ECG DELINEATION FOR QT INTERVAL ANALYSIS USING AN UNSUPERVISED LEARNING METHOD

Habib Hajimolahoseini, Javad Hashemi, Damian Redfearn

Cardiac Arrhythmia Signal Analysis Lab
School of Medicine, Queen's University
Kingston, K7L 3N6, ON, Canada

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.

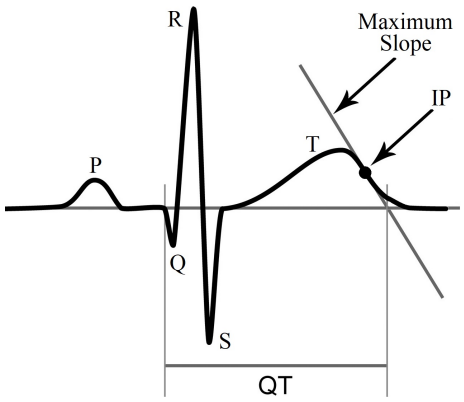

Fig. 1. A normal ECG, its components and QT interval.

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]:

$$f_c \triangleq \frac{3f_s}{2\pi\sigma}, \tag{1}$$

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:

$$y_n = \mathrm{LoG}_n^{(\sigma)} * x_n. \tag{2}$$

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

$$z_m = \{1 \le n \le N \big| y_n.y_{n-1} \le 0\}, \quad m = 1, \cdots, M, \tag{3}$$

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.

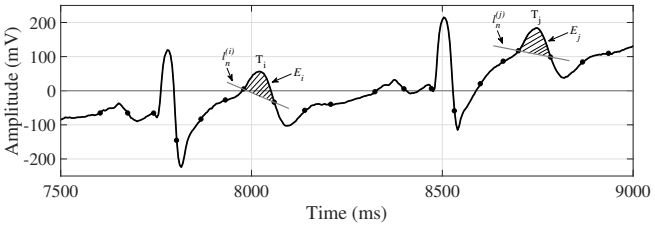

Fig. 2. An ECG signal with baseline wandering. The dark dots represent the IPs extracted using (3). The shaded areas show the truncated energy proposed in (5)

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:

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

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:

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

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

$$l_n^{(m)} \triangleq \frac{x_{z_{m-1}}(z_m - n) + x_{z_m}(n - z_{m-1})}{z_m - z_{m-1}}, \tag{6}$$

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_i) is considerably lower than that of the second T wave (T_j), their truncated energy is almost equal ($E_i \approx E_j$). Moreover, the isoelectric segments represent a very low truncated energy while their energy may be high duo 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:

$$D_m \triangleq s_{z_m} - s_{z_{m-1}} \tag{7}$$

where

$$s_{z_m} = x_{z_m} - x_{z_m - 1} \tag{8}$$

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 $\mathbf{f}_m = [W_m \; E_m \; D_m]$.

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 3D 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:

$$p(\mathbf{f}|\mathbf{\Theta}) = \sum_{i=1}^{C} \tau_i \mathcal{N}(\mathbf{f}|s_i, \boldsymbol{\mu}_i, \mathbf{\Sigma}_i), \tag{9}$$

where $\mathcal{N}$ represent a multivariate Gaussian distribution with mean $\boldsymbol{\mu}_i$ and covariance matrix $\mathbf{\Sigma}_i$. The unknown parameter vector $\mathbf{\Theta}$ is also defined as:

$$\mathbf{\Theta} = \{\tau_1, \cdots, \tau_C, \boldsymbol{\mu}_1, \cdots, \boldsymbol{\mu}_C, \mathbf{\Sigma}_1, \cdots, \mathbf{\Sigma}_C\} \tag{10}$$

$\mathbf{s} = (s_1, \cdots, s_C)$ is also a vector of four binary indicator variables which indicates the cluster to which $\mathbf{f}_m$ belongs. Finally, τ_i is the probability that $\mathbf{f}_m$ belongs to the ith cluster.

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

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

$$\begin{aligned} \omega_{mi} &= p(s_{mi} = 1|\mathbf{f}_k, \mathbf{\Theta}) \\ &= \frac{\mathcal{N}(\mathbf{f}_m|s_i, \boldsymbol{\mu}_i, \mathbf{\Sigma}_i)}{\sum_{j=1}^{C} \tau_j \mathcal{N}(\mathbf{f}_m|s_j, \boldsymbol{\mu}_j, \mathbf{\Sigma}_j)} \end{aligned} \tag{11}$$

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

$$\begin{aligned} \tau_i^{\text{new}} &= \frac{\sum_{m=1}^{M} \omega_{mi}}{M}, \\ \boldsymbol{\mu}_i^{\text{new}} &= \frac{\sum_{m=1}^{M} \omega_{mi} \mathbf{f}_m}{\sum_{m=1}^{M} \omega_{mi}}, \\ \mathbf{\Sigma}_i^{\text{new}} &= \frac{\sum_{m=1}^{M} \omega_{mi} (\mathbf{f}_m - \boldsymbol{\mu}_i^{\text{new}})(\mathbf{f}_m - \boldsymbol{\mu}_i^{\text{new}})^T}{\sum_{m=1}^{M} \omega_{mi}}, \end{aligned} \tag{12}$$

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.

Method		P_{on}	P_{peak}	P_{off}	QRS_{on}	QRS_{off}	T_{on}	T_{peak}	T_{off}
Proposed	$\mu \pm \sigma$	7.1±9.0	12.8±12.2	6.8±15.4	1.1±8.2	7.8±10.3	12.6±23.0	1.5±9.0	10.3±11.2
	TPR	98.78	97.21	98.33	100	100	98.64	98.01	97.23
[5]	$\mu \pm \sigma$	10.0±24.5	13.1±14.9	-7.4±17.2	-	-	33.1±27.8	15.4±6.8	31.2±21.8
	TPR	97.84	96.08	99.21	-	-	80.45	90.87	88.45
[8]	$\mu \pm \sigma$	-13.1±14.1	-4.1±12.0	-7.2±13.8	-1.6±8.2	2.0±8.7	15.1±20.1	0.8±11.9	-21.5±15.2
	TPR	98.62	99.02	98.99	100	100	95.21	97.17	93.77
[11]	$\mu \pm \sigma$	9.8±18.7	5.0±11.3	-4.2±14.6	3.2±11.5	6.2±9.7	7.2±31.9	1.0±13.8	-14.2±24.0
	TPR	97.02	97.27	98.35	100	100	97.77	97.78	94.25

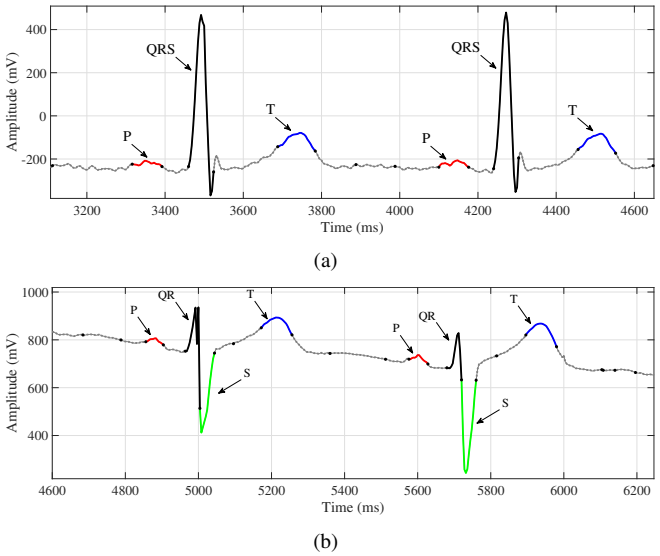

Fig. 3. The ECG delineation results when (a) there is no distinguishable S wave and (b) when S wave is distinguishable.

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

[1] John R Hampton, *The ECG Made Easy E-Book*, Elsevier Health Sciences, 2013.

[2] Robert J Myerburg, "Cardiac arrest and sudden cardiac death," *Heart disease: a textbook of cardiovascular medicine*, 2005.

[3] Julia Rosemary Thorpe, Trine Saida, Jesper Mehlsen, Anne-Birgitte Mehlsen, Henning Langberg, Karsten Hoppe, and Helge BD Sorensen, "Comparative study of t-amplitude features for fitness monitoring using the epatch® ecg recorder," in *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE*. IEEE, 2014, pp. 4172–4175.

[4] Ahcène Goutas, Youcef Ferdi, Jean-Pierre Herbeuval, Malika Boudraa, and Bachir Boucheham, "Digital fractional order differentiation-based algorithm for p and t-

waves detection and delineation," *ITBM-RBM*, vol. 26, no. 2, pp. 127–132, 2005.

[5] Yogendra Narain Singh and Phalguni Gupta, "Ecg to individual identification," in *Biometrics: Theory, Applications and Systems, 2008. BTAS 2008. 2nd IEEE International Conference on*. IEEE, 2008, pp. 1–8.

[6] Emilio Soria-Olivas, Marcelino Martinez-Sober, Javier Calpe-Maravilla, JF Guerrero-Martinez, Javier Chorro-Gascó, and J Espi-Lopez, "Application of adaptive signal processing for determining the limits of p and t waves in an ecg," *IEEE Transactions on Biomedical Engineering*, vol. 45, no. 8, pp. 1077–1080, 1998.

[7] P Strumillo, "Nested median filtering for detecting t-wave offset in ecgs," *Electronics Letters*, vol. 38, no. 14, pp. 682–683, 2002.

[8] Juan Pablo Martínez, Rute Almeida, Salvador Olmos, Ana Paula Rocha, and Pablo Laguna, "A wavelet-based ecg delineator: evaluation on standard databases," *IEEE Transactions on biomedical engineering*, vol. 51, no. 4, pp. 570–581, 2004.

[9] Francisco Rincón, Joaquin Recas, Nadia Khaled, and David Atienza, "Development and evaluation of multilead wavelet-based ecg delineation algorithms for embedded wireless sensor nodes," *IEEE Transactions on Information Technology in Biomedicine*, vol. 15, no. 6, pp. 854–863, 2011.

[10] João PV Madeiro, Paulo C Cortez, João AL Marques, Carlos RV Seisdedos, and Carlos RMR Sobrinho, "An innovative approach of qrs segmentation based on first-derivative, hilbert and wavelet transforms," *Medical engineering & physics*, vol. 34, no. 9, pp. 1236–1246, 2012.

[11] Arturo Martínez, Raúl Alcaraz, and José Joaquín Rieta, "Application of the phasor transform for automatic delineation of single-lead ecg fiducial points," *Physiological measurement*, vol. 31, no. 11, pp. 1467, 2010.

[12] ISN Murthy and UC Niranjan, "Component wave delineation of ecg by filtering in the fourier domain," *Medical and Biological Engineering and Computing*, vol. 30, no. 2, pp. 169–176, 1992.

[13] Mohammad R Homaeinezhad, M ErfanianMoshiri-Nejad, and H Naseri, "A correlation analysis-based detection and delineation of ecg characteristic events using template waveforms extracted by ensemble averaging of clustered heart cycles," *Computers in biology and medicine*, vol. 44, pp. 66–75, 2014.

[14] Swati Banerjee and Madhuchhanda Mitra, "Application of cross wavelet transform for ecg pattern analysis and classification," *IEEE transactions on instrumentation and measurement*, vol. 63, no. 2, pp. 326–333, 2014.

[15] O Sayadi and MB Shamsollahi, "A model-based bayesian framework for ecg beat segmentation," *Physiological measurement*, vol. 30, no. 3, pp. 335, 2009.

[16] L Clavier, J-M Boucher, R Lepage, J-J Blanc, and J-C Cornily, "Automatic p-wave analysis of patients prone to atrial fibrillation," *Medical and Biological Engineering and Computing*, vol. 40, no. 1, pp. 63–71, 2002.

[17] Zümray Dokur, Tamer Ölmez, Ertugrul Yazgan, and Okan K Ersoy, "Detection of ecg waveforms by neural networks," *Medical engineering & physics*, vol. 19, no. 8, pp. 738–741, 1997.

[18] Ilía Nikolaevich Bronshtein and Konstantin Adol'fovich Semendyayev, *Handbook of mathematics*, Springer Science & Business Media, 2013.

[19] GE Sotak and Kim L Boyer, "The laplacian-of-gaussian kernel: a formal analysis and design procedure for fast, accurate convolution and full-frame output," *Computer Vision, Graphics, and Image Processing*, vol. 48, no. 2, pp. 147–189, 1989.

[20] John Canny, "A computational approach to edge detection," *IEEE Transactions on pattern analysis and machine intelligence*, , no. 6, pp. 679–698, 1986.

[21] Herman Blinchikoff and Helen Krause, *Filtering in the time and frequency domains*, The Institution of Engineering and Technology, 2001.

[22] Sanaz Seyedin, Saeed Gazor, and Seyed Mohammad Ahadi, "On the distribution of mel-filtered log-spectrum of speech in additive noise," *Speech Communication*, vol. 67, pp. 8–25, 2015.

[23] Sean Borman, "The expectation maximization algorithm-a short tutorial," *Submitted for publication*, pp. 1–9, 2004.

[24] Hernan Dario Vargas Cardona, Alvaro Angel Orozco, and Mauricio A Alvarez, "Unsupervised learning applied in mer and ecg signals through gaussians mixtures with the expectation-maximization algorithm and variational bayesian inference," in *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE*. IEEE, 2013, pp. 4326–4329.

[25] Ary L Goldberger, Luis AN Amaral, Leon Glass, Jeffrey M Hausdorff, Plamen Ch Ivanov, Roger G Mark, Joseph E Mietus, George B Moody, Chung-Kang Peng, and H Eugene Stanley, "Physiobank, physiotoolkit, and physionet," *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.