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A New Method for Electrocardiogram Features Extraction Using Slope Change Coefficients

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***Abstract*—A new method of Electrocardiogram (ECG) features extraction is proposed in this paper. The purpose of this study is to detect the main characteristics of the signal: P, Q, R, S, and T, then localize and extract its intervals and segments. To do so we first detect peaks, onsets and offsets of the signal's waveform by calculating the slope change (SC) coefficients and consequently, the peaks of the signal are determined. The SC coefficients are based on the calculation of the integral of two-scale signals with opposite signs. The simulation results of our algorithm applied on recordings of MIT-BIH arrhythmia electrocardiogram database show that the proposed method delineates the electrocardiogram waveforms and segments with high precision.**

***Keywords*—ECG waveform peaks, ECG segments and intervals, Slope change coefficients**

I. Introduction

THE measures of the action potentials generated by the heart during cardiac cycles is called electrocardiogram (ECG) signal. The relationship between ECG and cardiac action is used to monitor the heart's health. Any distortion in the transmission of impulses through the heart can appear as distorted ECG waveforms. The QRS complex, P and T waves are the principal elements characterizing ECG records (*Fig. 1*): (i) the P wave is the first deflection recorded which is small, smooth, and precedes the QRS complex. (ii) The QRS complex represents the spread of electrical activation through the ventricular myocardium in which electrical forces are generated by its depolarization then recorded on the ECG as a spiky deflection. (iii) The broad and rounded wave T represents the electrical recovery and repolarization of the ventricles. It follows each QRS complex and is separated from the QRS by a quasi-constant segment for normal ECG [1,2].

The ECG signal is also characterised by several segments and intervals such as : (i) PR interval which measures the distance between the beginning of the P wave and the beginning of the QRS complex, it represents the depolarization of the atria and the AV node. Its normal duration is between 0.12 and 0.22 seconds. (ii) PR segment is the time period between the end of the P wave and the beginning of the QRS complex, it represents the transmission time of the depolarization front by the AV node. (iii) ST segment is the segment lying between the end of the QRS complex (or J point) and the beginning of the ascending phase of the T wave. This segment corresponds to the time during which all the myocardial cells are depolarized and therefore, in the normal case, it must be isoelectric, otherwise, the amplitude level and the slope of this segment are indicators of the ischemic state of the myocardium. (iv) QT interval is the time between the beginning of the QRS complex and the end of the T wave. It is an indication of the length of the ventricular depolarization and repolarization phases. Its duration varies between 0.3 and 0.38 seconds. (v) RR interval is the distance between two successive R waves and it represents the ventricles frequency [4].

The table I shows the average values of some ECG features for a normal rhythm.

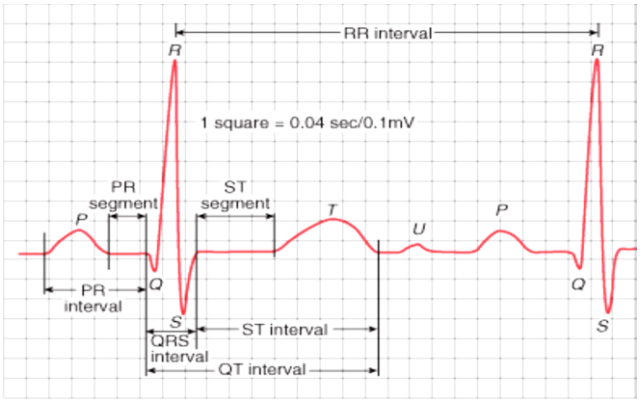

Fig. 1. Features of ECG signal.

TABLE I
RANGE OF AVERAGE VALUES OF ELECTROCARDIOGRAM SIGNAL FEATURES (MODIFIED FROM [3]).

ECG features	Duration (s)	Amplitude (mV)
P wave	0.08-0.1	0.25
QRS complex	0.08-0.1	Q_amp<0, R_amp>0, S_amp<0
T wave	0.16-0.2	T_amp>0
RR interval	0.6-1.2	/
PR interval	0.12-0.22	R_amp>0
ST interval	0.35-0.45	Isoelectric (=0)
QT interval	0.3-0.38	/

Several clinical researches have shown that hypoglycemia affects certain cardiac characteristics of the heart, such as: PR interval shortening, ST segment depression, T wave flattening and QT interval prolongation [2]. Associations between the QT interval duration and glucose levels have been also, investigated in both healthy and diabetic subjects, where, the blood glucose concentration can affect the electrical activity of the heart. However, changes of heart rate (RR) and QT interval were used

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as inputs in a system for hypoglycemia detection [3]. Shah *et al.* [5] have also proved that QT dispersion can be the least successful in predicting the risks of drug-induced Torsades de Pointes: which represents a polymorphic ventricular tachycardia seen in the setting of QT prolongation.

Furthermore, the identification of the ECG features allows the diagnosis of some cardio-myopathies and the classification of waves as normal or not normal (e.g. premature ventricular contraction (PVC), supraventricular contraction (SVC), ventricular late potentials (VLP), etc.) [6,7]. This is the reason why a number of algorithms have been developed to delineate the signal in an automatic ways. Some of those algorithms were based on applying the power spectral density of RR-interval to classify apnea [8]. In [9,10], convolutional neural networks algorithms were applied to classify ECG heartbeats and auto-diagnosis. Machine learning methods gave good results in terms of waves' classification as the method of [11] based on classifiers including linear regression, K-nearest neighbor, classification and regression tree and support vector machine (SVM). The SVM classifier method was presented as an effective cardiac arrhythmia classification algorithm combined with a generalized discriminant analysis (GDA) feature reduction scheme [12]. Other studies have used wavelet transforms to detect R waves as in our method in [13], where we have localized the QRS complexes by using dyadic and discrete wavelets transform. The wavelets were used also in [14] to extract fetal ECG from the mother one. Kumar *et al.* [15] have used fast Fourier transform in order to detect R peaks, which gave good results.

Our contribution presented in this paper is the utilization of slope change coefficients to delineate the ECG features based on localizing the peaks of the signal that detect changing in slopes of the ECG signal. Then, a count of different peaks of this signal is applied in order to extract the position of the waves and the segments of the signal.

II. Slope Change Coefficients

The proposed decomposition of the signal $x(t)$ into slope change (SC) coefficients is calculated by (1). These coefficients are constructed by calculating the integral of the combination of two scale signals with opposite signs:

$$SC(k) = -\int_{k-1/2}^{k} x(t-k)dt + \int_{k}^{k+1/2} x(t-k)dt \quad (1)$$

The SC coefficients are characterized by their sensitivity to steepness changes where lower slopes have coefficients' absolute values lower than those of sharper slopes. However, the sign of the coefficients is inversely dependent on slope direction. The minimum of the signal is represented by a positive-negative couple of SC coefficients, while the maximum is represented by a negative-positive couple of SC coefficients (*Fig. 2.b*).

Those SC coefficients are characterized by sub-sampling the signal by 2. So, in order to recover the samples size and to detect the optimum values of the signal (represented as mentioned previously by SC coefficients couples of min.-max. or max.-min), we apply a high-pass interpolation filter g on SC coefficients as following:

$$y(k) = \sum_{k=-\infty}^{+\infty} SC(l)g(l-2k) \quad (2)$$

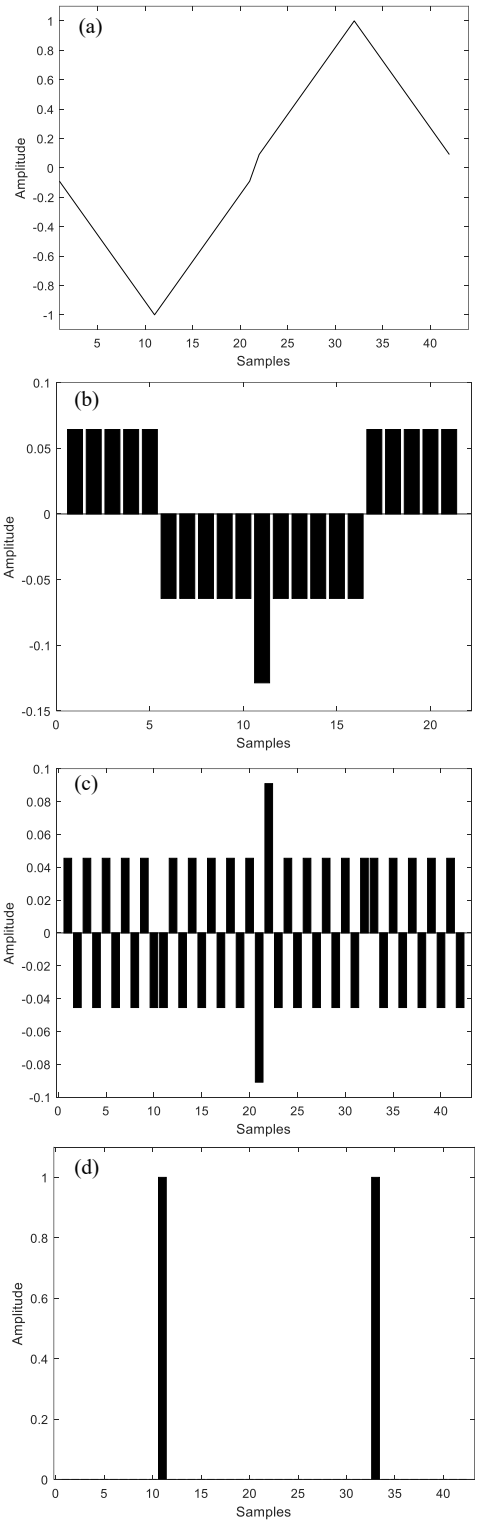

Fig. 2. Changing in slopes detection: (a) double triangular signal, (b) SC coefficients, (c) high-pass interpolation filter and (d) peaks of the signal.

$$y(k) = -\int_{l-1/2}^{l} \sum_{l=-\infty}^{+\infty} g(l-2k)\, x(t-l)dt + \int_{l}^{l+1/2} \sum_{k=-\infty}^{+\infty} g(l-2k)\, x(t-l)dt \quad (3)$$

The resulting discrete signal $y(k)$ will detect, by exploiting the proprieties of high-pass filter, the min.-max. (resp. max-min.) couples of SC coefficients and will interpolate the samples by 2. The maxima (resp. minima) of the signal x(k)

are represented by two successive positive (resp. negative) $y(k)$ samples (*Fig. 2.c*).

In the final step, we localize the peaks of the signal, as follows:

1) If $y(k)$ and $y(k+1)$ have the same sign, then:

$$Pe(k+1) = 1$$

2) If $y(k)$ and $y(k+1)$ have opposite signs, then:

$$Pe(k+1) = 0$$

The resulting signal $Pe(k)$ will detect all the samples positions of the changes of slope directions (i.e. position of optimum values of the signal).

III. ECG Signal Features Delineation

A. R peaks detection

To delineate the ECG signal's features, we first detect R peaks as follows:

1) Applying a five samples derivative filter on the ECG signal using the following equation:

$$ECGd(k) = (1/8)[-ECG(k-2) - 2ECG(k-1) + ECG(k+2) + 2ECG(k+1)] \quad (4)$$

The frequency response of this filter has a cut-off frequency equal to 30 Hz, this frequency is almost that of the QRS complexes. The derivative filter outputs a signal characterized by a min.-max. couple for the peak signal input. For the ECG signal, these couples will determine intervals in which we find the probable R waves (Fig. 3.b), because the amplitudes of these couples will be optima comparing to other couples representing other waves.

2) Detecting these couples by setting up two thresholds: positive threshold pTh and negative threshold nTh. These thresholds are calculated as the mean value of the five last thresholds:

$$\begin{cases} pTh_i = mean\{pTh_{i-5}, \dots, pTh_{i-1}\} \\ nTh_i = mean\{nTh_{i-5}, \dots, nTh_{i-1}\} \end{cases} \quad (5)$$

3) After that, the amplitude of the filtered signals will be compared to those thresholds. The sets of amplitudes exceeding the threshold values will be candidate to be limits of search intervals. The equation (6) define these limits ($InfL$ and $SupL$):

4) Now, we detect R_i peak by choosing the non-zero values included in the interval $[InfL_i\ SupL_i]$. Fig. 3.c shows that the R peak, in this case, is located at the sample's position equal to 253, which is the exacte position of R wave.

Baseline shifts can affect the accuracy of detection when using zero crossings of the min.-max. couples of the derivative filter which represent, in the case of isoelectric lines, the wave peak. However, our method based on the using the signal's peaks gives high detection precision with ± 2.78 ms.

Our detection algorithm was applied on ten MIT-BIH arrhythmia database records of 30 minutes each [16]. Few recordings have been selected randomly from healthy patients and the others contain signals with major arrhythmic events. he evaluation results of our algorithm are shown in table II using the false detection rate (i.e. the false detections of R complexes).

These false detections are the sum of false positive (FP) and false negative (FN) is noted from the table II, that the detection results are very satisfactory, given a rate of total false detections equals to 0.02 %. As a result of R waves detection, the heart rate RR is systematically delineated by calculating the distance between each two successive R peaks.

In the following sections, we will continue with the delineation of characteristic waves of the ECG signal. To do that, we will use the properties of the SC coefficients and the extracted peaks of signal by applying them on the different waveforms. Fig. 4 shows different features of the electrocardiogram signal: P wave, QRS complex, T wave and the ST segment.

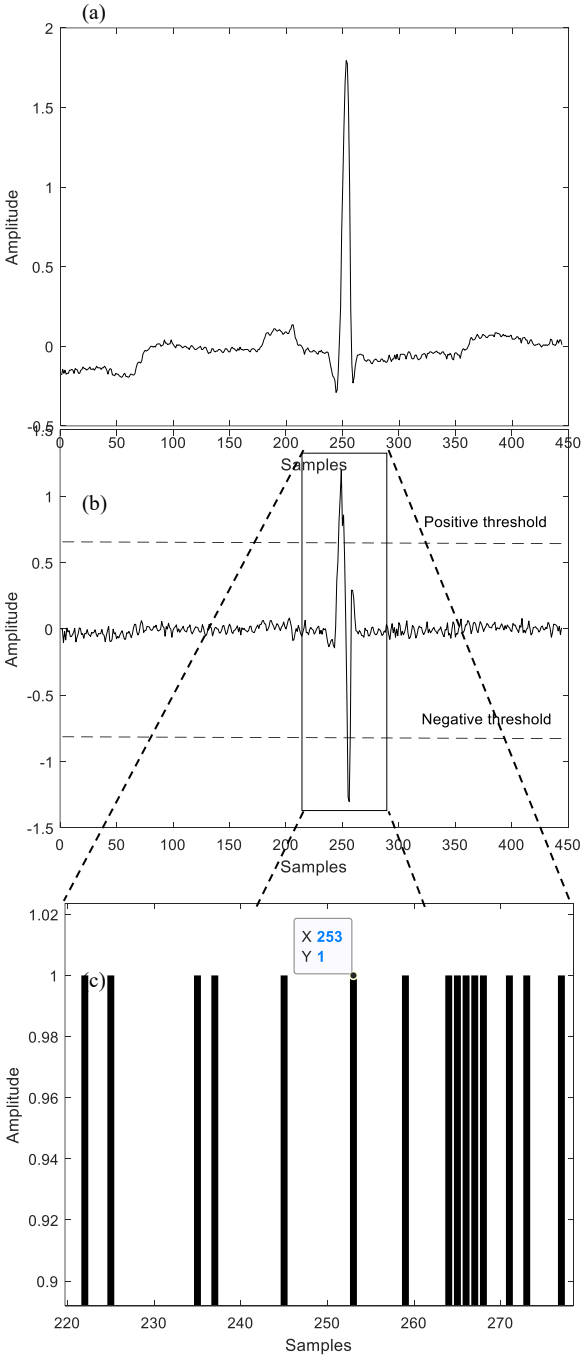

Fig. 3. R peaks detection: (a) ECG signal, (b) Derivative filter of the ECG signal and (c) ECG's peaks

TABLE II
R PEAKS DETECTION ACCURACY OF TEN MIT-BIH RECORDINGS.

Record.	False positive	False negative	Accuracy (%)
100	0	0	100
101	1	1	99.95
102	1	1	99.91
103	0	0	100
115	0	0	100
118	0	0	100
122	0	0	100
215	1	1	99.94
220	0	0	100
234	0	0	100
Total	2	3	99.98

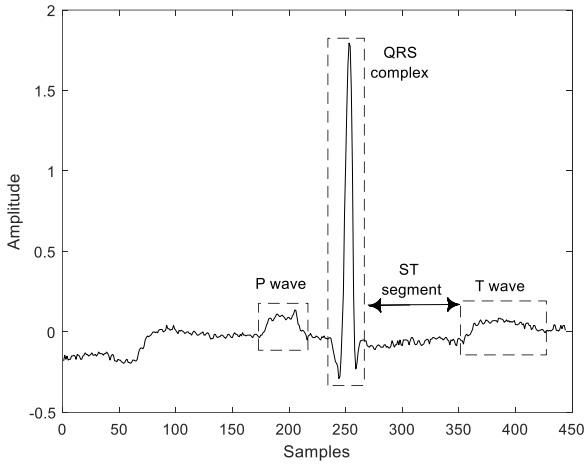

Fig. 4. ECG signal features: P wave, QRS complex, T wave and the ST segment

B. QRS complex detection

After detecting all the R peaks of the ten recording of 30 minutes, we delineate the other ECG waveforms taking as reference these R peaks and verifying the succession orders of the non-zero values of the signal $Pe(k)$ in figure 3.c before and after the R position.

So, to completely localize the QRS complexes, we proceed as follows:

1) On the left side of R wave, we located Q wave which correspond to the first non-zero $Pe(k)$, however, the S wave correspond to the first non-zero $Pe(k)$ on the right side of R peak.

2) We locate the QRS complex onset and offset corresponding respectively; to the seconds non-zero $Pe(k)$ on the left and the right sides of R wave position.

Figure 5 shows the corresponding $Pe(k)$ signal to the QRS complex onset, offset, Q wave, R wave and S wave.

C. P waves detection

P wave is identically located, by firstly delineating P offset corresponding to the first non-zero $Pe(k)$ on the left sides of QRS onset. Secondly, we detect P amplitude's position as the second maximum localization (i.e. the corresponding $Pe(k)$ coefficient) of the two successive SC coefficients with the optimum amplitudes from all the SC coefficients on the left sides of P offsets in a region of a one fifth of the last RR interval. Finely, the two seconds successive SC coefficients having negative magnitudes on the left sides of P peaks correspond to P onsets (*Fig. 6*).

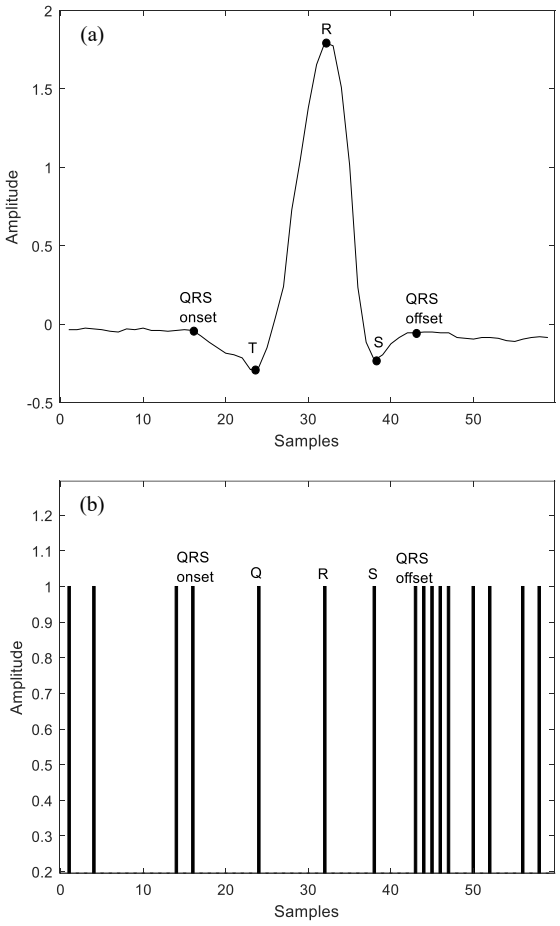

Fig. 5. QRS complexe delination: (a) QRS complex and (b) $Pe(k)$ of the QRS complex

D. T waves detection

The deformations of T waves are associated with several cardiac arrhythmias, for several types of pathological states; transient changes in repolarization of the action potential were associated with a potentially fatal arrhythmia. For this reason among others, we delineate the T waves. The T onset is located on the right side of QRS complex in an interval equal to one fourth of the last RR period, and corresponds to the two last successive and negative SC coefficients. T peaks correspond to the maximum couple from the couples of two successive SC having positive magnitudes on the right sides of P onsets between one fourth and two third of the last RR interval. Offset of T wave is represented by the two firsts successive and negative SC after the P peak (Fig. 7).

However, before applying the previous procedures of ECG signal delineation, we should utilize a high frequencies (HF) filtering to eliminate undesired fast variations that can mislead us during the calculation of the $Pe(k)$ and SC coefficients, because the high frequency noises behave like successive peaks with fast variation which have frequencies close to the P and T waves set's samples.

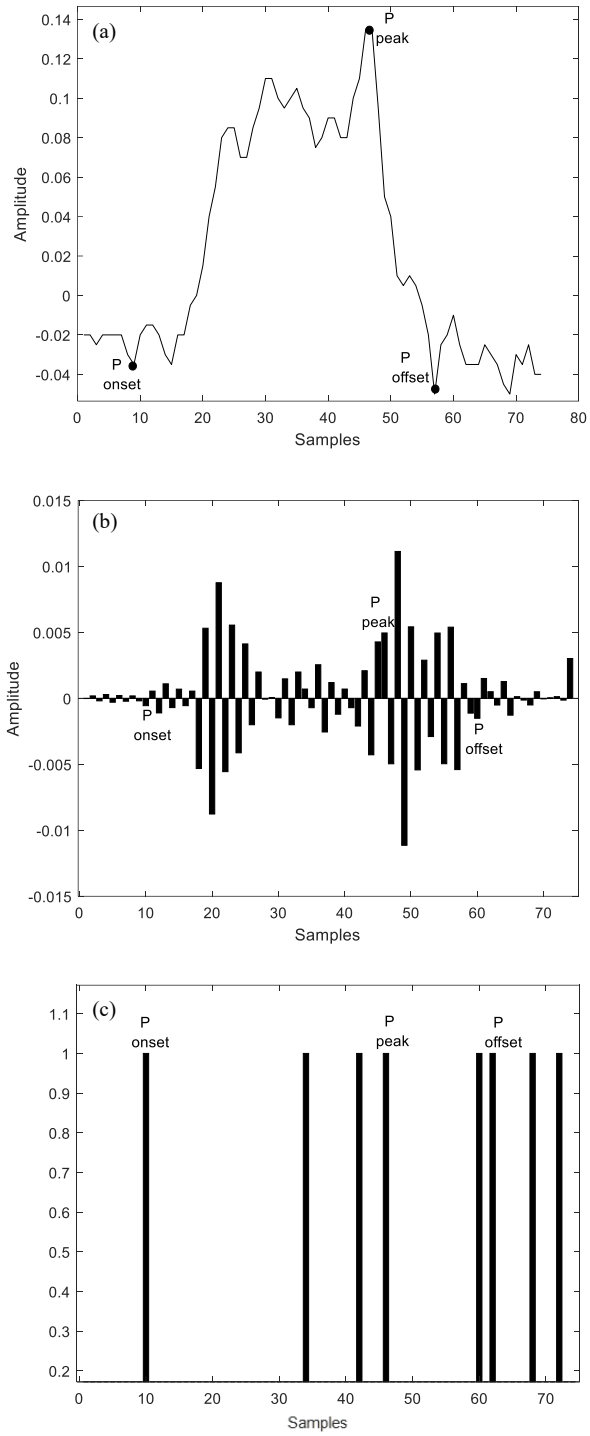

Fig. 6. P wave delination: (a) P wave, (b) SC coefficients of the P wave, (c) $Pe(k)$ signal of the P wave.

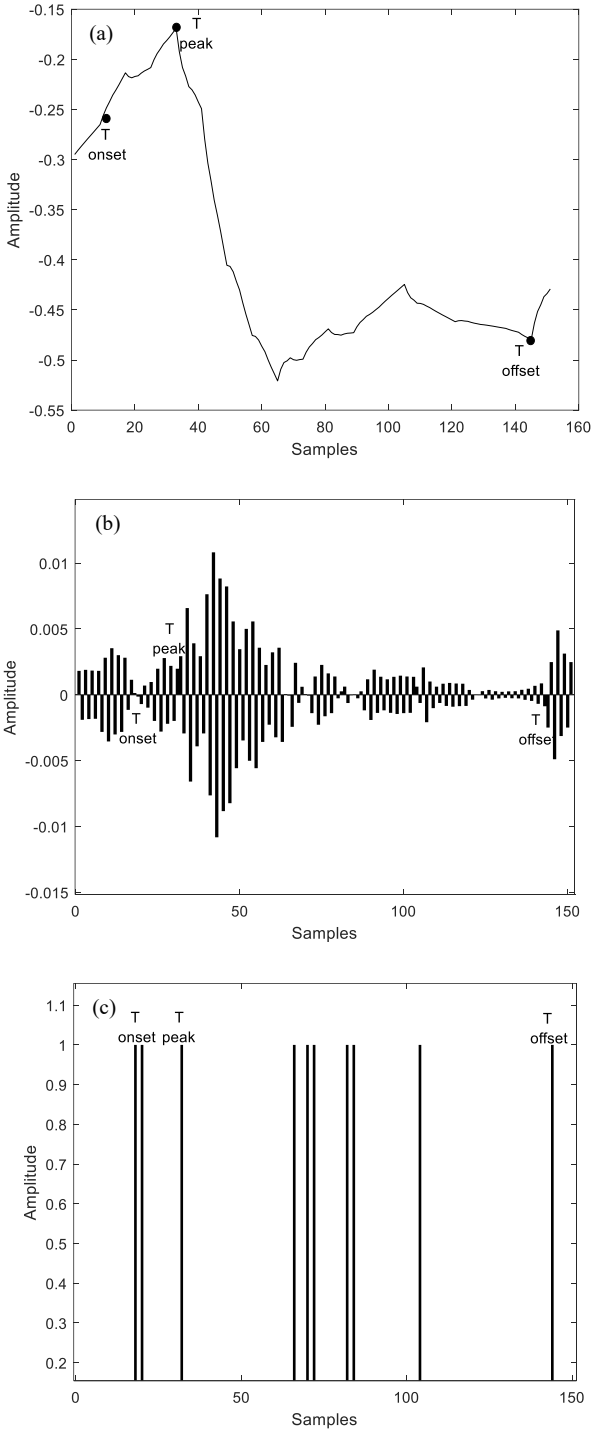

Fig. 7. T wave delination: (a) T wave, (b) SC coefficients of the T wave, (c) $Pe(k)$ signal of the T wave.

In order to eliminate fast variation perturbations, we have used the HF filtering procedure based on the application of thresholded invert discrete wavelet transform from [13]. Figure 8 shows the different waveforms before and after filtering. We can clearly differentiate between the two signals, where the first represents several small peaks that are eliminated in the second.

E. ST segments and QT intervals extraction

The ST segments are calculated as the distance between QRS offsets and T onsets. When the ST segment is isoelectric and uniform, it's a sign of a healthy patient; however, if it contains shifts and deformations, it will be a sign of ischemic patient. Figure 9 represents two sets of ST segments of records 100 and 115.

We can note that ST segments of record 100 don't contain any distortions (the baseline is isoelectric) and have almost equal lengths which mean that all the myocardial cells are normally depolarized.

However, the amplitude levels and the slope of the segments of the record 115 are variable and distorted with different leng ths varying from 0.14 to 0.31 seconds, which indicate the existence of an ischemic state of the myocardiumAs a result of the above delineations, especially the Q-onset and the S-offset position extractions, the QT interval is localized between these two points.

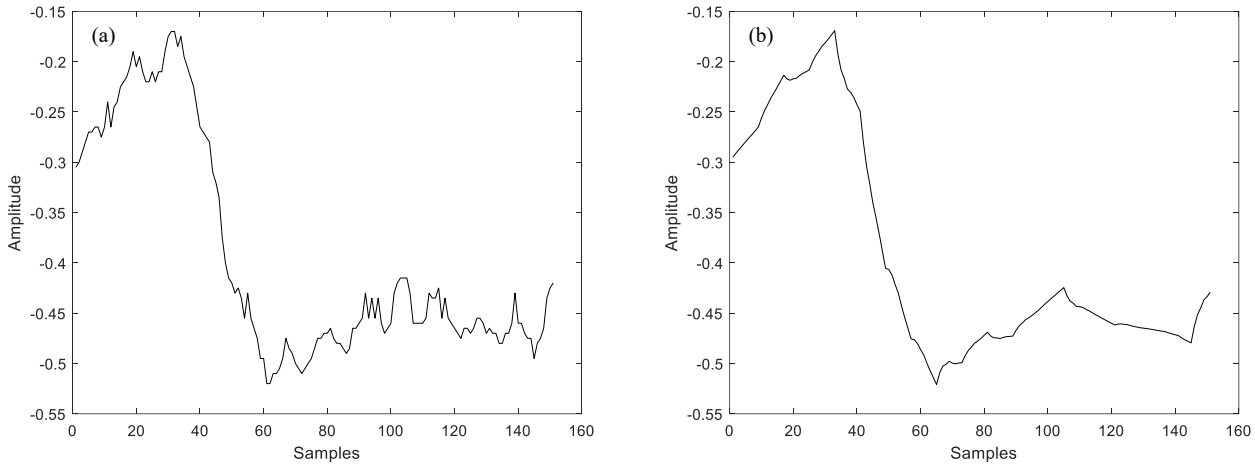

Fig. 8. T wave filtering : (a) T wave and (b) filtered T wave.

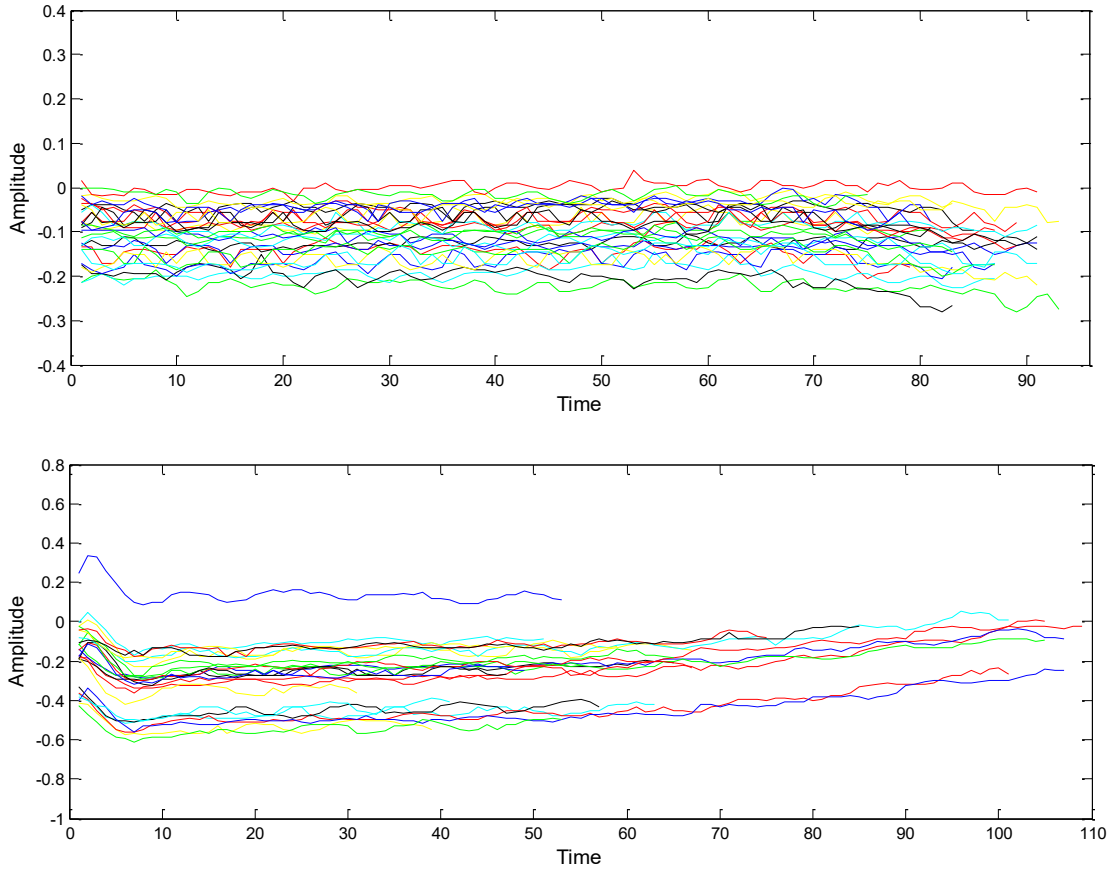

Fig. 9. Twenty eight ST segments : (a) of record 100 and (b) of record 115.

IV. Conclusion

In this paper, we have developed a new method for electrocardiogram signal's features delineation by firstly detecting R waves using slope change coefficients, which gives when applied to MIT-BIH arrhythmia database signals an accuracy rate equal to 99.98 %. Secondly, we have calculated the locations of peaks and their onsets and offsets. Features as P onsets, P peaks, P offsets, QRS onsets, QRS complexes, QRS offsets, T onsets, T peaks, and T offsets, are located with high precision even if there are shifts and deformations of the baseline.

From features delineation, we have extracted the forms and calculated the lengths of the intervals and segments, such as the RR interval, the ST segment, and the QT interval. These signal features were extracted for using them in the diagnostic of ECG arrhythmias and hypoglycemia detection... They can also be used as pre-processed inputs of neural network arrhythmias classifiers.

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