ECG DELINEATION FOR QT INTERVAL ANALYSIS USING AN UNSUPERVISED LEARNING METHOD

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ABSTRACT

This paper presents a novel approach for automatic ECG delineation with focus on QT interval estimation, using an unsupervised learning algorithm. A three-dimensional feature space is created which uses the characteristics of ECG waveform at its inflection points. To this end, three features are introduced, including the Truncated Energy, which makes our method robust to baseline wandering and noise. Using the fact that the logarithm of features exhibits a mixture of four Gaussian distributions, each for one of the P wave, QRS complex, T wave and baseline, an unsupervised clustering algorithm based on Expectation Maximization is applied. The experimental results reveal that the proposed algorithm extracts the ECG waves accurately, even if they have a very low energy and amplitude. No pre-processing and windowing approach is required in the proposed method resulting in a significantly higher resolution and lower computational complexity in estimating the onset and offset of ECG waves. Furthermore, the proposed algorithm is robust to noise and baseline wandering, thanks to the Laplacian of Gaussian filter employed for inflection point detection.

Index Terms—ECG Delineation, Fiducial Point Analysis, QT Interval, Unsupervised Clustering.

1. INTRODUCTION

Electrocardiogram (ECG) provides the most valuable information about the heart electrical activity. A wide range of cardiac diseases can be diagnosed by analyzing ECG and its characteristics. The ECG is composed of different components including a P wave and a QRS complex followed by a T wave, which represent depolarization/repolarization or contraction of different heart chambers (see Fig. 1). Most of the heart related issues can be diagnosed by measuring the amplitude and width of these waves and time difference between them [1]. Therefore, the accurate estimation of peak, onset and offset of P wave, QRS complex and T wave is required in advanced automatic ECG interpretation systems. Specifically, the QT interval indicates the duration of ventricular repolarization and depolarization, which is very useful in diagnosing heart arrhythmia [2]. As shown in Fig. 1, the QT interval is measured as the distance between the onset of QRS complex and the offset of T wave, defined as the intersection between maximum negative slope line of T wave and baseline.

Generally, the ECG delineation algorithms consist of two main stages: preprocessing and decision making. At the first stage, the ECG features are highlighted using a transformation or filtering approach while the fiducial points are located in the second stage using a threshold-base technique. A variety of approaches is employed for this purpose including filtering techniques (e.g. Low-Pass Differentiation (LPD) [3–5], adaptive filtering [6] and nested median filtering [7]), transformation techniques (e.g. wavelet [8,9], Hilbert [10], Phasor [11] and Fourier [12]), morphology techniques (e.g. pattern and correlation analysis [13,14]), Bayesian inference (e.g. extended Kalman filter [15] and hidden Markov models [16]) and Neural Networks [17].

1.1. Relation to Prior Work

The existing methods in this area suffer from a variety of issues. They are mainly sensitive to low-amplitude T and P waves, noise and baseline wandering. Moreover, their accuracy dependents on the threshold levels used for decision making which are mostly adjusted arbitrarily making most of
them semi-automatic algorithms. Furthermore, some of the existing methods require a prior knowledge about the P and T waves characteristics e.g. width and morphology. Therefore, a comprehensive automatic approach which is able to deal with different morphologies and amplitude levels of T and P waves in noisy ECGs with baseline wandering is highly desirable.

In this paper, we propose a novel approach which automatically delineates different waves of ECG signals using an unsupervised clustering algorithm. Our main focus in this work is on improving the accuracy of QT interval measuring. The ECG signal is first segmented to the curves surrounded by two consecutive Inflection Points (IPs), the samples at which the concavity of ECG changes from being convex to concave, or vice versa. A three-dimensional feature space is then created based on characteristics of ECG segments at their IPs including slope, concavity, energy and width to achieve more reliability and robustness in ECG delineation. Our experiments reveal that four distinct clusters can be observed in the proposed feature space corresponding to: P wave, QRS complex, T wave and isoelectric segments representing baseline. Thus, we use an Expectation Maximization (EM) algorithm for Gaussian mixtures in order to cluster them automatically. Since the proposed method is robust to noise and baseline wandering, no pre-processing step, including low-pass and highpass filtering is required in our algorithm which guarantees a lower computational complexity.

2. THE PROPOSED METHOD

The IPs are located by finding zero-crossings of the second derivative of ECGs [18]. However, since the IEGM recordings are corrupted by noise, applying the derivative functions would boost the noise and make the output signals unstable. To remedy this problem, we propose to use a one-dimensional Laplacian of Gaussian (LoG) filter [19]. The two-dimensional version of this filter is widely used in image processing applications for the purpose of edge detection [20]. The LoG is an FIR filter which delivers the second derivative of the Gaussian smoothed version of the input signal. In fact, the Gaussian part of LoG filter is a low-pass filter which eliminates those variations of signal concavity created by noise. On the other hand, the Laplacian filter performs as a high-pass filter which eliminates the effect of baseline variations. The cut-off frequency of Gaussian filter is defined as [21]:

$$f_c = \frac{3f_s}{2\pi\sigma},$$

where $f_s$ represents the sampling frequency. Therefore, substituting the sampling frequency $f_s$ and desirable cut-off frequency $f_c$ into (1), the appropriate standard deviation is obtained for LoG filter.

Let $x_n$ be the ECG signal at discrete time index $n$. The output of LoG filter is then calculated as:

$$y_n = \text{LoG}_n(x_n),$$

in which $*$ represents the convolution. The IPs are then identified by locating the zero-crossings of $y_n$:

$$z_m = \{1 \leq n \leq N \mid y_n \cdot y_{n-1} \leq 0\}, \quad m = 1, \cdots, M, \quad (3)$$

where $z_m$ contains the time indexes of IPs and $N$ and $M$ represent the number of signal samples and IPs, respectively. Figure 2 shows an ECG signal and the corresponding IPs.

2.1. Creating a 3D Feature Space

Once the IPs are located, the ECG waves surrounded by two consecutive IPs are evaluated in order to categorize them into one of four possible clusters: P wave, QRS complex, T wave and baseline. This is performed using the characteristics of these waves at their IPs. According to Fig. 2, the first prominent characteristic of ECG waves is their width. Therefore, we propose to use the distance between two consecutive IPs as the first feature:

$$W_m \triangleq |z_m - z_{m-1}|, \quad m = 1, \cdots, M, \quad (4)$$

The second characteristic of ECG waves is the energy they carry. The energy of an ECG wave is normally defined in the literature as the sum of squared values of that wave. However, because of the baseline wandering, this may not be accurate as low-energy waves positioned at the higher baseline values may mistakenly be considered as high-energy segments. Furthermore, the isoelectric segments may represent high energy values. These facts can be observed in Fig. 2. Therefore, we propose to define the Truncated Energy as the sum of distances between the signal values and the line connecting two IPs at the wave boundaries:

$$E_m \triangleq \sum_{n=z_{m-1}}^{z_m} (x_n - l_n^{(m)}), \quad (5)$$

In (5), $l_n^{(m)}$ is a linear function representing the line which crosses two IPs, defined as follow:

$$l_n^{(m)} = \frac{x_{z_m-1}(z_m - n) + x_{z_m}(n - z_{m-1})}{z_m - z_{m-1}}, \quad (6)$$
In Fig. 2, the truncated energy $E_m$ of two T waves is depicted as shaded areas. As seen in this figure, while the energy of the first T wave ($T_1$) is considerably lower than that of the second T wave ($T_2$), their truncated energy is almost equal ($E_1 \approx E_2$). Moreover, the isoelectric segments represent a very low truncated energy while their energy may be high due to baseline variations. This guarantees that ECG waves would fall under different categories in terms of $E_m$, regardless of baseline wanderings.

The third feature that we propose for an ECG wave is the difference between the slopes at its IPs:

$$D_m \triangleq s_{zm} - s_{zm-1}$$

(7)

where

$$s_{zm} = x_{zm} - x_{zm-1}$$

(8)

This feature is a measure of curvature which is useful for distinguishing between waves with the same energy but different morphology. The three features proposed in this section create a three dimensional feature space where each wave is represented by a vector $f_m = [W_m \ E_m \ D_m]$.

### 2.2. Unsupervised Clustering

At the next step of our algorithm, the ECG waves are clustered into four groups using their properties in feature space. Since the features have different quantities, we first normalize them in the range of $[0, 1]$ in order to avoid biasing by high-valued features. Furthermore, our observations show that ECG waves are more distinguishable in three-dimensional feature space when natural logarithm of features is employed. That is because logarithm compensates skewing of the features. Interestingly, our observations also reveal that the natural logarithm of features exhibit a distribution of mixture of four or five Gaussian components, depending on the ECG signal used in our experiment. The same observation is reported in [22] for inactive and active intervals of speech signals in logarithmic scale.

Therefore, we propose to use an EM algorithm for Gaussian mixtures in order to cluster the feature vectors automatically [23, 24]. Hence, we define the underlying density as a Gaussian Mixture Model (GMM) with $C$ components:

$$p(f|\Theta) = \sum_{i=1}^{C} \tau_i N(f|s_i, \mu_i, \Sigma_i),$$

(9)

where $N$ represent a multivariate Gaussian distribution with mean $\mu_i$ and covariance matrix $\Sigma_i$. The unknown parameter vector $\Theta$ is also defined as:

$$\Theta = \{ \tau_1, \cdots, \tau_C, \mu_1, \cdots, \mu_C, \Sigma_1, \cdots, \Sigma_C \}$$

(10)

$s = (s_1, \cdots, s_C)$ is also a vector of four binary indicator variables which indicates the cluster to which $f_m$ belongs. Finally, $\tau_i$ is the probability that $f_m$ belongs to the $i$th cluster.

The EM algorithm updates the parameter vector $\Theta$ using the following two steps until the log-likelihood function converges:

- **E-Step**: Using the Bayes rule, compute the membership weight $\omega_{mi}$ of the $m$th feature vector in the $i$th cluster:

$$\omega_{mi} = \frac{\mathcal{N}(f_m|s_i, \mu_i, \Sigma_i)}{\sum_{j=1}^{C} \tau_j \mathcal{N}(f_m|s_j, \mu_j, \Sigma_j)}$$

(11)

- **M-Step**: For the $i$th cluster, calculate new parameter values $\Theta^{\text{new}}$ using the membership weights:

$$\tau_i^{\text{new}} = \frac{\sum_{m=1}^{M} \omega_{mi}}{M},$$

$$\mu_i^{\text{new}} = \frac{\sum_{m=1}^{M} \omega_{mi} f_m}{\sum_{m=1}^{M} \omega_{mi}},$$

$$\Sigma_i^{\text{new}} = \frac{\sum_{m=1}^{M} \omega_{mi} (f_m - \mu_i^{\text{new}})(f_m - \mu_i^{\text{new}})^T}{\sum_{m=1}^{M} \omega_{mi}}.$$

(12)

Once the feature vectors are clustered using the EM algorithm, the clusters corresponding to P and T waves, QRS complex and baseline need to be identified. Our observations reveal that for those ECG leads in which the S wave is not distinguishable, four clusters corresponding to P and T waves, QRS complex and baseline are observed (Fig. 3.a). On the other hand, in some other ECG leads, the S wave is strong and hence five distinct clusters of feature vectors are observed (Fig. 3.b). To consider this issue, we first employ the EM algorithm for five clusters ($C = 5$) and correspond the cluster with the highest average truncated energy to QR wave. If a cluster with different polarity of truncated energy is recognized immediately after the QR wave, we consider it as S wave otherwise the QR wave is in fact the QRS complex. The experimental results for these two cases is depicted in Fig. 3.

### 3. RESULTS AND DISCUSSION

We employ the QT database available on PhysioNet website in order to evaluate our proposed algorithm in comparison with some other state-of-the-art methods [25]. This database includes 105 recordings of ECG signals with different P, QRS and T wave morphologies. The signals are sampled at the rate of 250 Hz and each recording includes two leads in which the peak, onset and offset of ECG waves are manually annotated by two experts. For every ECG recording, we apply the proposed algorithms to both leads and report the results for the lead with closer results to manually annotations.

The estimation error is defined as the difference between manual annotations and the output of delineation methods.
Table 1. The mean (µ) and standard deviation (σ) of error between annotations and estimation results (in millisecond) and TPR (%) for four different algorithms using QT database including two-lead ECG signals.

<table>
<thead>
<tr>
<th>Method</th>
<th>µ ± σ</th>
<th>P_{on}</th>
<th>P_{peak}</th>
<th>P_{off}</th>
<th>QRS_{on}</th>
<th>QRS_{off}</th>
<th>T_{on}</th>
<th>T_{peak}</th>
<th>T_{off}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed</td>
<td>7.1±9.0</td>
<td>12.8±12.2</td>
<td>6.8±15.4</td>
<td>1.1±8.2</td>
<td>7.8±10.3</td>
<td>12.6±23.0</td>
<td>1.5±9.0</td>
<td>10.3±11.2</td>
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<tr>
<td></td>
<td>10.0±24.5</td>
<td>13.1±14.9</td>
<td>-4.7±17.2</td>
<td>-</td>
<td>33.1±27.8</td>
<td>15.4±6.8</td>
<td>31.2±21.8</td>
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<tr>
<td>[5]</td>
<td>97.84</td>
<td>96.08</td>
<td>99.21</td>
<td>-</td>
<td>80.45</td>
<td>90.87</td>
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</tr>
<tr>
<td>[8]</td>
<td>-13.1±14.1</td>
<td>-4.1±12.0</td>
<td>-7.2±13.8</td>
<td>-1.6±8.2</td>
<td>20.8±7.7</td>
<td>15.1±20.1</td>
<td>0.8±11.9</td>
<td>-21.5±15.2</td>
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<td>[11]</td>
<td>9.8±18.7</td>
<td>5.0±11.3</td>
<td>-4.2±14.6</td>
<td>3.2±11.5</td>
<td>6.2±9.7</td>
<td>7.2±31.9</td>
<td>1.0±13.8</td>
<td>-14.2±24.0</td>
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TPR

<table>
<thead>
<tr>
<th>Method</th>
<th>µ ± σ</th>
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<td>[5]</td>
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<tr>
<td>[8]</td>
<td>95.21</td>
<td>97.17</td>
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The mean and standard deviation of error is then calculated as a measure of accuracy. The True Positive Rate (TPR) is also defined as the ratio of true positives to sum of true positives and false negatives. The results are reported in Table 1 for the proposed algorithm and three other methods including algorithms proposed in [5] which is based on low-pass filtering and differentiation, [8] which is based on wavelet transform and [11] which is based on phasor transform.

According to Table 1, although the T wave has significantly larger amplitude comparing to P wave, estimating its boundaries is more difficult than the other waves. It is mainly because T wave has a smooth transition at its boundaries. However, the proposed method provides the highest TPR in extracting T wave boundaries and lowest error in T wave offset and QRS onset estimation which is an asset in clinical applications where accurate estimation of QT interval is required.

4. CONCLUSION

In this work, an unsupervised clustering algorithm was proposed for automatic delineation of ECG signals. The IPs were first located using an LoG filter which makes the proposed algorithm robust to noise and baseline wandering. ECG signals were then segmented to the waves between two consecutive IPs and a 3D feature space was created based on three characteristics including truncated energy, width and sum of slopes at their boundaries to achieve more reliability and robustness. An EM algorithm for Gaussian mixtures was then applied for automatic clustering of features. Experimental results reveal that the proposed method provides the highest accuracy in estimating the QT interval comparing to the other methods. No pre-processing and windowing approach was employed in the proposed method guaranteeing a higher resolution and lower computational complexity in estimating the onset and offset of ECG waves. Since the proposed method is robust to noise and baseline wandering, no pre-processing step, including lowpass and highpass filtering is required in our algorithm which guarantees a lower computational complexity.

5. REFERENCES


