An Algorithm for EMG Noise Detection in Large ECG Data

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Abstract

Large collections of electrocardiogram recordings (ECG) are valuable for researchers. However, some sections of the recorded ECG may be corrupted by electromyogram (EMG) noise from muscle. Therefore, EMG noise needs to be detected and filtered before performing data processing. In this study, an automated algorithm for detecting EMG noise in large ECG data is presented. The algorithm extracts EMG artifact from the ECG by using a morphological filter. EMG is identified by setting a threshold for the moving variance of extracted EMG. The algorithm achieved 100% detection rate on the training data. The algorithm was tested on 150 test signals from three sets of test signals (50 signals in each set). Set 1 was created by adding EMG noise to EMG-free ECG signals, set 2 was manually selected ECG sections which contain EMG noise, and set 3 contained randomly selected ECG signals. Sensitivity was 100%, 94%, and 100% on sets 1, 2, and 3, respectively. All sets had 100% specificity. The algorithm has computational complexity of $O(N)$.

1. Introduction

The electrocardiogram (ECG) is widely used in cardiac disease diagnosis and research. Large collections of ECG data may be valuable for doctors and researchers to provide insight into understanding and prediction of disease. The electromyogram (EMG) is generated from electrical activity of the muscle. Sections of ECG may be interfered and corrupted by surface EMG which causes difficulties in data processing and analysis. Motion artifact may also be present in the signal. Thus, EMG noise needs to be detected and filtered. In this paper, a fast algorithm for detecting EMG noise is presented which uses a morphological filter. It has low computational complexity such that it can be applied in massive ECG collections. The outline of this paper is as follows. Section 2 describes data collection and ECG used in this study. The algorithm and training process are explained in section 3. Algorithm testing is in section 4. Section 5 and 6 are discussion and conclusion, respectively.

2. Data collection

Data used in this paper were collected from a rat model of aldosterone-induced cardiac fibrosis for 12 weeks [1, 2]. The ECG was monitored from subcutaneous leads located above the xiphoid process and anterior mediastinum. The data was continuously recorded using implantable monitors (Datasciences, Inc., St. Paul, MN) for the entire experiment, at sampling rate of 1000 Hz. At the end of experiment, each rat produced approximately 12 GB of data. In this paper, ECG from ten rats were used in the study.

3. Methods

3.1. Morphological filter

Morphological filters have been widely used in the field of image processing. It has applications in filtering unwanted shapes of the signal while leaving the other parts of signal unchanged. The fundamental operations of morphological filters are erosion and dilation which are expressed in Eq. 1 and 2, respectively. The input signal is denoted as x where L is its length. s is the structuring element which determines the shape of signal that is eliminated by the morphological filter. B is length of the structuring element and must be less than L. $x \ominus s$ is denoted as erosion and $x \oplus s$ is dilation. Opening and closing are two operations defined in term of erosion and dilation. Opening is defined as erosion followed by dilation while closing is dilation followed by erosion [3]. The morphological filter is constructed based on these operations and illustrated in Fig. 1.

$$(x \ominus s)(i) = \min_{j=1,\cdots,B} x(i+j-1) - s(j) \quad \text{for } i = 1, \cdots, L-B+1 \tag{1}$$

$$(x \oplus s)(i) = \max_{j=i-B+1,\cdots,i} x(j) + s(i-j+1) \quad \text{for } i = B, B+1, \cdots, L \tag{2}$$

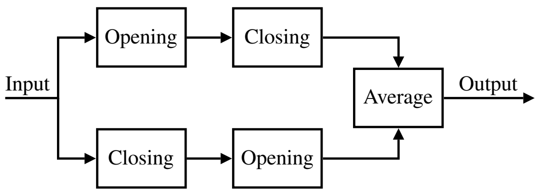

Figure 1. Diagram of morphological filter

3.2. Algorithm

EMG is produced by muscle electrical activity. In recorded ECG, EMG interference appears as rapid fluctuations which vary faster than ECG waves. An example of EMG in recorded ECG is shown in Fig. 2. EMG noise in the ECG can be detected by measuring degree of signal fluctuation excluding the fluctuations of QRS complexes. Fig. 3 depicts a diagram of the developed EMG detection algorithm. The algorithm is described as follows.

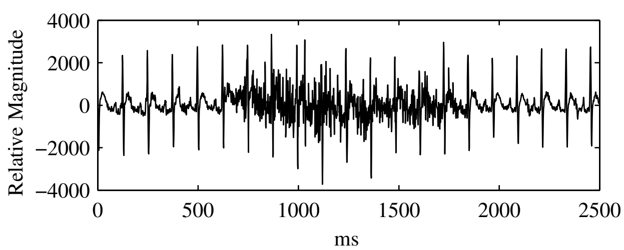

Figure 2. Recorded ECG corrupted by EMG noise

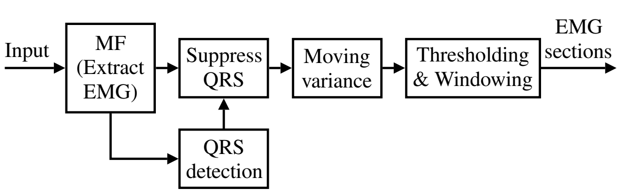

Figure 3. Diagram of EMG detection algorithm

1. *Extracting EMG noise*: Impulsive noise, such as EMG, can be separated from ECG by using morphological filter with a dome-like structuring element which is smaller than ECG waves [3]. In Fig. 4, the output of the morphological filter results in ECG with EMG noise suppressed. The EMG noise can be retrieved back by subtracting the output of the morphological filter from the input ECG. Because we emphasize extracting EMG and do not need to preserve the quality of ECG waves, a square-wave structuring element produces a similar result. Thus, a fast morphological filter for a unit square-wave structuring in [4] can be applied and helps speed up computation process. By experimentation, a square-wave structuring element with width of 0.07 seconds provides the best result. However, a portion of the QRS complex is also present in the output. Suppressing the QRS complexes is the next step.

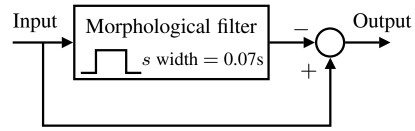

Figure 4. Morphological filter for extracting EMG noise

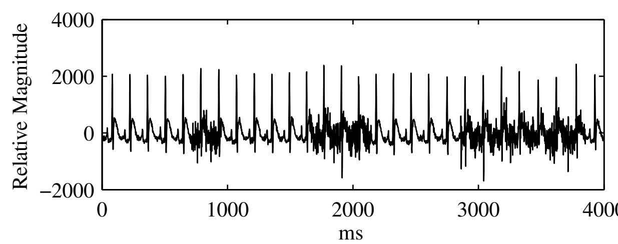

Figure 5. ECG signal which contains EMG noise

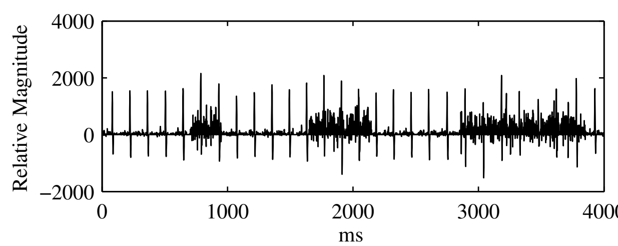

Figure 6. Extracted EMG noise and by-product QRS complexes

2. *Suppressing QRS*: The output from the EMG-extraction morphological filter contains EMG noise and partial QRS complexes which need to be suppressed. By using the beat detection algorithm in [5], the QRS complexes can be located. R-wave is identified as a reference of the QRS complex by searching the maximum in the neighborhood of the detected position. Then, samples around the R-wave (left 0.008 second and right 0.011 second) are reduced in their magnitude to one-tenth of their original size.

3. *Calculating moving variance*: Moving variance is denoted as signal variance within a sliding window.

Degree of EMG noise can be measured from level of signal fluctuation which is associated with moving variance of signal. A low computation moving variance is expressed in Eqs. 3 to 5. Size of the sliding window will be described in the next section.

For $i = W_2 + 2, \cdots, L - W_2$

$$m_1(i) = m_1(i-1) - \frac{x(i - W_2 - 1) + x(i + W_2)}{W} \quad (3)$$

$$m_2(i) = m_2(i-1) - \frac{x(i - W_2 - 1)^2 + x(i + W_2)^2}{W} \quad (4)$$

$$v(i) = m_2(i) - m_1(i)^2 \quad (5)$$

Moving variance is denote as v. Input signal, x, has length of L samples. The sliding window is stretched to left and right by W_2 samples. Its total length is $W = 2W_2+1$. $m_1(W_2+1)$ and $m_2(W_2+1)$ are first and second moment of first $W_2 + 1$ samples, respectively. Moving variance of W_2+1 and last $L-W_2+1$ samples is calculated by using the standard variance formula.

4. *Thresholding and windowing*: Sections of EMG noise can be identified by setting a threshold on the calculated moving variance. However, magnitude of recorded signals is subjective and depends on recording settings and configurations. Therefore, moving variance is normalized by the square of average of R-wave amplitudes of the ECG passage. Fig. 7 displays EMG noise and its normalized moving variance. Sections where the normalized moving variance exceeds the threshold is labeled as EMG noise. Nevertheless, moving variance may rise after the onset of EMG and fall prior to the end of EMG because it needs sufficient amount of EMG the sliding window in order to increase the variance. Thus, detected EMG section is expanded to left and right for 0.05 seconds. Fig. 8 shows EMG sections detected by the algorithm. A process to determine threshold value will be explained in the following section.

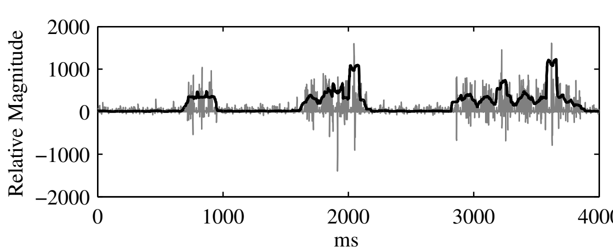

Figure 7. Extracted EMG noise (gray) and normalized moving variance$*10^4$ (black)

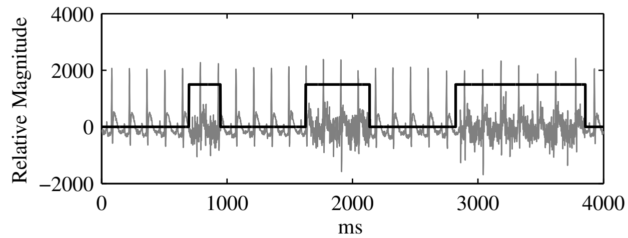

Figure 8. Input ECG signal (gray) and detected EMG sections (black)

3.3. Training

The algorithm parameters, size of moving variance window and moving variance threshold, were determined by training on a set of data and tuned to achieve the best detection rate.

Training set

Training signals were generated by adding EMG bursts at different lengths and strengths to EMG-free ECGs. From ten rats, twenty EMG-free ECGs were selected (two ECGs from each rat). Each ECG has length of 30 seconds. Seven EMG bursts were added to each ECG at different lengths of 0.4, 0.5, 0.7, 1, 3, and 5 seconds with 2 seconds apart from each other. By reusing the same ECG, the amplitude of EMG bursts was adjusted to 0.4, 0.5, 0.7, and 0.8 of average of R-wave amplitudes. Totally, eighty training signals were created from twenty EMG-free ECGs. Note that all additive EMG bursts were selected from different EMG signals.

Procedure

The criterion for correct detection is defined as follow. The algorithm is considered to have a correct detection when the algorithm detects the entire EMG section and the detected section is not longer than 0.05 second from the onset and the end of the actual EMG interval. The process of determining the size of the moving variance window and threshold value for EMG detection is divided into two stages. First, trail and error was applied to find a reasonable range of window size (0.04 to 0.2 second) and threshold value (0.008 to 0.02). Then, the threshold value was selected at 0.015 and window size was adjusted for the best detection rate, achieved at W = 0.081 second. Then, at the best window size, the threshold value was varied. The algorithm achieved 100% detection rate at a threshold equal to 0.01.

4. Results

Test set

Three sets of signals were used to test the algorithm. Each set contains fifty signals from ten rats. There are totally 150 test signals.

Set 1: Test signals were created by using the same method for the training set except that the signals had length of ten seconds and contained one burst of EMG noise. The bursts begin after two seconds of ECG. Their lengths and amplitudes were randomly chosen from lengths and amplitudes used for the training set.

Set 2: Signals were manually selected from the recorded signals which have spontaneous EMG noise. Each signal had one section of EMG noise.

Set 3: To test the performance of the algorithm in the real data, set 3 contained signals which were randomly selected from the recorded signals. Each signal had length of 30 seconds. In this set, EMG noise may not present in every signal.

Results

By using the correct detection criterion for training, the result is presented in Table 1. Set 1 and 3 have sensitivity of 100%, while set 2 has sensitivity of 94%. Three out of fifty signals in set 2 have detection intervals approximately 0.06 second shorter than the actual EMG intervals. Specificities are 100% for all test sets. Therefore, none of the ECG sections are detected as EMG noise

Table 1. Results from testing the EMG detection algorithm on 3 test sets

	Sensitivity (%)	Specificity (%)
Set 1	100	100
Set 2	94	100
Set 3	100	100

5. Discussion

By using the fast implementation of morphological filter in [4], each opening and closing operation requires less than 4 comparisons on the average per sample. Therefore, the fast morphology filter has complexity of $O(N)$. The other parts of the algorithm also have a complexity of $O(N)$. As a result, the algorithm has computational complexity of $O(N)$.

QRS detection is very crucial to the algorithm. Missing the QRS causes an increase in moving variance and normal ECG will be detected as EMG noise. The QRS detection is sensitive to baseline fluctuations and high T-waves [5]. Since the morphological filter eliminates both of them, the possibilities of missing the QRS are when there is spurious noise which may cause EMG to be detected when none is present.

6. Conclusion

In this paper, a fast EMG detection algorithm was explained. EMG is extracted by two steps. First, a designed morphological filter with a unit square-wave structuring element with width of 0.007 second extracts EMG and QRS complexes. Then, QRS complexes are detected and suppressed. EMG is detected by setting a threshold on its moving average. Moving average size and threshold value are 0.081 seconds and 0.01, respectively. The detection section is expanded to left and right by 0.05 second to compensate for delayed rise and hastened fall of the moving average. The algorithm achieved 100% detection rate on the training set. On test sets, the algorithm has sensitivity of 94-100% and specificity of 100%. Computational complexity of the algorithm is $O(N)$.

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