AN EFFICIENT QRS DETECTION METHOD FOR ECG SIGNAL CAPTURED FROM FINGERS

Md Saiful Islam, Naif Alajlan

Advanced Lab for Intelligent Systems Research
College of Computer and Information Sciences, King Saud University
Riyadh 11543, Kingdom of Saudi Arabia
saislam@ksu.edu.sa, najlan@ksu.edu.sa

ABSTRACT
We propose a novel QRS detection method for ECG signal captured from fingers (briefly finger-ECG). In this work, we use curvature as an estimation of energy of ECG signal. We need only three computationally simple steps for the detection of QRSs. A single threshold is used to determine QRSs from local minima of energy making the method linear i.e. \( O(n) \) in computational time which is \( O(n^2) \) for slope based methods for a signal of \( n \) samples. The method is tested on 224 records of finger-ECG signal, and we have obtained superior performance than the state-of-the-arts slope-based method. Average time error of detection is also significantly lower by this method. This method has a single parameter of adaptive threshold, which required no tuning for our database whereas the slope based method required tuning of parameters. This method is potentially suitable for real time applications of finger-ECG in e-health and biometrics.

Index Terms— Finger-ECG, biomedical signal processing, QRS detection, health monitoring, ECG biometrics

1. INTRODUCTION
ECG signal is essentially captured from fingers for many biomedical [1, 2] and biometrics applications [3-5]. Finger-based ECG devices for use at home are likely to grow significantly among risk patients for continuous health monitoring [1]. In particular, automatic finger probe is considered as a promising and emerging technology which could be operated by patients themselves at home for screening of atrial fibrillation [1, 6, 7], which is the most common cardiac arrhythmia associated with high risk of stroke, dementia, and death. ECG signal also captured from fingers for acceptability of ECG as a biometric modality. However, this single lead (lead I) signal has a considerable low signal to noise ration (SNR) making it more challenging for automatic analysis.

QRS complex is the most prominent feature of an ECG signal. Robust QRS detection is the first step in many ECG signal analysis techniques [1, 4, 8, 9]. Most of QRS detection methods identify the peak of R-wave, which is the positive deflection after the Q wave. Numerous time and frequency-domain methods of QRS detection have been proposed in the last five decades. First derivative based methods [10-14] are preferred for efficiency, which is one of the important considerations for finger-based systems. In this approach, the slope of the ECG curve is used as the estimation of energy of the signal. As the slope at the R-peak is zero, it is required to transform with a function (e.g. Hilbert [10, 12], squaring [13, 14]) to yield maxima at the R-peaks. Then nested iteration is required with two thresholds to detect the R-peaks from the transformed function making the method quadratic in terms of computing time, i.e. \( O(n^2) \) for a signal with \( n \) samples. Moreover, for finger-ECG signal, the four parameters of adaptive threshold [10] remain subject to manual tuning from person to person, making it inconvenient for automatic analysis.

In this paper, we have proposed a novel and efficient QRS detection method using the curvature of ECG signal as an estimation of energy. We have observed that R-peak has the highest negative curvature with respect to the other points of a heartbeat. Hence, the proposed QRS detection method consists of three computationally simple steps: computation of curvature, finding local minima, and rejection of non-R-peaks with an adaptive threshold. In fact, the curvature of the plane curve is able to differentiate linearly between R-peaks and the non-R-peaks. Hence, just a single threshold is required to detect the R-peak which makes the method linear in terms of computing time, i.e. \( O(n) \). The proposed method was evaluated with 224 ECG records captured from finger by a commercially available ECG device [15]. We obtained 99.91% sensitivity and 100% positive predictivity of QRS detection, which are superior to those of the state-of-the-arts slope based methods. These
results were obtained without requiring any tuning of the parameter of the adaptive threshold. Furthermore, the average time error (0.82 millisecond) of detected R-peaks is significantly lower in the proposed method.

Rest of the paper is organized as follows. In section 2, we describe our database of finger-ECG. In section 3, we reviewed state-of-the-arts real time slope-based methods of QRS detection and analyze their limitations for finger-ECG signal. In section 4, we describe the proposed curvature based QRS detection method. Experimental results are discussed in section 5. The paper is concluded with discussion and possible future works in section 6.

2. COLLECTION OF FINGER-ECG SIGNAL

For data collection, we used a commercially available finger-based ECG device known as ReadMyHeart [15]. This is a single lead device (lead I) which generally captures ECG signal for fifteen seconds from the thumbs at a sampling frequency of 250 Hz. Signal can be obtained by placing the thumbs of both hands on two dry conducting electrodes. The device takes ten seconds for internal adjustment and then captures ECG signal for another fifteen second. Data can be exported to computer using a USB port and can be viewed on ECG graph. Signal can also be converted into `txt` format for automatic analysis. Table I gives the specification of this device.

In order to capture finger-ECG signal, a user only needs to place his or her thumbs of both hands on the electrodes without requiring any other preparation. Generally, this is done in sitting position with hands resting on a table. We captured two specimens of finger-ECG signal for each of 112 subjects of different ages (20 – 78 years) and sexes (67 male and 45 female). All people volunteered for finger-ECG acquisition were leading regular life, and we did not ask about their cardiac problems. As a captured finger-ECG signal is often contaminated with different types of noise, such as power-line interface, baseline wanders, and patient-electrode motion artefacts, etc., we preprocess it by a band-pass Butterworth filter of order four with cut-off frequencies of 0.25 to 40 Hz to remove noises. Fig. 1(a) shows a segment of such a preprocessed Finger-ECG signal.

3. PRIOR WORKS

In 1985, Pan and Tompkins [14] proposed a real time QRS

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sampling Rate</td>
<td>250 Hz</td>
</tr>
<tr>
<td>Number of electrodes</td>
<td>2 (Lead I)</td>
</tr>
<tr>
<td>Measurement time</td>
<td>15 Sec</td>
</tr>
<tr>
<td>Power Supply</td>
<td>DC (3V)</td>
</tr>
<tr>
<td>Size</td>
<td>12 × 8 × 2 cm</td>
</tr>
<tr>
<td>Weight</td>
<td>134 g</td>
</tr>
</tbody>
</table>

Fig. 1. QRS detection for same finger-ECG segment by proposed curvature based method (left) and improved Hamilton-Tompkins method (right).

In 2008, Arzeno et al. [10] proposed an improvement of Hamilton-Tompkins method based on the analysis of performances of four modified versions of it. They also proposed an adaptive threshold to avoid person-specific threshold tuning. This improved method does not require calculating the time-averaging of the transformation method as proposed by original Hamilton-Tompkins method. A variable threshold is automatically determined based on RMS value of calculated energy of a 1204-point window. However, this threshold selection depends on four parameters, which still require tuning for our database of finger-ECG signal. More specifically, the improved Hamilton-Tompkins method (with the parameters specified in [10]) failed to detect any QRS for two records from our database. This method also fails in several cases as listed in [10]. Fig. 3 (right column) gives some example of false negative and false-positive detection for several records from our database of finger-ECG signal.

In order to detect the missing peaks, the method requires a nested search of a segment with a lower threshold (e.g. 0.5 times of first threshold). Suppose an ECG record has n samples. In the best case, all QRSs are detected in the first iteration requiring only linear computational time O(n). Now, suppose for a particular ECG record the method
detects two consecutive QRSs with an interval of \( m \) samples in the first iteration such that
\[
RR(i) > 1.5 \times RR(i - 1),
\]  
where \( RR(i) \) is the length of the \( i \)-th RR segment already detected by first threshold. Due to the search with second threshold the computational time for this segment is \( O(m) \). If both \( n \) and \( m \) are sufficiently large, then the computational time of this method becomes
\[
O(n) \times O(m) = O(m \times n) = O(n^2).
\]  

4. PROPOSED CURVATURE-BASED METHOD

Although slope has been extensively investigated for QRS detection, curvature has rarely been used for this purpose [16]. We have observed that signed curvature (i.e. energy) has the following advantages for QRS detection:

- The negative energy at a positive R-peak is relatively higher than that at other positive peaks such as a P-peak and a T-peak as shown in the left side of Fig 1(b).
- Other two sharp negative peaks such as Q-peak and S-peak have positive energy, so they are readily filtered out.
- R-peak are linearly separable from other positive peaks if we use signed curvature as the energy as shown in Fig. 2.
- The location (time) of a detected R-peak is not shifted significantly (i.e. less error of detection) unlike the slope based method as shown in Fig 1(b). Only a small shift may occur due to the convolution operation in (4), and (5).

Hence, we propose a three steps method for QRS detection such as energy estimation, finding local minima, and non-R-peaks rejection. These three sequential steps are discussed in section 4.1 below. In section 4.2, we analyze the computational efficiency of the method.

4.1. Steps of the QRS Detection Algorithm

Step 1: Energy Estimation

Suppose \( x(i), i = 1, \ldots, n \), is a preprocessed ECG signal. The curvature of the signal can be defined as
\[
k = \frac{x''^2}{(1 + x'^2)^{3/2}},
\]  
where \( x' \) and \( x'' \) are the first and second derivatives respectively of the plain curve \( x \).

In order to estimate the energy, we need to compute the first derivative (\( x' \)) and second derivative (\( x'' \)) of \( x \). These are computed by a convolution operation with a Gaussian derivative kernel \( g'(\sigma) \) as follows
\[
x' = x \otimes g'(\sigma),
\]  
\[
x'' = x' \otimes g'(\sigma),
\]  
where \( \otimes \) is the convolution operator and \( \sigma \) is the standard deviation of the Gaussian derivative kernel of radius nine. The kernel is defined as follows
\[
g'(\sigma) = \frac{-x}{2.5\sigma^2} e^{-x^2/(2\sigma^2)}.
\]

Then the energy \( k(i) \) is estimated by (3). Left side of Fig. 1(b) shows the energy for the finger-ECG segment in Fig 1(a).

Step 2: Finding Local Minima

Local minima of energy within a window of 250-ms (refractory period) radius is calculated. If the energy at the center of a sweeping window is the lowest, then it is considered as the local minima. All such local minima are stored for further analysis as discussed in the next section.

Step 3: Non-R-peaks Rejection

There are two types of local minima detected in the second step: R-peaks and non-R-peaks. Non-R-peaks may be produced by P-wave, T-wave, or noises with sharp positive deflection. We have empirically analyzed the differences of energy at R-peak and a non-R-peak. From eighty randomly selected finger-ECG records, we computed the distribution of energy (i.e. curvature) of both types of peaks as shown in Fig. 2. It can be observed that R-peaks are linearly separable from non-R-peaks.

Based on this observation, an adaptive threshold is automatically determined for an ECG record to reject non-R-peaks. In order to determine the threshold a number of local minima having the low energy (i.e. high negative energy) is selected first. The number is less than duration of the ECG signal in seconds. The threshold is the 0.5 times of the average energy of selected low energy peaks. Now, all peaks having energy lower than the threshold is accepted as the valid R-peaks. Then a two samples window search in the ECG is performed to determine the location of real peaks.

![Fig. 2. Distribution of energy between R-peaks and non R-peaks](image)
4.2. Computational Efficiency

The proposed method consists of three sequential steps. In the first step, two convolution operation is carried out subsequently (not nested) requiring a time $O(n)$. Once the derivatives are computed the energy is computed with $O(n)$ time. In order to compute the local minima in the second step, we need to compare energy at each point of a fixed length window with its center. Hence, it also requires $O(n)$ time. Finally, the single thresholding requires insignificant time as the number of detected peaks is significantly less than $n$. Hence the computational time of this method is linear to the number of samples $n$ in the ECG signal, i.e. $O(n)$.

5. EXPERIMENTS AND RESULTS

We have implemented the proposed curvature based method using MATLAB. In order to compare the performance of our method, we also implemented the improved Hamilton-Tompkins method which is considered as the most effective and robust among five slope based methods in [10]. Table II shows the particulars of different steps of these two methods. Both of these methods were applied on our database of 224 finger-ECG records to detect QRSs. With the assistance of a physician, we counted the detected true-positive (TP) and false-positive (FP) QRSs for each record by each method. We also identified false negative (FN) QRSs for each record. Then the sensitivity (Se), positive predictivity (+P), and average time error (Ater) of detection were computed as follows:

$$Se = \frac{TP}{TP + FN} \times 100, \quad (7)$$

$$+P = \frac{TP}{TP + FP} \times 100, \quad (8)$$

$$Ater = \frac{\sum \text{detected peak time} - \text{actual peak time}}{TP}. \quad (9)$$

There are 4322 QRSs for all 224 records. By the proposed method, only four FNs were yielded. The average performances of both methods are shown in Table III. The improved Hamilton-Tompkins method yielded several false positive, which is overcome by the proposed method (Fig. 3(a) shows an example marked by an arrow). With the specified parameters of adaptive threshold in [10] the improved Hamilton-Tompkins failed to detect any QRS in two records. For the same reason, a good number of low amplitude QRSs were undetected in several records. Fig. 3(b) shows an example where improved Hamilton-Tompkins (right) failed but the proposed method (left) successfully detected QRSs. We selected twelve records where one or both methods failed to identify QRSs correctly and

![Fig. 3. Examples of QRS detection for three finger-ECG records: results on the left side are by proposed curvature based method and right side by improved Hamilton-Tompkins method.](image)

<table>
<thead>
<tr>
<th>Method</th>
<th>TP</th>
<th>FN</th>
<th>FP</th>
<th>Se (%)</th>
<th>+P (%)</th>
<th>Ater (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Improved Hamilton-Tompkins</td>
<td>4276</td>
<td>46</td>
<td>3</td>
<td>98.94</td>
<td>99.93</td>
<td>12.61</td>
</tr>
<tr>
<td>Curvature based method</td>
<td>4318</td>
<td>4</td>
<td>0</td>
<td>99.91</td>
<td>100</td>
<td>0.82</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Method</th>
<th>TP</th>
<th>FN</th>
<th>FP</th>
<th>Se (%)</th>
<th>+P (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Improved Hamilton-Tompkins</td>
<td>423</td>
<td>46</td>
<td>3</td>
<td>90.00</td>
<td>99.30</td>
</tr>
<tr>
<td>Curvature based method</td>
<td>466</td>
<td>4</td>
<td>0</td>
<td>99.15</td>
<td>100</td>
</tr>
</tbody>
</table>

Table III: Average performance of QRS detection

Table II: Particulars of different steps

- **Method**: Improved Hamilton-Tompkins, Proposed Curvature based method
- **Energy estimation**: Improved Hamilton-Tompkins: Slope, Proposed Curvature based method: Radius
- **Window**: Size 200 ms, ms to find local maxima
- **Parameters of threshold**: Four times of first threshold, one
- **Second threshold**: 0.5
- **Search-back range**: ±10 samples, ±2 samples

- **Fig. 3. Examples of QRS detection for three finger-ECG records: results on the left side are by proposed curvature based method and right side by improved Hamilton-Tompkins method.**

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computed sensitivity and positive predictivity as shown in Table IV. Fig. 3(c) shows an example when both methods failed to identify a low amplitude QRS.

6. DISCUSSION

We have developed a novel method for QRS detection based on the curvature of ECG signal. The method requires three computationally simple steps to detect QRSs. Linear computational time is required by this method, which is quadratic for existing slope based methods. The method was tested on a database of 224 finger-ECG records. We obtained 99.91% sensitivity and 100% positive predictivity which are superior to the existing method. This method has a single parameter of adaptive threshold, which required no tuning for our database. All these make this method suitable for real time applications of finger-ECG in biomedical engineering and biometrics. Although the proposed method has better performed for our database of finger-ECG, we are yet to test it on the benchmark databases of ECG signal, which is our intended future work.

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8. REFERENCES