Real-Time ECG Delineation with Randomly Selected Wavelet Transform Feature and Random Walk Estimation*

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***Abstract*— Detection of Electrocardiogram (ECG) characteristic points can provide critical diagnostic information about heart diseases. We propose a novel feature extraction and machine learning scheme for ECG delineation. A new feature, termed as randomly selected wavelet transform (RSWT), is proposed to effectively represent ECG morphology. With the RSWT feature pool, a regression tree is trained to estimate the probability distribution to the direction toward the target point, relative to the current position. The continual random walk through 1D space will eventually produce a reliable region from which the final position of the target point is derived. The evaluation results on QT database show better detection accuracy compared with other studies while providing real-time processing capability.**

I. Introduction

Automatic annotation of electrocardiograms (ECGs) has received increasing attention because of its vital role in the diagnoses of many cardiac diseases [1]. Most of the clinically useful information in ECG can be inferred from the intervals and amplitudes of the ECG characteristic points (the peaks and limits of the individual QRS waves, P wave, and T wave).

There are many QRS complex detection and ECG delineation methods to determine the positions of ECG characteristic points. QRS complex detection methods [2], [3], [4] including empirical mode decomposition and threshold-independent QRS detection algorithm. However, since P and T waves may have low amplitude and a variety of morphologies, most of these QRS detection methods cannot be straightforwardly applied to the detection of P and T waves. Other delineation methods including low-pass differentiation (LPD) [5], [6], hidden Markov models [7], and spline representation [8] can delineate P and T waves, with pre-defined models and manually adjusted data-sensitive parameters.

Wavelet transform is a popular technique in ECG characteristic point detection [9]. Inspired by this method, Martinez et al. [10] developed a single-lead ECG delineation system based on wavelet transform. Based on an improved QRS complex detection method proposed in [11], their system estimated the P and T wave peaks, on-sets, and off-sets, which showed acceptable detection accuracy on public ECG databases. Chen et al. [12] modelled three categories of T wave and designed their decision rule accordingly. Dumont et al. [13] applied evolutionary algorithms to tune parameters of an ECG wavelet transform-based delineator, and achieved similar detection accuracy as in [10]. P wave detection and delineation are also achieved with phase free stationary wavelet transform in [14].

Some recent studies have adopted statistical machine learning techniques in the detection of ECG characteristic points. Saini et al. [15] proposed a K-Nearest Neighbor classification approach for ECG recognition, which was evaluated on multiple ECG databases. However, the K-NN method suffers from the curse of dimensionality when the feature dimension is high, and the trained K-NN classifier model is memory consuming. Based on partially collapsed Gibbs sampler, Bayesian method was proposed in [16], [17]. By exploiting the strong local dependency of ECG signals, the method showed relatively high detection accuracy of ECG characteristic points on the QT database. However, their method still have challenges when ECG signals don't meet their prior knowledge. In our previous work, a time-domain feature randomly selected signal pair difference (RSSPD) was proposed for ECG characteristic point detection in [18]. This detection scheme is preliminarily evaluated on pre-selected 30 records on QT database and achieved acceptable performance.

In this paper, we propose a fast ECG delineation scheme by leveraging wavelet transform and machine learning techniques to detect characteristic points in ECG waveform. We devise a novel wavelet transform-based feature, termed as randomly selected wavelet transform (RSWT) feature. The RSWT feature effectively represents the morphology of ECG waveform. With the RSWT feature pool, we build a random forest regressor for each characteristic point. The regression tree is trained to estimate the probability distribution to the direction toward the target point, relative to the current position. Then we devise a random walk testing scheme to refine the final position of each ECG characteristic point. Our evaluation result on the QT database [19] shows comparable accuracy to other state-of-the-art works and a prominent detection speed. This means our method can perform well in applications like real-time ECG monitoring and diagnosis.

II. Framework

Electrocardiogram (ECG) is a non-invasive way to measure the heartbeat rhythms. The heart's electrical activity can be captured by the voltage variance of ECG. The ECG signal from a normal heart has typical features such as the QRS complex, the T wave, and the P wave.

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Our work can infer eight types of ECG characteristic points: onset, peak and offset of P wave, onset, offset of QRS complex and its fiducial mark (typically at the R-wave peak, according to the annotation definition in QT database), peak and offset of T wave (onset of T wave isn't included in QT database).

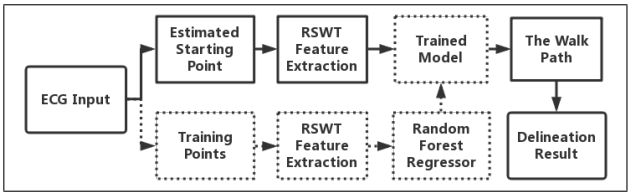

Fig. 1. The proposed framework for ECG delineation.

The proposed random walk framework consist of 2 stages: model training and ECG delineation. At first we train a random forest regressor model for each type of ECG characteristic points, then devise a testing scheme for ECG delineation, as is shown in Fig. 1.

In the random walk model training process, the inputs are the ECG signal and their expert annotations. We train a random forest regressor model for each type of expert annotations. For each annotation position, we select N_{sel} training positions with distance to the annotation position d_{annot} conform to the Normal distribution:

$$d_{annot} \sim N(0, \sigma_{annot}) \tag{1}$$

Where the σ_{annot} is kept a small value to confine the distance to the annotations. For each training position, we assign a value of 1.0 or -1.0 according to the relative direction between the training position and the annotation position. Then the RSWT feature, which is described in detail later, is extracted according to the training positions. Finally, we adopt the random forest training algorithm to train the regression model for our random walk scheme. The baseline removal and noise reduction process can be combined within the feature selection by the random forest regressor.

In the ECG delineation module, we process the ECG with a beat-by-beat fashion. Since the R wave of the QRS complex is relatively easy to detect, we first adopt an QRS detection process, which can server as the basis for positioning other characteristic points. Based on the R wave peak positions given by the DPI algorithm [4], we detect the positions of other characteristic points with a random walk estimation scheme.

III. RSWT Feature Extraction

We design a new feature for random forest regressor to derive the position of ECG characteristic points. This feature is extracted from the stationary wavelet transform coefficients to represent the relative amplitude differences of wave morphologies.

In the feature extraction process, a set of features are extracted from one of the given ECG sample point positions. The ECG time-domain signal is first transformed to 8 levels of stationary wavelet domain with Daubechies 2 wavelet (db2). We chose the db2 wavelet because the Daubechies Wavelet is widely reported for the accuracy of details compared to other methods. Moreover, this wavelet shows similarity with QRS complexes and the energy spectrum is concentrated around low frequencies [20]. Then a fixed-size window with length L_w is positioned on each level of wavelet coefficients, with window center located on the target sample point. We set the value of the window length L_w to $3 \times f_s$ to collect enough surrounding features of the window center, where f_s is the sampling frequency of the input ECG. We extract features from the set of windows to determine the relative position of the ECG characteristic point between the window center. The RSWT feature for each ECG sample position was extracted from a set of signal windows centered on the sample position guided by a pre-set pattern. This randomly selected pattern was fixed and unchanged throughout the entire training and testing process.

$$F(pair_{x_1,x_2}) = \begin{bmatrix} A_{x_1} - A_{x_2} \\ \|A_{x_1} - A_{x_2}\| \end{bmatrix} \tag{2}$$

Equation 2 describes the feature computation process, where $pair_{x_1,x_2}$ denotes the pair with index positions x_1 and x_2. A_{x_1} denotes the amplitude of the signal in position x_1. $\|\cdot\|$ denotes the absolute value sign.

IV. Random Walk ECG Delineation Scheme

A. Training with Random Forest Regressor

After the features are extracted, we adopt a random forest regressor to estimate the probability distribution at current testing location.

Random forest regressor is an ensemble method to estimate value output with a bag of regression trees. The advantage of random forest is that it is not prone to overfitting, and produce a limiting value of the generalized error when the number of trees increased. Each regression tree in random forest is minimized in correlation while maintaining strength. Moreover, random forest is relatively robust to outliers and noise, and it is simple and easily parallelized [21].

The random forest regressor used in this paper is from the Python scikit-learn tools, with a slightly modified version of the random forest proposed in [21]. In contrast to the original

- Estimate target label position P_0 according by adding bias to QRS location P_{QRS}:
  $P_0 = P_{QRS} + \delta_{target}$
- Iterate N_{it} times, for i from 0 to $N_{it} - 1$:
  - Extract RSWT feature from current location P_i
  - Derive random forest regression output R_{out}
  - Derive the probability of direction between current position and target label positon, P_{left} and P_{right}
  - Randomly decide go to left or right according to P_{left} and P_{right}
  - Update P_{i+1} according to equation 5

Fig. 2. Pseudo code of Random Walk Scheme.

publication [21], the scikit-learn implementation combines classifiers by averaging their probabilistic prediction, instead of letting each classifier vote for a single class.

In the random forest regressor, the decision tree number N_{tree} is set to 30, and the max depth limit of each decision tree D_{tree} is set to 10.

B. Testing with Random Walk Algorithm

This section describes a fast detection scheme for ECG characteristic point detection while maintaining high accuracy. As is shown in Fig. 2, the random walk algorithm executes for a fixed number of times and estimate the final position of the target characteristic point according to the random walking path. Since the testing scheme do not need to test each ECG sample point, therefore accelerates the detection speed of the algorithm.

The testing process of other characteristic points starts with estimations of their position P_{seed}. The estimation is calculated by the position of the QRS and the relative bias of the characteristic point, as shown in equation 3.

$$P_{seed} = P_{QRS} + \delta_{target} \tag{3}$$

Where P_{QRS} is the position of R peak in QRS complex, and δ_{target} is the bias of current target label.

The bias δ_{target} is derived from the average of the biases of every characteristic point with the same type in the training data, as is shown in equation 4.

$$\delta_{target} = \frac{\sum_{i=1}^{n}[P_{target}(i) - P_{QRS}(i)]}{n} \tag{4}$$

Where n is the total number of target label in the training dataset, $P_{target}(i)$ and $P_{QRS}(i)$ are the i_{th} expert annotation position of the target label and QRS label, respectively.

After deriving P_{seed}, a random walk process is initiated to form a walk path, which is then used for estimating the position of the target label. The random walk process is conducted for each QRS detected to generate other ECG characteristic point positions in each heart cycle.

The random walk process will run for N_{iter} iterations. At the beginning of i_{th} iteration, we extract RSWT features from the current walk position α_i and set the RSWT feature of current sampling point as input of the regression tree model, then derive the output R_{out}. Thus we can estimate the probability P_{left} and P_{right} of target label according to R_{out}, where P_{left} is the probability that the nearest target point lies in the left of α_i, so is P_{right}. Since there are only two directions in the 1-d ECG signal, therefore $P_{left} + P_{right} = 1$. In the next step, we randomly set the direction of current sample point according to the value of P_{left} and P_{right}. And the next walk position is given by:

$$\alpha_{i+1} = \alpha_i + \chi \cdot \varepsilon \tag{5}$$

Where ε is the fixed step size of random walk process and χ is the decision random variable given by:

$$\chi = \begin{cases} -1, & P_{left} > P_{right} \\ 1, & P_{right} > P_{left} \end{cases} \tag{6}$$

The random walk process will stop after N_{iter} iterations. The array of walk positions will form a random walk path that converges to the final position of target label, as is shown in figure 3.

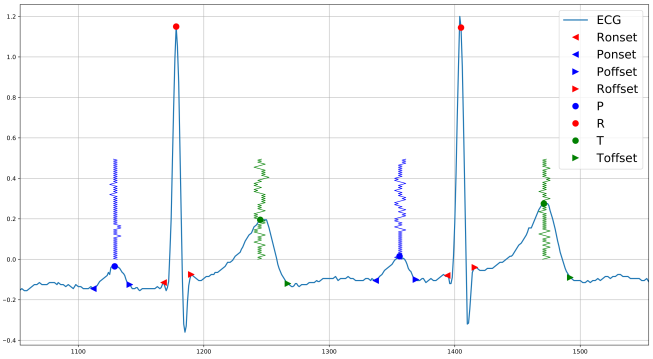

Fig. 3. Random walk path of P and T wave peak, tested on record sel872, QT database.

By adjusting the step size in random walk scheme (initially we set $\varepsilon = 3$), the required iterations for each point can be controlled to balance the trade-off between accuracy, stability, and efficiency. In our experiments, sufficient accuracy and stability is achieved with only 64 steps. By fixing the number of steps, the computation time is stable regardless of the ECG size.

According to the performance of training dataset, we found that the walk path generally tend to vibrate around the target point after $\frac{N_{iter}}{2} = 32$ iterations. The final output of the random walk process is calculated by the walk path:

$$\alpha_{output} = \frac{\sum_{i=\frac{N_{iter}}{2}}^{N_{iter}} \alpha_i}{\frac{N_{iter}}{2}} \tag{7}$$

V. Experiments

A. Comparison of Detection Accuracy

To evaluate the performance of the random walk algorithm, we experiment on the QT database [19] and compare with several other state-of-the-art algorithms.

The QT database contains 105 records, with annotations of P, QRS, and T waves (except for T-onset). We randomly select 75 records out of 105 records as training set, the remaining 30 records as testing set, to evaluate the random walk algorithm. This process is repeated for 30 rounds to derive the averaged detection accuracy. The performance of wave delineation is measured by the average M and standard deviation SD of error values, which indicates the detection accuracy of the proposed method. For each expert label, the error is defined as the distance between the detection output and the current expert label.

Table I shows the comparison results between the proposed algorithm, RSSPD [18], the wavelet algorithm [10], [14] and the Gibbs sampler algorithm [16], [17]. Our method can detect more types of characteristic point compared with algorithms [14], [16], [17]. We can also detect any other

TABLE I
DETECTION ACCURACY ON THE QT DATABASE

Method	Metric	P-on	P-peak	P-off	QRS-on	QRS-off	T-peak	T-off
Random Walk (ours)	M±SD (ms)	-1.4±10.4	0.7±8.7	-1.6±9.4	-1.5±7.8	1.4±7.6	-0.77±9.3	0.73±11.5
RSSPD [18]	M±SD (ms)	0.4±22.0	N/A	2.1±12.9	0.2±10.2	0.5±14.4	N/A	1.4±17.2
Phase free SWT [14]	M± SD (ms)	-0.3±12.2	N/A	5.8±9.1	N/A	N/A	N/A	N/A
Beat-to-beat BGS [16]	M±SD (ms)	3.4±14.2	1.1±5.3	2.7±9.8	N/A	N/A	-0.8±4.1	-3.1±14.0
Multi-beat PCGS [17]	M± SD (ms)	1.7±10.8	2.7±8.1	2.5±11.2	N/A	N/A	0.7±9.6	2.7±13.5
WT [10]	M±SD (ms)	2.0±14.8	3.6±13.2	3.5±18.0	4.6±7.7	0.8±8.7	0.2±13.9	-1.6±18.1

[1]N/A indicates the statistics is not available.

type of characteristic points by adding training samples to the random forest regressor if there are enough annotations. Besides, our SD is relatively better than algorithms [18], [10] which means we achieve better robustness.

B. Random Walk Runtime Efficiency

The testing speed of the random walk scheme is related to the estimation position P_{seed}, step size ε, and N_{iter}. We set the estimation position of each ECG characteristic point relative to the R peak detected in ECG, as is shown in equation 3. And we finally adjust N_{iter} and ε to 64 and 3 according to the experiments.

In the experiment of this paper, we use a computer with 24GB of Ram, $IntelCore^{TM}$ i7-4790 CPU @ 2.6GHz. On average, a 100s ECG segment with sampling frequency of 500Hz will result in 25s of testing time with random walk scheme yet 125s with our previous work RSSPD [18]. It is acceptable for applications that displays ECG and its annotations in real-time.

VI. CONCLUSION

We have proposed a novel fast ECG delineation scheme with high speed and acceptable detection accuracy. The proposed random walk testing scheme adopt random forest regressor to determine the position of target ECG label position. Other type of ECG characteristic points can also be detected by adding training samples to the random forest regressor. Therefore the random walk testing scheme is suitable for real-time ECG delineation applications.

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