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ECG to Individual Identification

Yogendra Narain Singh and Phalguni Gupta

Abstract—This paper presents an individual identification system using single lead electrocardiogram (ECG). The proposed techniques for P and T wave delineation are based on time derivative and adaptive thresholding. The performance of proposed delineators is evaluated on manually annotated Physionet QT database. The accuracy of delineators are quantified on mean error and standard deviation of differences between manually annotations and automated results. Especially, lower values of error in standard deviation for onset and offset of P wave fiducials are obtained as 8.1 and 6.29 while for T wave fiducials are 9.4 and 11.2 (where units are in *ms*). It shows the performance of P and T wave delineators is optimum and also stable in comparison to other published results. Found fiducials are processed for the extraction of heartbeat features. From each heartbeat, 19 stable features related to interval, amplitude and angle are computed. The feasibility of ECG as a new biometric is tested on proposed identification system designed on template matching and adaptive thresholding. The accuracy of identification system is achieved to 99% on the dataseize of 125 recordings prepared from 25 individual ECG of Physionet.

I. INTRODUCTION

The Electrocardiogram (ECG) is a record of time-varying bioelectric potential generated by electrical activity of the heart. Beginning of the century from the introduction of string galvanometer by Willem Einthoven [1], ECG has become a fundamental tool of diagnosing intraventricular conduction disturbances and arrhythmia [2]. The interpretation of ECG may lead to the recognition of electrolyte abnormalities and assist in deduction of electrical and/or structural cardiac dysfunctions. In current trend of research, ECG is not only used in experimental trials of drugs to recognize the potential cardiac effects but also in surveillance it can be used as a potential biometric for identifying the individuals.

In recent past, different studies have been conducted for the use of ECG in biometrics. Biel *et al.* [3] have conducted the biometric experiment on ECG recorded from a group of 20 subjects. Twelve features have been selected from each record for identification of a person in a predefined group. Shen *et al.* [4] have investigated the feasibility of ECG as a new biometric for identity verification. The experiment has been conducted on 20 individuals on seven features, extracted from mainly QRS complex. Using the techniques of neural network and template matching the experiment of human identity verification has been performed. The issues of these studies are mainly: (1) the extraction of ECG features and

their accuracy; and (2) the investigation of ECG to change in physiology of the heart.

Steven *et al.* [5] have proposed a set of ECG descriptors to characterize the trace of a heartbeat. Fifteen features have been selected from each heartbeat of 29 individuals. They have been reported the uniqueness of extracted patterns among individuals, unaffected to electrode positions and individual state of anxiety. The drawback of this experiment is the delineation process of ECG characteristic waveforms: P, QRS complex and T wave using an unified approach. Since the fundamental frequency of these waveforms are different therefore the delineation techniques usually depart from one waveform to another.

In the literature one can find different techniques of ECG delineation. These include the techniques of real-time QRS complex detection using filtering and adaptive thresholding [8]; and the Wavelet transform ([9], [10]). In [11], Salim *et al.* have proposed hidden Markov tree model (HMT) for ECG delineation. To facilitate automated ECG delineation, a multiscale morphological derivative transform-based singularity detector has been proposed by Yan Sun *et al.* in [12]. Using morphological filtering the tasks of baseline correction and minimization of noise artifacts have been accomplished.

This paper proposes new methods for delineation of electrocardiographic P and T waves. It computes the characteristic wave fiducials using time derivative and adaptive thresholding techniques. The P wave delineator computes first derivative of waveform samples considering the effect of its neighboring samples. The computation procedure of first derivative is inspired from Menard [13] and adapted by Friesen [14] *et al.*. The significance of the proposed method is adaptive thresholding based waveform delineation that not only consider the estimates of time derivative but it also consider the estimates of high frequency noise present in the beat. That makes the delineation process to be robust. The delineation of T wave is performed using derivative curve analysis. The waveform is analyzed respect to its derivative peak. Vertical offset of samples to the line drawn from derivative peak to its extremities are determined. At both ends, found sample of maximum offset returns the end fiducial of the waveform. The power of the method is its potential to capture the cardiac electrical variations which are usually found at the end of T wave.

Once the ECG is delineated, the features of classes interval, amplitude and angle are extracted from each heartbeat. Finally, the biometric experiment is conducted on proposed identification model which is designed on statistical pattern recognition and adaptive thresholding techniques.

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A. Physiology and ECG

ECG varies among individuals due to the differences in anatomy and physiology of the heart. Normally, a progressive change in individual anatomy takes place from birth to adolescence (~ 16 years of age). It has resulted that some features of ECG varies during aging. A glance of change in normal limits of ECG parameters with age and sex are shown in Table I [15]. It shows the heartrate substantially decreases with age, causing an increase in the duration of P wave, QRS complex and PR interval. The amplitude of P wave does not change significantly during aging while the amplitudes of R and S waves decrease from child to adolescence. A progressive change in T wave from childhood to adult has been reported by David [16]. These changes are not consistent and vary from one individual to another. Therefore, it is harder to make any generalization.

From these observations it can be concluded that aging effects the ECG mainly up to the age of adolescence. These effects are particularly reflected in P wave duration and PR interval. The dependence of QT interval on heartbeat variations can be minimized using Bazett's QT interval correction [17]. The corrected QT interval [17] is found to be relatively constant over the years. Aging does not influence any sexual differences in cardiac electrophysiological properties in the adults [18].

The rest of the paper is organized as follows: Section II presents the methodology adopted for the identification system based on ECG dominant fiducials. The proposed techniques of P and T wave delineation are discussed in Section III. Section IV discusses the extraction of ECG features from dominant fiducials including features normalization. A detailed explanation of proposed identification model is given in Section V. The experiment results of identification system including the results of P and T wave delineators are presented in Section VI. Finally, conclusions are drawn in Section VII.

II. PROPOSED METHODOLOGY

The schematic description of ECG based individual identification system is shown in Figure 1. The method is implemented in a series of steps: (1) preprocessing, includes correction of signal from noise artifacts and classification of waveforms, (2) data representation, includes delineation of dominant waveforms, (3) feature extraction, includes recognition of dominant features between the diagnostic points, (4) identification and (5) decision making using the technique of template matching and adaptive thresholding.

ECG data is acquired from the individuals and subsequently it is digitized. Preprocessing of ECG involves the correction of signal from low and high frequency noises. Low frequency noise is resulted from baseline oscillations, body movements and respiration while high frequency noise is resulted from power line interferences and digitization of analog potential [14]. Digital filters of linear phase characteristics are employed in the experiment. Data representation involves the detection of dominant complexes: QRS complex, P and T waves from the signal. The heartbeats are detected

TABLE I
NORMAL VALUES OF ECG MEASUREMENTS FOR MALE AND FEMALE
RESPECTIVELY IN UPPER ROW AND LOWER ROW.

Parameters	1-3 years	3-5 years	5-8 years	8-12 years	12-16 years	mean $\pm$ S.D.
Heart Rate (bpm)	119 128	98 101	88 89	78 80	73 76	91.2 $\pm$ 18.27 94.8 $\pm$ 20.9
P width (ms)	80 83	87 84	92 89	98 94	100 98	91.4 $\pm$ 8.17 89.6 $\pm$ 6.43
PR Interval (ms)	118 113	121 123	129 124	134 129	139 135	128.2 $\pm$ 8.76 124.8 $\pm$ 8.14
QRS width (ms)	71 68	75 71	80 77	85 82	91 87	80.4 $\pm$ 7.92 77 $\pm$ 7.78
QT _c Interval (ms)	412 417	412 415	411 409	411 410	407 414	410 $\pm$ 2.07 413 $\pm$ 3.39
Amplitude P wave(mV)	0.15 0.16	0.13 0.13	0.12 0.12	0.12 0.14	0.13 0.15	0.13 $\pm$ 0.01 0.14 $\pm$ 0.02
Amplitude R wave(mV)	0.77 0.68	0.63 0.65	0.62 0.49	0.59 0.54	0.58 0.48	0.64 $\pm$ 0.08 0.57 $\pm$ 0.09
Amplitude S wave(mV)	0.27 0.35	0.21 0.20	0.22 0.22	0.22 0.16	0.19 0.13	0.22 $\pm$ 0.03 0.21 $\pm$ 0.08

using QRS complex delineator. Once the heartbeat is detected, temporal time windows are defined before and after QRS complex fiducials to seek for P and T wave delineations in each beat of ECG. The localization of P and T waves along to their end fiducials are respectively done by proposed delineators. Found end fiducials are later to be used in the feature extraction process.

Feature extraction is concerned to the detection of differences in transmembrane voltages in myocardial cells that occur during depolarization and repolarization. These differences are classified into interval, amplitude and angle features. From the extracted features, selected features are formed a feature vector. In identification, distance (e.g., Euclidean distance) between feature vectors of a test template and template stored in the database is computed. Finally, decision making process decides how well the claimed template matches to its counterpart stored in the database using adaptive thresholding criterion.

III. AUTOMATED ECG DELINEATION

A. QRS complex Delineator

QRS complex delineator is implemented using the technique of Pan and Tompkins [8] with some improvements. It employs digital analysis of slope, amplitude and width information of ECG waveforms. The fiducials of QRS complex are delineated according to the location and convexity of R peak.

B. P wave Delineator

Atrial activity of the heart is characterized as P wave in the ECG. It is a low amplitude waveform and has a low signal to noise ratio. The delineation technique utilized in this study works directly over the digitized electrocardiogram without compromising the accuracy of detected fiducials. It uses first derivative approach to delineate P waves from ECG. The first derivative of the ECG, y_{nT} at time instant T is calculated using the following time difference equation [13],

$$y_{nT} = -2 * x_{(n-2)T} - x_{(n-1)T} + x_{(n+1)T} + 2 * x_{(n+2)T}$$

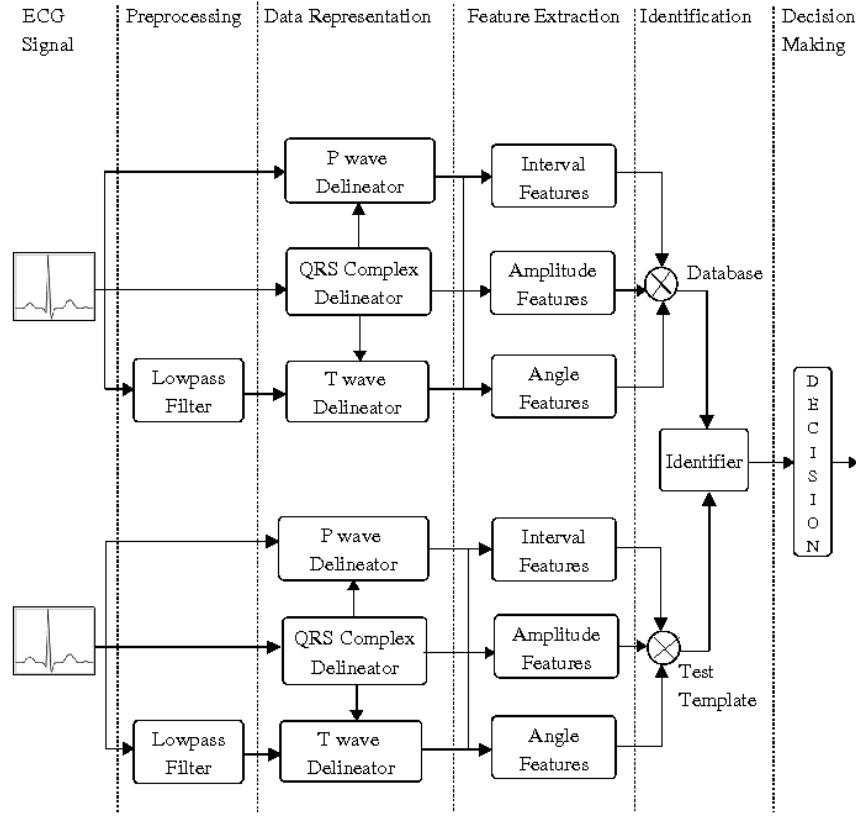


Fig. 1. Schematic description of ECG based individual identification system.

where x_{nT} represent the data sample of size n at discrete instance of time T .

In order to determine P wave and its end fiducials, a time window is set prior to the beginning of QRS complex fiducial, QRS_{onset} . The time window that approximately contains P wave is set heuristically and extended from QRS_{onset} to the beginning of heartbeat, $Beat_{begin}$ as shown in Figure 2. The $Beat_{begin}$ fiducial can be determined by searching of first isoelectric sample prior to the start of artial deflection.

For the detection of P waves, delineator computes the slope threshold (θ). The slope threshold continuously adapts and set between the mean of most recently detected significant slopes (μ_{MS}) and the mean of high frequency noise ($\mu_{HF_{noise}}$) present in the detected beats.

$$\theta = 0.30 * (\mu_{MS} - \mu_{HF_{noise}})$$

The level of high frequency noise present in the beat can be estimated, firstly, the passing of beat to highpass filter,

$$y_{nT} = x_{nT} - 2 * x_{(n-1)T} + x_{(n-2)T}$$

which determines the presence of artifacts in the beat. The mean of filtered signal over a stream of samples is computed next. Then noise metric, HF_{noise} is estimated as the ratio to the maximum of averaged signal, HF_{noise}^{MA} and the QRS amplitude, h_{QRS} using the formula,

$$HF_{noise} = K * \frac{HF_{noise}^{MA}}{h_{QRS}}$$

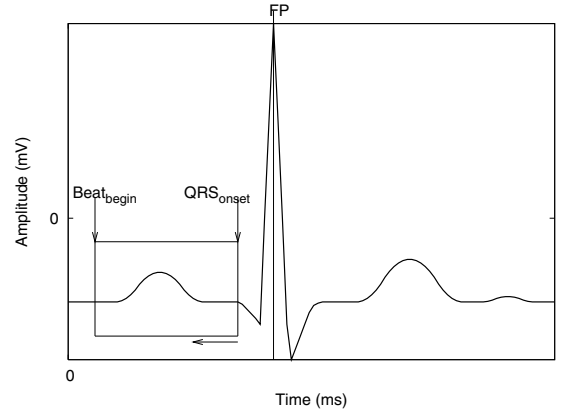


Fig. 2. Setting of time window for P wave delineation.

where the multiplier K is set to 40 in this experiment.

Detection of P_{onset} , P_{peak} and P_{offset} Fiducials: The fiducials of P wave are determined as follows: Firstly, the end of P wave, P_{offset} is determined by tracing the ECG signal in time-reverse order within the time window as shown in Figure 2. The location of P_{offset} is found to be at sample where the slope is most negative. The location S_m shown in Figure 3 is the P_{offset} fiducial. In this traversal the peak of P wave is found to be at sample where the sign of slope is changed (zero crossing) with some adjustments. The method traces the entitled signal posteriorly from P_{offset} fiducial

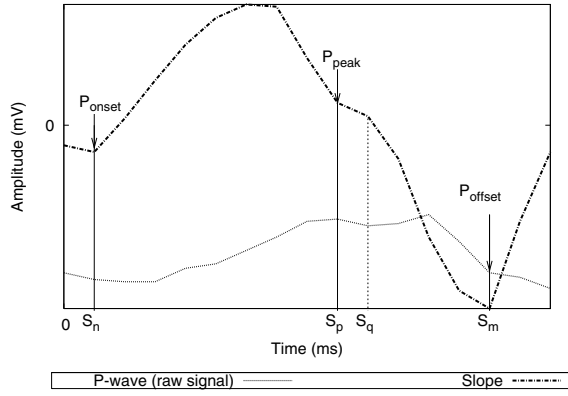


Fig. 3. Detection of P wave fiducials within the time window.

and found the sample S_q of zero crossing. Found sample is the probable location of its peak. Due to the presence of high frequency noise in the beat some adjustment in the located position of peak is needed. The effects of high frequency noise can be minimized by finding the sample neighboring to S_q where slope exceeds to HF_{noise} ; let the found sample be S_p . If samples S_q and S_p are same then it is a peak, otherwise peak is found at the sample where slope exceeds to noise. Found peak position at sample S_p is shown in Figure 3. After localization of peak, remaining signal is traced posteriorly for the detection of P_{onset} fiducial. It is found at sample where estimated value of HF_{noise} exceeded to the slope. Found location S_n shown in Figure 3 is the P_{onset} fiducial.

C. T wave Delineator

In order to achieve the reliable performance of T wave delineator the signal is firstly corrected from oscillatory patterns of reference potential. A recursive lowpass filter is used for this purpose,

$$y_{nT} = 2 * y_{(n-1)T} - y_{(n-2)T} + x_n - 2 * x_{(n-4)T} + x_{(n-8)T}$$

A time window that approximately contains T wave is defined apriori to the delineation process. The boundaries of time window are set heuristically relative to QRS_{offset} fiducial, extended from $QRS_{offset} + 80ms$ to $QRS_{offset} + 470ms$ as shown in Figure 4. The peak of T wave is determined using time derivative approach and adaptive thresholding technique similar to P wave.

1) *Detection of T_{onset} and T_{offset} Fiducials:* The beginning of T wave is concerned to the start of ventricles repolarization which is raising (dropping for negative T wave) slowly. While the ending of T wave is concerned to the end of repolarization cycle which is terminating much faster. The changes resulted from abnormal function of epicardium and/or endocardium can also be seen in the latter part of T wave. Along to that, it is also noticed that the end segment has lower stimulation relative to level of noise present in the beat. This makes the detection of end fiducials, T_{onset} and T_{offset} especially T_{offset} more cumbersome. Keeping the concern of these observations, the end fiducials of T wave are determined efficiently using the approach based on derivative

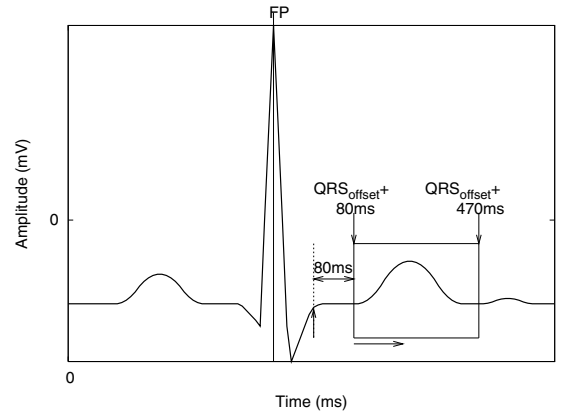


Fig. 4. Setting of time window for T wave delineation.

curve analysis where the morphology of the waveform is considered to be positive.

The approach utilizes the advantage of time derivative to capture the signal variations. A snapshot of filtered signal and the signal after implementing derivative approximation along with the raw signal is shown in Figure 5. For the determination of T wave end fiducials, process starts with finding of derivative peak within the time window. The peak is determined at sample where maximum change in slope is to be occurred. Let the found location be d_{peak} . The procedure used to determine T_{offset} fiducial is as follows: Once d_{peak} is known, derivative signal is traced upto d_R positions in time-forward order. The d_R position can be set at the right boundary of time window, $QRS_{offset} + 470ms$. Let a line L_R is drawn extending from d_{peak} to d_R positions assuming their coordinates are (x_{peak}, y_{peak}) and (x_R, y_R) respectively. Then, equation of L_R can be formulated as,

$$L_R \equiv y - y_{peak} = \Delta * (x - x_{peak})$$

where $\Delta = \frac{y_R - y_{peak}}{x_R - x_{peak}}$. Along to the entitled signal, vertical offset of each sample of interval $[d_{peak}, d_R]$, to the line L_R is computed. Let d_i be some sample position in the interval $[d_{peak}, d_R]$ whose coordinate be (x_i, y_i) . The vertical offset, δ_i corresponds to d_i can be computed using the following formula,

$$\delta_i = |y_{peak} + \Delta * (x_i - x_{peak}) - y_i|$$

where y_i is the vertical offset of sample corresponding to position x_i in the entitled signal. The aim is to find the position where vertical offset is maximum and the sample corresponding to found position is to be the location of T_{offset} . Therefore, maximum among δ_i 's is selected, e.g. $\delta_{max}^R = \max(\delta_i)_{i=d_{peak}}^{i=d_R}$. Let the found position where vertical offset is maximum be d_k . The sample corresponding to position d_k is T_{offset} fiducial as shown in Figure 5. The T_{onset} fiducial can be determined similarly by tracing the derivative signal posteriorly from derivative peak.

IV. AUTOMATED FEATURE SET DETECTION

Once the ECG is delineated, peak and limits of QRS complex, P wave and T wave are known. From known fiducials

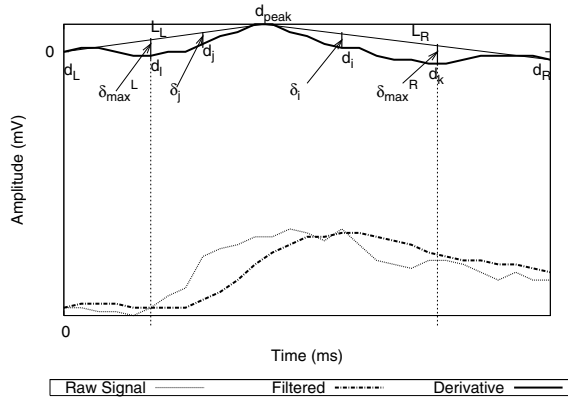


Fig. 5. Detection of T wave end fiducials within the time window.

19 features which are shown in Table II are extracted from each heartbeat where each derives from one of the classes:

A. Interval Features

Following features related to heartbeat intervals are computed. PR_I is the time interval between P_{onset} and QRS_{onset} fiducials. PR_S is the time interval between P_{offset} and QRS_{onset} fiducials. QT_{CI} is the corrected time interval between QRS_{onset} and T_{offset} fiducials, according to Bazett's formula. ST_S is the time interval from QRS_{offset} to T_{onset} fiducials and ST_I is the time intervals from QRS_{offset} to T_{offset} fiducials.

Other interval features are computed relative to R_{peak} fiducial. The time interval from R_{peak} to P wave fiducials, P_{offset} , P_{peak} and P_{offset} are defined as RP_L , RP and RP_R respectively. The time interval from R_{peak} to Q_{peak} is defined as RQ and time interval from R_{peak} to S_{peak} is defined as RS . Similarly, time interval from R_{peak} to T wave fiducials, T_{onset} and T_{offset} are defined as RT_L and RT_R , respectively. The computed time interval features are shown in Figure 6(a). Along to these intrabeat interval features one interbeat interval feature, RR is also extracted. RR is defined as the time interval between two successive R peaks as shown in Figure 6(b). This feature is used to correct the QT interval from the effects of change in heartrate.

B. Amplitude Features

The amplitude features are computed relative to the amplitude of R peak. This class of features are dependent to QRS complex which is usually invariant to change in the heartrate. RQ_A is defined as the difference of amplitudes between R and Q waves. RS_A is defined as the difference of amplitudes between R and S waves. Similarly the difference in amplitudes of P wave and T wave to R wave are defined as RP_A and RT_A , respectively. These amplitude features are shown in Figure 6(c).

C. Angle Features

The features related to angular displacement between different peak fiducials of P, Q, R, S and T waves are extracted from each beat. The aim is to extract a class of

TABLE II
CONSIDERED CLASS OF FEATURES ARE SELECTED FROM ECG
DOMINANT FIDUCIALS. (♣: USED TO CORRECT QT INTERVAL)

Class Label	Features	Representation
Interval	PR interval	PR_I
	PR segment	PR_S
	corrected-QT interval	QT_{CI}
	ST segment	ST_S
	ST interval	ST_I
	R_{peak} to P_{onset} segment	RP_L
	R_{peak} to P_{peak} segment	RP
	R_{peak} to P_{offset} segment	RP_R
	R_{peak} to Q_{peak} segment	RQ
	R_{peak} to S_{peak} segment	RS
Features	R_{peak} to T_{onset} segment	RT_L
	R_{peak} to T_{offset} segment	RT_R
	RR interval♣	RR
Amplitude Features	RQ amplitude	RQ_A
	RS amplitude	RS_A
	RP amplitude	RP_A
	RT amplitude	RT_A
Angle Features	Angle Q	$\angle Q$
	Angle R	$\angle R$
	Angle S	$\angle S$

features which are stable and prone to the change in heartrate. $\angle Q$ is defined as the angular displacement between directed lines joining from Q_{peak} to P_{peak} and from Q_{peak} to R_{peak} peak fiducials. $\angle R$ is defined as the angular displacement between directed lines joining from R_{peak} to Q_{peak} and from R_{peak} to S_{peak} peak fiducials. Similarly, $\angle S$ is defined as the angular displacement between directed lines joining from S_{peak} to R_{peak} and from S_{peak} to T_{peak} peak fiducials. These angle features are shown in Figure 6(d).

D. Feature Normalization

Normalization is an important issue to obtain consistent features with change in heartrate. The heartrate varies due to change in pressure inside the heart and ventricular volume. Change in heartrate consequently changes the duration of P wave, PR interval and QT interval. Thus the features of P and T waves are normalized by dividing them to the beat length, $PR_I + QT_{CI}$ while RQ and RS are used as raw features.

In order to investigate the effects of varying heartrate on peak fiducials of different waveforms, it is found that atrial deflection do not change with heartrate. Ventricular activation and the recovery of ventricles form stimulation are fairly invariant with change in heartrate. Therefore, raw amplitude and angle features are used in the experiment.

V. IDENTIFICATION MODEL

The identification model proposed in this study is designed on pattern matching and adaptive thresholding techniques. Two ECG records are declared to be similar if their feature vectors are similar. Alternatively, if difference between the corresponding components of feature vectors is below than a threshold then they are declared to be similar. The computation basis of threshold is as follows: First of all, an ECG dataset (record of T_{sec}) is partitioned into m subdata

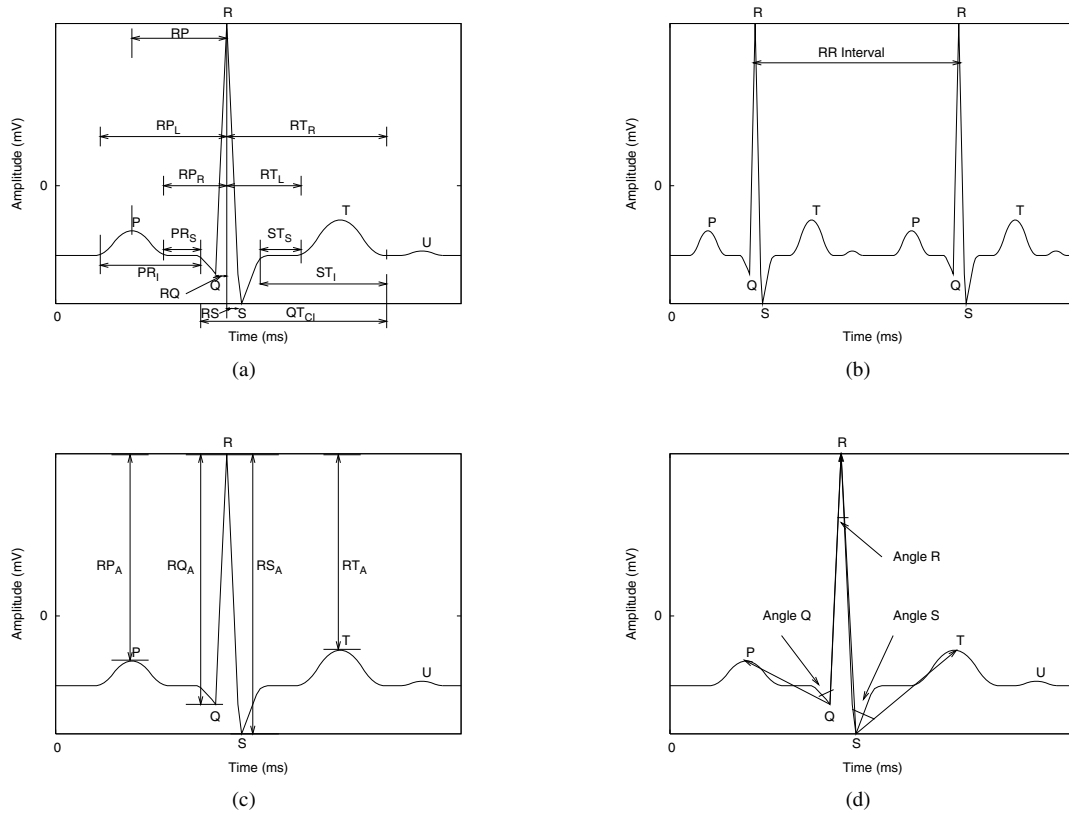


Fig. 6. Selected class of features from ECG dominant fiducials: (a) interval features, (b) RR interval, (c) amplitude features and (d) angle features.

sets (each of S sec, where $S < T$). From each subdata set a pattern of d features is extracted. Let X be the pattern matrix of size $m \times d$.

$$X = \begin{pmatrix} f_{1,1} & f_{1,2} & \dots & f_{1,d} \\ f_{2,1} & f_{2,2} & \dots & f_{2,d} \\ \vdots & \vdots & & \vdots \\ f_{m,1} & f_{m,2} & \dots & f_{m,d} \end{pmatrix}$$

where $f_{i,j}$ represents the j^{th} feature components of i^{th} subdata set. The purpose of dataset partitioning is to recognize similarity between the feature vectors of an individual ECG. The similarity between components of feature vectors are evaluated on the basis of Euclidean distance which is determined as follows,

$$(|f_{i,1} - f_{j,1}|)(|f_{i,2} - f_{j,2}|) \dots (|f_{i,d} - f_{j,d}|) \Big|_{i=j=1, i \neq j}^{i=j=m}$$

The Euclidean distance matrix of size $m \times m$ is generated for each column of the pattern matrix X . The maximum is selected from each distance matrix which shows optimum deviation between the components of feature vectors at different heartbeats of an individual ECG. Let $\delta_l = \text{Max}(|f_{i,l} - f_{j,l}|)$ for $l = 1, 2, \dots, d$, be the maximum difference computed for each column l of matrix X . Then, maximum of Euclidean distances between feature components are obtained from the set of m patterns of an ECG of k^{th} individual, δ^k as follows,

$$[\delta^k] = \begin{pmatrix} \delta_1^k & \delta_2^k & \dots & \delta_d^k \end{pmatrix}$$

where $[\delta^k]$ is the row matrix of size $1 \times d$. Similarly for n ECG datasets, a matrix $[\delta^{1,\dots,n}]$ of size $n \times d$ is generated.

$$[\delta^{1,\dots,n}] = \begin{pmatrix} \delta_1^1 & \delta_2^1 & \dots & \delta_d^1 \\ \delta_1^2 & \delta_2^2 & \dots & \delta_d^2 \\ \vdots & \vdots & & \vdots \\ \delta_1^k & \delta_2^k & \dots & \delta_d^k \\ \vdots & \vdots & & \vdots \\ \delta_1^n & \delta_2^n & \dots & \delta_d^n \end{pmatrix}$$

For each k^{th} ECG data set, $[\delta^k]$ is determined. Different components of row matrix $[\delta^k]$ are stored in different buffers which are estimated separately. The detection threshold for each component of set $[\delta^k]$ is calculated using the estimates of maximum Euclidean distance. Let θ_l be the threshold for component l (for $l = 1, 2, \dots, d$) of the set $[\delta^k]$. Then detection threshold for that component can be set slightly above to the mean of maximum Euclidean distance according to formula,

$$[\theta_1, \theta_2, \dots, \theta_d] = [\mu(Y_1) + \sigma(Y_1), \mu(Y_2) + \sigma(Y_2), \dots, \mu(Y_d) + \sigma(Y_d)]$$

where

$$Y_1 = [\delta_1^1, \delta_1^2, \dots, \delta_1^n]^T, \dots, Y_d = [\delta_d^1, \delta_d^2, \dots, \delta_d^n]^T$$

The model estimates detection threshold according to the change in the ECG. The goodness of the proposed technique is that all components of feature vector are participated

TABLE III

DELINEATION PERFORMANCE OF PROPOSED P AND T WAVE DELINEATORS AND ITS COMPARISON WITH DIFFERENT METHODS IN QT DATABASE.
(N/R: NOT REPORTED)

Technique	Parameters	P_{onset}	P_{offset}	T_{onset}	T_{offset}
	# annotations	3194	3194	3542	3542
WT-based Detector Martinez <i>et al.</i> [10]	$\mu_{\varepsilon} \pm \sigma_{\varepsilon}$ (ms)	2.0 ± 14.8	1.9 ± 12.8	N/R	-1.6 ± 18.1
	# annotations	2500	2500	2500	2500
MT-based Detector Yan Sun <i>et al.</i> [12]	$\mu_{\varepsilon} \pm \sigma_{\varepsilon}$ (ms)	9.0 ± 9.4	12.8 ± 13.2	7.9 ± 15.8	8.3 ± 12.4
	# annotations	25000	25000	25000	25000
[This Work]	$\mu_{\varepsilon} \pm \sigma_{\varepsilon}$ (ms)	5.18 ± 8.1	4.4 ± 6.29	1.1 ± 9.4	6.1 ± 11.2
Tolerance Limit CSE [19]	σ_{ε} (ms)	10.2	12.7	...	30.6

equally in deciding the threshold level. For decision making, one can set the decision limit of feature components according to the detected threshold.

VI. EXPERIMENTAL RESULTS

The performance of ECG based identification system including the performance of automated P wave and T wave delineators are evaluated on Physionet QT database [20]. The database provides an evaluation tool for validation and comparison of experiments based on ECG delineation.

Since the performance of ECG based identification system is dependent on the accuracy of delineators. Therefore, delineation performance of the proposed P and T wave delineators are evaluated and discussed separately. The delineation performance of P and T waves is measured on mean error (μ_{ε}) and standard deviation (σ_{ε}) of the differences between automated results and the manually annotated results. The mean error is used to measure the closeness of results with the expert annotated results while σ_{ε} measures stability in the delineation process. Found statistical results, μ_{ε} and σ_{ε} are compared with the published results of WT detector of Martinez *et al.* [10] and morphological-transform detector (MT) of Yan Sun *et al.* [12] in Table III. The accepted σ_{ε} tolerance of measurements recommended by the CSE committee [19] is also given in last row of the table.

The experiment is conducted on 25 first lead individual ECG recordings of Physionet QT database. Among them 15 recordings are taken from MIT-BIH Arrhythmia database which contains the ECG of mostly inpatient men and women of age between 47 to 84 years. Remaining, 10 recordings are taken from MIT-BIH Normal Sinus database of subjects age between 20 to 50 years having no significant arrhythmia. During experiment first 8 seconds of each recording is used for training and setting of parameters to the delineators. The performance of proposed P and T wave delineators are evaluated on testing annotations of 1000 peaks which are selected randomly from rest of the recording. Thus, a total of 25000 (25×1000) peak annotations are examined by the proposed delineators.

The performance of proposed delineators are found outstanding. Lower values of standard deviation for P and T wave end fiducials are found in comparison to WT and MT detectors. These values are well within the acceptable limit

TABLE IV

PERFORMANCE OF INDIVIDUAL IDENTIFICATION SYSTEM OVER TEST DATASET OF SIZE 125 AT DIFFERENT THRESHOLD LEVELS.

Threshold Level	# FR	FRR (%)	GAR (%)	# FA	FAR (%)	Accuracy (%)
15	0	0	100	2	2	99
16	1	1	99	1	1	99
17	2	2	98	0	0	99
18	3	3	97	0	0	98.5
19	3	3	97	0	0	98.5

recommended by CSE committee. It shows stability in the detection of P and T wave end fiducials. Lowest value of mean error is found for T_{onset} fiducial while mean error for P_{onset} , P_{offset} , and T_{offset} are found better than MT detector.

The performance of an identification system is measured on the parameters of false accept rate (FAR) and false reject rate (FRR) reported by the system. The Receiver Operating Characteristic (ROC) is plotted between genuine acceptance rate, GAR (i.e., $1 - FRR$) and FAR to measure the system performance. The accuracy (Acc) of system is also determined using the factors FAR and FRR as, $Acc(\%) = 100 - \left(\frac{FAR + FRR}{2} \right)$.

For biometric experiment, five data samples of nearly 100 beats are selected randomly from each individual recording and the feature vector is generated. Thus, 125 (25×5) data samples are prepared in the database for training the system. The test of positive identification is conducted between different data samples of an individual ECG recording while the test of negative identification is conducted between data samples of different ECG recordings. The ECG recordings of European ST-T database are used for testing the negative identification.

In identification process, the pattern of a template is tested over the patterns stored in the database (one-to-many matching). The decision of best match is taken on the basis of threshold whose level is set on the number of feature components are matched. For example, a test pattern is matched to its counterpart stored in the database if 17 out of 19 components listed in Table II are matched. The performance of proposed identification system is examined

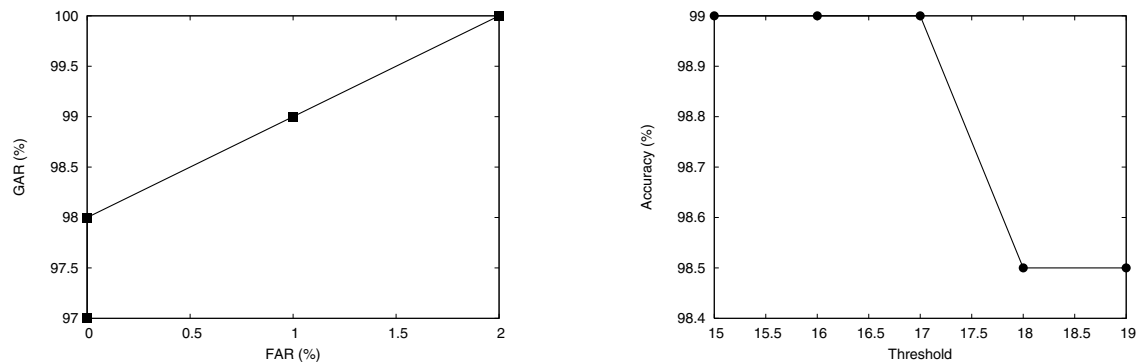


Fig. 7. Performance of the identification system (a) ROC curve and (b) accuracy curve

on different settings of threshold level between 15 to 19 and the results are given in Table IV. It shows that at threshold level 15, only 2 individuals are wrongly identified while none of them is wrongly rejected. Alternatively, the system is achieved $GAR = 100\%$ at $FAR = 2\%$. At threshold level 17, none of them is wrongly accepted while 2 individuals are wrongly rejected. Thus, system is achieved the accuracy of 99% at threshold level 17 where 98% of genuine subjects are identified correctly while no subject is forged to the system. The resulted performance of identification system is shown using ROC curve and accuracy curve in Figure 7 (a) and (b), respectively.

VII. CONCLUSIONS

This paper has shown that dominant fiducials delineated from ECG recordings exhibit features that are unique to an individual. A series of experiments has been conducted for ECG delineation and individual identification on bench mark database. The database consists of normal and inpatient men and women of age 50 ± 23 years. The performance of P and T wave delineators described here has been found optimum. From that, stable features have defined. The identification results have shown that the proposed method of automated ECG delineation is useful to distinguish ECG signals among individuals. From these observations it has been concluded that each individual ECG has a unique set of heartbeat features that can be used as potential biometric for individual identification.

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