting the original independent components into the corresponding waveform envelopes. The automated recognition algorithm, comprising two main parts: a peak recognition process and an ECG feature identification algorithm, can distinguish between the corresponding waveform envelopes of ECG and EMG signals. The peak recognition process on the basis of a specific threshold level (0.6 peak value) is to convert the corresponding waveform envelopes into binary format. The specific threshold level was estimated by the peak amplitude ratio between the ECG and EMG signal so that the specific threshold level can reflect the scale of ECG to lower back SEMG. Following the peak recognition process, the ECG feature identification algorithm is applied to the converted corresponding waveform envelopes based on the three criteria: number of peaks, peak-to-peak interval and variance of peak-to-peak intervals. The results showed that the source components corresponding to ECG-artifact were successfully identified by the automated ECG artifact recognition algorithm, with the sensitivity of 100% and specificity of 99%. The recognition algorithm can be considered reliable. It is also superior to the manual recognition on the basis of visual inspection since it circumvents the inter-observer variation, and complex and time-consuming process.

Apart from the proposed ICA-based automated feature recognition method for ECG artifact removal, many scientific literatures [1, 3, 8] suggested the spectral filtering method for removing ECG artifact such as the utilization of Butterworth filter with 30 Hz cutoff (BW HPF 30) [3]. The spectral filtering method eliminates EMG artifact components by removing the ECG artifact frequency range. Nonetheless, it is more likely to remove some EMG components corresponding to the range of ECG artifact frequency from the raw SEMG signals. Consequently, it may contort the original EMG components to a certain extent, thereby substantially affecting the reliability of the SEMG assessment results. In other words, the results of SEMG assessment by the proposed ICA-based method are more reliable than those by the spectral filtering method since our ICA-based method was capable of maintain the relative low distortion of EMG signals.

The automated ECG-artifact removal method in the system could be widely applied in some SEMG-based clinical assessment tests. It can significantly enhance the reliability of SEMG-based assessment as its SEMG-based evaluation is susceptible to the existence of the ECG artifact. This would indicate that the automated ECG-artifact removal method is one of the crucial parts in the system for keeping the reliability of the assessment results at the high level.

Some studies suggested complicated methods like neural network for distinguishing the target and noise source components after ICA separation. Nevertheless, the relatively simple ECG artifact algorithm was capable of separating independent source components into EMG and ECG components as a result of the obvious discrepancy between the EMG and ECG components, following the processes of ICA, Hilbert transform and median filter. These processes substantially highlighted ECG components mixed with the EMG signals. The algorithm was only dedicated to the identification of ECG components. Its reliability and efficacy was validated based on the all simulated SEMG signals with ECG artifacts in the previous study [17]. It is doubtful that the algorithm is able to successfully distinguish between ECG and EMG components in the actual raw SEMG signals obtained from subjects. Therefore, the algorithm was testified by conducting the SEMG-based clinical test in this study. The findings showed that the performance of the algorithm in the identification of the real SEMG signals is effective and reliable.

In conclusion, the automated feature recognition method for ECG-artifact removal, as illustrated in this study, comprises two main procedures: the process of ECG-artifact decomposition via ICA and the identification of ECG artifact characteristics. Based on the results, it was found that ECG noise signals in the SEMG measurement were separated, recognized and eliminated successfully through this method. All in all, the application of this method in the system could be considered effective and reliable.

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