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On the post-design aspects of human/animal electrocardiogram P-QRS-T detection algorithms

M. Javadi*

Department of Mechatronics Engineering, Islamic Azad University, South Tehran Branch, Tehran, P.O. Box 11365/4435, Iran.

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ST-segment;
PP-interval;
T-wave alternans;
P-wave alternans.

Abstract. This paper describes how one can design a computer program and implement it on an ordinary PC or PDA for detecting very long duration electrocardiogram (ECG) PQRST events with processing capability (time complexity) of less than 1300 clock/samples, with an accuracy of more than 99.86%. For detecting and delineating QRS complexes, a noise-robust instantaneous concavity analysis was applied. For detecting and delineating P- and T-waves, the analysis of local extremums of the QRS-eliminated signal was used. The proposed method was applied to several databases (more than 1,000,000 beats; normal or abnormal) with different sampling frequencies and bit-rates. After application of the algorithm, the average detection sensitivity, $Se = 99.96\%$, and positive predictivity, $P+ = 99.94\%$, were obtained for the QRS complex. The average delineation errors were about -3.0 msec, 2.5 msec and 2.8 msec for P-QRS-T events, respectively. By implementing the proposed algorithm computer program to selected databases, the required variation for the core parameter sets of the program was about 0.0% for all sampling frequencies and bit rates. The maximum computational complexity required during application of the method to databases was estimated to be lower than 1300 clocks/sample. These merits make the algorithm eligible for implementation by a mobile-phone or PDA.

1. Introduction

The most important applications of the ECG signal can be summarized for three different aims: a) Heart-Rate (HR) evaluation of a subject; normal or abnormal, b) detection of some certain arrhythmias and dysrhythmias, such as premature atrial/ventricular contractions, ventricular tachycardia, atrial fibrillation, etc., and c) estimation of heart axis deviation for which this parameter has valuable applications in the area of heart abnormality recognition, from an electrophysiological (EP) point of view.

In general, the shape and physiological parameters of a registered ECG signal depend upon several parameters, such as type of subject (human or mammalian animal), gender, position (physical condition) of the under-study subject, type of mammalian animal (rat, mouse, dog, pig, rabbit etc.), type of therapy and prescribed drugs and chemicals, lead type (limb, chest, augmented, and any other user-defined electrode synthesis), acquisition conditions (external noise and disturbance sources), specifications of the acquisition system (sampling frequency, bit-rate, and standards of the producing country), and many other minor items [1].

Up to now, several ECG signal PQRST event detection-delineation algorithms have been proposed by researchers, based on a diverse number of mathematical theories and signal processing techniques, including mathematical models [2], Hilbert transform [3], first derivative [4], statistical higher-order

*. *Tel.: +98 21 88830826; Fax: +98 21 88830012*
E-mail address: mjavadi@azad.ac.ir (M. Javadi)

moments [5], second-order derivative, wavelet transform and filter banks [6-8], soft computing (neuro-fuzzy, genetic algorithm) [9], Hidden Markov Model (HMM) applications [10], ensemble averaging [11], information processing-based approaches, such as independent (principal) components analysis [12], linear (generalized) discriminant analysis [13], etc. [14,15].

Most ECG PQRST event detection-delineation algorithms impose fairly large scale computational burdens, which makes their application feasibility impossible over long duration ECG signals by means of an ordinary PC, PDA or mobile phone central processor. On the other hand, by dropping some parts of the previously proposed detection algorithms with the aim of decreasing computational complexity, the probability of significant error occurrence will definitely be increased.

Therefore, the lack of a fully robust algorithm, with a very low computational burden, which is affordable by a PDA or a mobile phone, as well as having output accuracy competitive with previously introduced peer-reviewed studies, is felt. The aim of this study is to introduce a human/animal ECG P-QRS-T detection-delineation algorithm subjected to CPU speed constraint. In this constraint, the maximum available CPU speed is assumed about 250 MHz, which is a specified speed for mobile phones and PDAs. The constitutive methods applied in this study are mainly based on ECG signal concavity enhanced by adding appropriate reinforcing algorithms. The method includes a noise robust differentiation technique, a double threshold discriminating program regulation, Gaussian filtering, post analyses and variance-based detection of non-impulsive events. For rendering the merits of the presented algorithm, it was applied to several databases. After implementing the method, the estimated computational burden of the algorithm is about 1300 clocks/sample, whose load is affordable by a PDA, mobile phone, etc.

After detecting-delineating ECG PQRST events, the post-processor of the algorithm, which includes the following features, was designed (RR-, PP-, TT-, PR- and QT- intervals detectors, ST-segment detector, QRS duration analyzer, time-value-aligned cumulated QRS complexes and, T- and P-wave alternans ratios). A general block-diagram of the proposed second-order-based QRS detection-delineation algorithm is depicted in Figure 1.

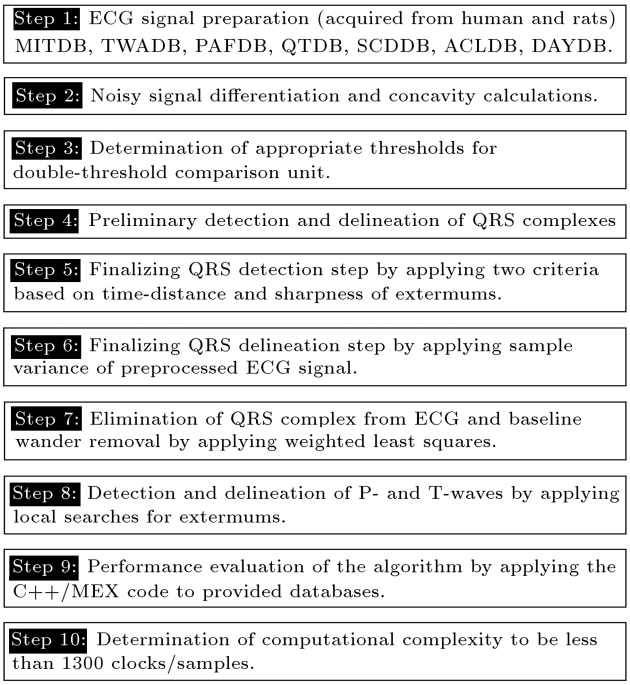


Figure 1. General block-diagram of the proposed second-order derivative-based P-QRS-T detection-delineation algorithm.

2. Methods

2.1. Double-Threshold (DT) comparison logic

This comparing unit is based on the saturation-with-hysteresis theory, and this comparison technique utilizes two different thresholds, called Upper and Lower Bounds (UB, LB). If the input to the comparing unit is higher than the upper threshold, then the output of the comparing unit will be "high" value. On the other hand, if the input to the filter is lower than the lower threshold, the output will be the "low" value. Otherwise, if the value of input remains between the upper and the lower bounds, the output of the filter will be uniformly equal to its latest value. The mathematical representation of the DT can be written as follows:

$$x_{\mathrm{DT}}(t) = \begin{cases} 1.0 & x(t) \geq \mathrm{UB} \\ 0.0 & x(t) \leq \mathrm{LB} \\ x_{\mathrm{DT}}(t - \Delta t) & \mathrm{LB} < x(t) < \mathrm{UB} \end{cases} \quad (1)$$

in which Δt is the time step of the discretized ECG signal. In other words, in the digital time domain, Δt is the distance between samples of the discretized signal.

2.2. Noisy signal differentiation and concavity calculations

In the ECG signal, the QRS complex is the most impulsive event between other events [16]. This event is a strong upward-downward wave with sharp ascending-descending parts, which implies high slope values with significant alteration. Consequently, based on mathematics, in the location of the QRS complex incidence, high concavity values can be observed. Thus, in the proposed QRS detection-delineation algorithm, the values of instantaneous concavity, with some appended additional calculations, are the core constitutive elements.

In order to determine the instantaneous concavity value of a signal, its numerical differentiation should be estimated [17,18]. As a key point, numerical differentiation of a signal with high-frequency noise and disturbances will certainly be accompanied by significant errors, leading to the loss of useful information. A noise robust differentiating procedure is devised for application to the noisy signal, according to the following procedure.

In order to determine the instantaneous differentiation of a signal, $s(t)$, a window with the time duration of WL (40 msec) is slid onto the $s(t)$, and the approximate differentiation of the signal, denoted by $\dot{s}_{\text{app}}(t)$, is calculated as follows:

$$\frac{d}{dt}\left[s(t)\right]_{\text{app}} = \dot{s}_{\text{app}}(t) = \frac{1}{\text{WL}}\int_{t-\text{WL}/2}^{t+\text{WL}/2} \frac{s(t)-s(v)}{t-v}dv,\ v \neq t, \tag{2}$$

where WL is the length of the sliding window. This length is chosen to be about 40 msec, because the frequency content of the QRS complex is usually about 10-25 Hz. Hence, a QRS complex has a length of about 40-100 msec. Therefore, a sliding window with an approximate length of 40 msec seems to be suitable for calculating the approximate differentiation of the ECG signal for detecting-delineating the QRS complex. By application of a sliding window with this length, the effects of disturbing factors with frequency content higher than 25 Hz will be eliminated, as well as the lowest possible distortion of QRS structural components. According to Eq. (2), to calculate the slope at time t, a window with length 40 msec and center t, is considered, and the average slope of the lines drawn from the signal value at time t and all other samples of the segment, is assigned as the differentiation of the signal at time t (Figure 2).

In order to calculate the instantaneous concavity value of the ECG signal, the second order differentiation (two times sequential differentiation) should be applied to the original signal, according to Eq. (3):

$$u(t) = abs\left(\frac{d}{dt}\left[\frac{d}{dt}\left[s(t)\right]_{\text{app}}\right]_{\text{app}}\right), \tag{3}$$

where $s(t)$ is the original ECG signal, $u(t)$ is the absolute concavity of $s(t)$ and $\frac{d}{dt}\left[\bullet\right]_{\text{app}}$ is the operator of the proposed approximate differentiation technique.

In Figure 3(a), an example showing, simultaneously, the noisy ECG signal and its estimated instantaneous concavity value, is depicted.

3. Implementation of the algorithm

In some parts of the algorithm, the detection and decision making subroutines require application of the appropriate thresholds. Almost all thresholds and coefficients of this study are determined based on empirical assessments and endeavors.

3.1. Detection and delineation of QRS complexes

As a first step for detection-delineation of QRS complexes, the concavity of the original ECG signal is calculated according to the aforementioned noise-robust differentiation technique. Several empirical tests indicate that in the location of the QRS incidence, a strong peak can be seen in the ECG concavity curve. Therefore, by applying a variable-threshold-based detection technique to the ECG concavity curve, the location of QRS complexes can be detected appropriately.

3.1.1. Determination of appropriate thresholds for detecting-delineating QRS complexes

The reason for applying a variable-threshold technique is originated from the fact that with the occurrence of some cardiac phenomena such as bundle branch blocks, premature beats, fibrillations and flutters, the value of the ECG signal concavity in the lo-

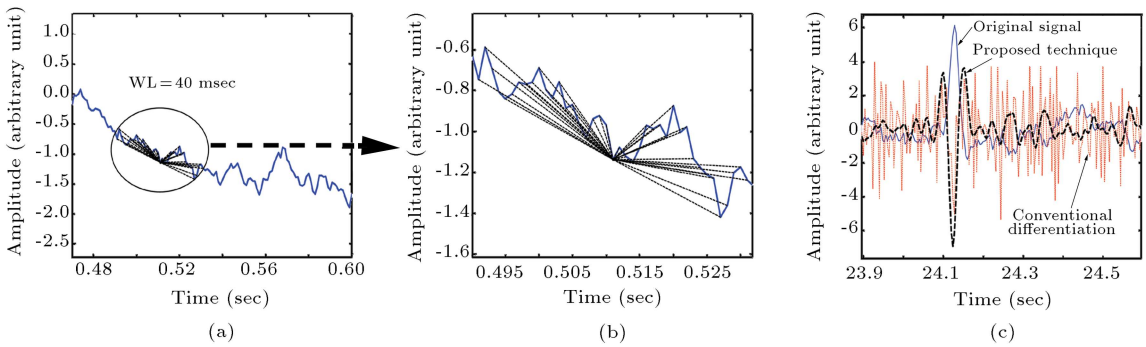


Figure 2. The procedure for calculating instantaneous differentiation of signal at time t: (a) Choosing the analysis window; (b) the lines drawn between the center of window and all other samples; and (c) comparison between conventional and the proposed differentiation techniques.

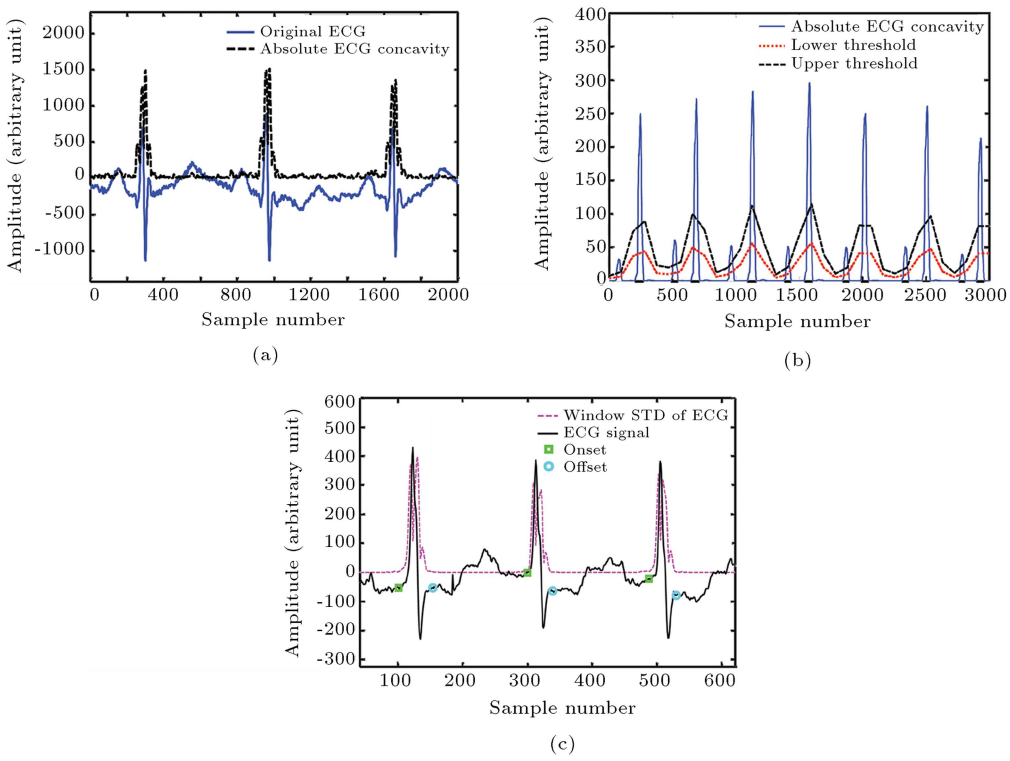


Figure 3. (a) The concavity curve obtained from an arbitrary ECG signal. (b) Obtained thresholds by sliding the Gaussian analysis window on the concavity measure and by conducting the local amplification technique. (c) The instantaneous std trend obtained by applying a sliding window and a constant-value threshold.

cation of ventricular depolarization will have time-varying values. Therefore, a fixed value threshold might cause false-positive/negative errors, which justifies application of a variable-valued discriminating border.

As a heuristic solution, one way to determine the value of the threshold is to slide a window onto the concavity curve. Next, the absolute maximum value of the excerpted segment is calculated and a proportionally amplified version of this value is adopted as the desired threshold. This method has a drawback, however, by which a significant sensitivity to the window length is encountered. As an explanation, if the window length is chosen to be a large value, the probability of missing a weak-value concavity QRS complex occurring between two strong QRS complexes will increase. On the other hand, if the window length is chosen to be a small value, the probability of possessing no QRS complex by the sliding window will drastically increase, which leads to falsely marking P- or T-waves, or some other parts of the ECG signal, as a QRS complex. Hence, according to the fact that the RR-intervals are beat-varying quantities, this method will have small practical value. To solve this problem, a window with a certain length, WL is chosen and normal (Gaussian) function is supposed as the weight function for the segment excerpted by the window. The mean and standard deviation values of the distribution are chosen empirically as midspan and 40% of the window length, respectively.

Then, by forward sample-by-sample sliding of this window onto the ECG concavity signal, $u(t)$, and by calculating the following quantity, the Gaussian-based weighted measure, called $u_w(t)$, is obtained:

$$\begin{cases} u_w(t) = \int_{t-\mathrm{WL}/2}^{t+\mathrm{WL}/2} f_V(v,t,\mathrm{WL})u(v)dv \\ f_V(x,t,\mathrm{WL}) = \frac{1}{\sqrt{2\pi}\sigma}\exp\ [-\frac{1}{2\sigma^2}(x-t)^2] \\ \sigma = 0.40 \times \mathrm{WL} \end{cases} \tag{4}$$

At the final step, a sliding analysis window is moved on the $u_w(t)$ trend, and during each slide, an amplified value of the excerpted segment maximum value is chosen as the comparison threshold.

$$\begin{cases} u_{\mathrm{thrs}}(t) = K_G \times \max\left[u_w(v)\right] \\ t - \mathrm{WL}/2 \le v \le t + \mathrm{WL}/2 \end{cases} \tag{5}$$

where $0.0 \le K_G \le 1.0$. For obtaining appropriate LB and UB values, one can choose K_G 0.4 and 0.5, respectively, and two thresholds will be obtained. Afterwards, by applying a DT filter (Section 3.1) and two calculated thresholds, UB and LB, the obtained ECG concavity curve is changed to a digital decision statistic (Figure 3(b)).

Although the sensitivity of this windowing method to the window length, WL is lower than the

previous window technique, even in this case, the WL should be determined scrupulously. The best minimum value for WL is an interval that contains at least one QRS complex. In addition, a good choice for maximum WL value is the interval that does not contain so many QRS complexes, so as to prevent missing low-concavity QRS complexes. In order to find an appropriate value for WL to determine the best possible variable threshold curve, the following steps should be followed. The detection algorithm should be run two times. In the first step, the WL is chosen as a constant value and some significant QRS complexes are detected. Then, in the second running stage, by using the obtained QRS complexes, the variable threshold method (Eq. (5)) is used and all complexes are detected. In the case of fixed-size window length, the WL should be chosen as large as at least one QRS complex lying within this window (for example, time duration about 2 seconds). By implementing the algorithm with this window length, some QRS complexes will be detected and some others may be missed. To find the missed complexes, for each detected peak to peak interval, a WL equal to interval length is chosen, and detection of QRS complexes in this region is continued until new peak to peak intervals become smaller than 400 msec, or no further QRS complex can be detected. It should be noticed that by being dependent on the criterion, which, in this case means that the window length is equal to the RR-interval, the algorithm may detect P- or T-waves or other non-QRS waves as the QRS complex. So, a refinement procedure is devised for solving this problem.

3.1.2. Detection refinement for removing falsely detected QRS complexes

Criterion#1. If the time distance between two successive QRS complexes is lower than 200 msec, one of them is superfluous. In this case, the event with the larger concavity value is accepted as the genuine QRS complex and the other event is rejected.

Criterion#2. Based on a heuristic inference, in which the concavity of P- and T-waves is much smaller than the concavity of QRS complexes, each QRS complex is tested using its former event. According to the criterion of this stage, if the concavity of each event is lower than 0.1 of the previous event concavity value, it is proven that the tested event is a non-QRS event and, consequently, should be rejected.

These conditions are checked one after the other. According to these conditions, if the time distance between two successive QRS complexes is lower than 200 msec, the complex with larger concavity is accepted. Also, complexes with very small concavity values are rejected.

3.2. Detecting R-, Q- and S-waves

In the ECG signal, the R-wave possesses maximum instantaneous concavity value, i.e. R is the sharpest location of the QRS complex. In the segment of each detected QRS component, a local search for finding the absolute maximum and minimum slopes is conducted, and the zero crossing slope is considered the R location of the QRS complex.

In order to detect Q- and S-waves, first, a region around the R-location, which definitely contains these waves, should be assigned. Empirical assessments show that the onset location of a QRS complex occurs at an interval with a length of 0.2 of the RR-interval between the R-peak and its previous complex. Also, the S-wave certainly occurs in an interval beginning from the R-peak with duration equal to 20% of the R-location distance from the next beat. After determination of the appropriate interval for detecting Q- and S-waves, a new technique, based on standard deviation, is introduced, aiming for detection of Q- and S-waves. Prior to application of the standard-deviation-based technique, the noise and baseline wander of the ECG signal should be removed [19].

3.2.1. Calculation of variance

A sliding window with the length of WL=15 msec is slid onto the filtered signal and the sample variance of the excerpted segment is calculated as follows:

$$\begin{cases} u_{\text{std}}(t_k) = \sqrt{\frac{1}{\text{WL}} \int_{t-\text{WL}/2}^{t+\text{WL}/2} [s(v) - \mu(t_k)]^2 dv} \\ \mu(t_k) = \frac{1}{\text{WL}} \int_{t-\text{WL}/2}^{t+\text{WL}/2} s(v) dv \end{cases}$$

$$q_k \le t_k \le s_k,$$

$$q_k = R_k - 0.2 \times (R_k - R_{k-1}),$$

$$s_k = R_k + 0.2 \times (R_{k+1} - R_k). \tag{6}$$

After this operation, the curve of the instant sample-variance quantity is generated (Figure 3(c)).

3.2.2. Detection of Q- and S-waves by means of the sample variance curve

For detecting Q- and S-waves, a threshold is calculated, which is the sum of the mean value and 0.1 of the maximum-minimum value differences associated with the excerpted segment, i.e:

$$\tau_{\text{QS}}(k) = \frac{1}{s_k - q_k} \int_{q_k}^{s_k} s(v) dv + 0.1 \times (\max\ [s(t_k)] - \min\ [s(t_k)]),$$

$$q_k \le t_k \le s_k. \tag{7}$$

Then, the first sample greater than the threshold, $\tau_{\text{QS}}(k)$, is chosen as the Q-wave and the last sample

of the trend greater than the threshold is chosen as the S-wave location, respectively (Figure 3(c)).

3.3. Detection and delineation of P- and T-waves (non-impulsive events)

ECG non-impulsive events, such as P- and T-waves, have lower amplitude versus QRS complex, so, they cannot be detected easily when a detection decision statistic is calculated jointly between impulsive and non-impulsive events. Accordingly, the first step must be the detection of QRS complexes and then the elimination of their effect for seeking P- and T-waves between S of the current QRS complex and Q of the next QRS complex. To detect P- and T-waves, a suitable detection DS (decision statistic) is required. Because of the non-impulsive nature of these waves, several practical assessments indicate that the DS quantity cannot be the concavity curve used for the detection of the QRS complex. According to the fact that the human cognition system considers amplitude as the main quantity for detecting P- and T-waves, the main detection feature to detect these events is supposed to be absolute amplitude. To this end, local extremums of the preprocessed QRS-eliminated signal are determined and then two largest extremums are named as T- and P-waves, respectively. Because the P-wave might be absent from some parts of the signal due to some cardiac electrical conduction system failure, the amplitude of the marked event as a P-wave is very low, so, this condition can be sensed by comparing its amplitude with the associated R-wave amplitude. Accordingly, if the candidate P-wave has an amplitude lower than the coefficient 0.1 (obtained empirically) of its associated R-wave, it will be removed. After localizing P- and T-waves, the delineation process can be fulfilled by identifying the nearest extremums surrounding the P- or T-wave locations. For example, the location of the T-wave onset is the nearest extremum of the signal before the T-wave incidence location. For determining extremum values, it is assumed that the signal is free of noise (this assumption does not happen in real applications). Usually, the noise effect is reduced by applying some preprocessing. In this stage, preprocessing includes a lowpass filter with a cut in frequency of about 30 Hz and an adaptive smoother filter [20].

3.3.1. Baseline wander removal specified for detecting P- and T-waves

The main weakness of any P- and T-wave detection algorithm is due to the effects of the baseline wander and artifacts, especially when the baseline has greater changes relative to the amplitude of P- and T-waves. Therefore, the baseline must be removed before running the algorithm for detecting P- and T-waves. In this study, Weighted Least Squares (WLS) is used for guessing the parameters of the baseline. In fact, the weight trend is the inverse of the absolute concavity value with some additional modifications for preventing dividing by zero.

Because the detection window length is a very small value, the first assumption is that, in this interval, the baseline is a line with two parameters, i.e. slope and bias. The parameters of this line are estimated by applying the weighted least squares technique. For determining a suitable weight function, the inverse value of absolute ECG signal concavity is used. Also, the weight value in the QRS region is assumed to be zero (Figure 4(a)), i.e:

$$W_{\mathrm{LS}}(t) = \begin{cases} 0 & t \in \mathrm{QRS} \\ \frac{1}{0.2 \times \max[u(t)] + u(t)} & \mathrm{Otherwise} \end{cases} \quad (8)$$

where $u(t)$ is the absolute concavity of the original signal.

Afterwards, the obtained $W_{\mathrm{LS}}(t)$ is used as the weighting function for the excerpted segment. Consequently, the unknown parameters of the line are estimated as follows (Figure 4(b)):

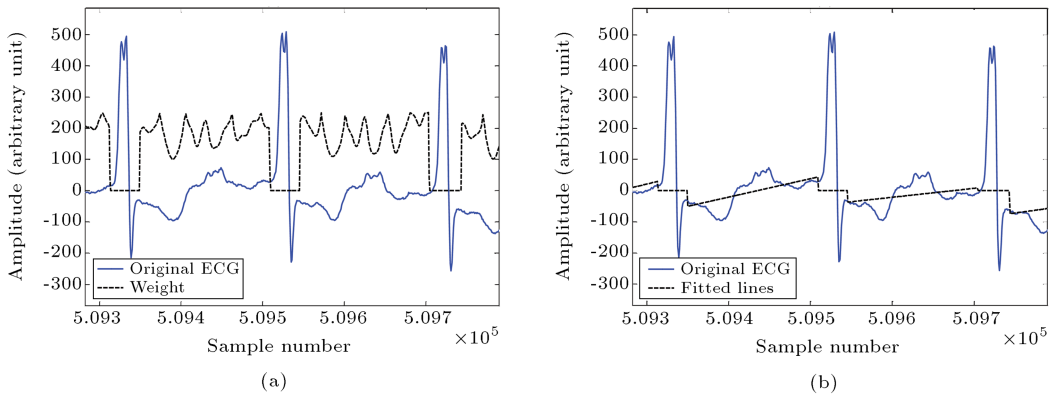


Figure 4. (a) Weight that is calculated by inverse of concavity used for fitting line. (b) Fitted line by means of least squares method and calculated weights.

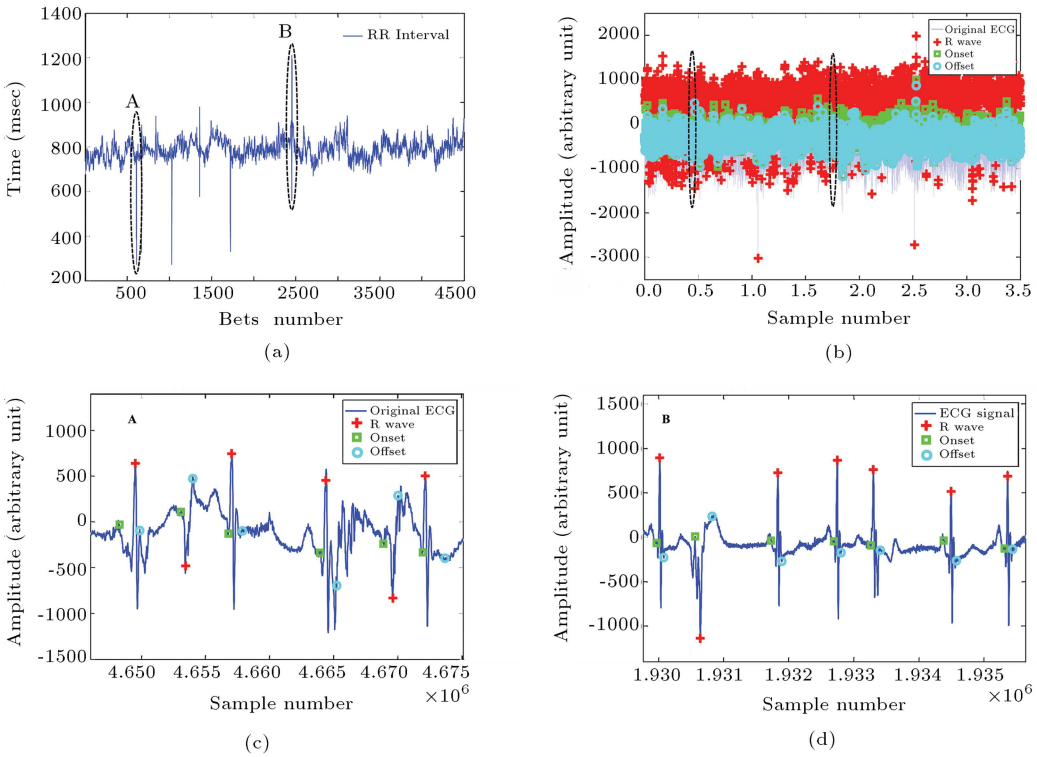


Figure 5. A generic example of the proposed detection-delineation algorithm applied to record 31 of the SCDDB database: (a) The obtained RR-tachogram with some suspicious locations; (b) the location of uncertain results obtained based on the RR-tachogram; (c) and (d) the sufficiently magnified (zoomed) of the detected-delineated signal around the uncertain targets.

$$\begin{cases} \varepsilon(t) = W_{\mathrm{LS}}(t) \times s(t) \\ L_k(t) = a_k t + b_k \\ \begin{bmatrix} a_k \\ b_k \end{bmatrix} = \mathrm{LS}[\varepsilon(t)] \end{cases} \qquad s_{k-l} \le t \le q_k \tag{9}$$

An illustrating example for the estimated baseline at each $s_{k-1}q_k$ interval is shown. By subtracting the baseline from the original segment, $s(t)(s_{k-1} \le t \le q_k)$, the detection and delineation of P- and T-waves can be completed.

4. Results

4.1. Performance evaluation of the proposed algorithm by applying the method to several databases

For rendering the merits of the presented algorithm, it was applied to several databases, including: the MIT-BIH arrhythmia database (MITDB) [21,22] (SF=366 Hz, BR=11 Bits), the T-wave alternans database (TWADB) [23] (SF=500 Hz, BR=16 Bits), the paroxysmal atrial fibrillation database (PAFDB) [24] (SF=128 Hz, BR=12 Bits), the QT-database (QTDB) [25] (SF=250 Hz, BR=not mentioned), the sudden cardiac death database (SCDDB) (SF=250 Hz, BR=not mentioned), the DAY general hospital holter database (DAYDB) [5] (SF=1000 Hz, BR=32 Bits), and the animal catheter laboratory database (ACLDB) [26] (SF=200 Hz or 1000 Hz, BR=16 Bits). The selection criteria for adopting databases were: a) sampling frequency, b) bit-rate, c) duration of signal, d) noise level, e) amount of baseline wander, f) amount of low-quality segments, g) arrhythmias of signal, h) acquisition machines, and i) human/animal EKGs. In Figure 5, an example of applying the computer program of the algorithm to a record of the SCDDB under a noisy condition is shown. It should be noticed that similar figures can be obtained by implementing the computer code to other databases, which are omitted to be shown.

The secondary objective of this study is to describe the design procedure of an algorithm whose parameters have the lowest possible dependency on the above mentioned items. For applying the computer program of the algorithm to databases, the parameters were selected according to Table 1. For the aim of presenting the high-accuracy performance of the proposed technique, the results of applying the algorithm to several databases such as MITDB, and QTDB, for QRS detection validation (Table 2) and QTDB for P-QRS-T detection-delineation validation (Table 3), are reported.

Table 1. List of parameters that should be set in order to implement the algorithm to several databases.

Parameter	Description	Stage	Value	
			Human	Rat
WL	Window length	Differentiation (Section D.2)	40 ms	100 ms
		Initialization step (Section C.1.1)	2 s	500 ms
		Secondary step (Section C.1.1.)	Equal to previous RR interval	Equal to previous RR interval
		Variance calculation (Section C.2.1)	15 ms	3 ms
σ	Standard deviation	Thresholing (Section C.1.1)	0.4× window length	0.4× window length
K_G	Gain coefficient for obtaining thresholds	For upper bound (Section C.1.1.)	0.5	0.5
		For lower bound (Section C.1.1)	0.4	0.4

Table 2. Performance evaluation of several QRS detection algorithms: Application to MITDB.

Detection algorithm	# of annotations	TP	FP	FN	Error (%)	Se (%)	P+(%)	Average process time
This study	109428	109381	70	39	0.09	99.96	99.94	1,300
Homaeinezhad et al. [12]	109428	109375	81	53	0.12	99.95	99.93	118,400
Ghaffari et al. [5]	109428	109367	89	61	0.14	99.94	99.91	97,900
Ghaffari et al. [8]	109428	109327	129	101	0.21	99.91	99.88	93,200
Martinez et al. [9]	109428	109208	153	220	0.34	99.80	99.86	91,600
Li et al. [7]	104182	104070	65	112	0.17	99.89	99.94	96,100
Hamilton et al. [27]	109267	108927	248	340	0.54	99.69	99.77	96,500

5. Discussions

5.1. The electro-phono cardiogram system

In this study, a hardware system is designed in order to acquire, simultaneously, the electrocardiogram and phonocardiogram signals, (Figure 6(a)). This system can acquire three-lead chest ECG signal with arbitrary sampling frequency. The phonocardiogram signal is acquired by a 12-bit resolution and 4 KHz sampling frequency protocol. The system saves the acquired signal on a SD-RAM memory with an arbitrary format. In Figure 6(b), the attachment of lead wires and an electronic stethoscope sensor to the body of a patient is illustrated. Figure 6(c) shows the electro-phono cardiogram signal, which is acquired under real time conditions.

5.2. Applying proposed algorithm to male rats

Male rats (weighing $280 - 310$ g) housed in the animal quarters of the Tehran University of Medical Sciences Laboratory, under standardized conditions: 12h light/dark cycle, 20-22°C ambient temperature and $40 - 50\%$ humidity, with free access to FED standard rat chow and tapwater ad libitum. All animal care and experiments were conducted in accordance with the institutional guidelines of Tehran University of Medical Sciences (Figure 7).

Depending on the fact that rats or mice belong to the family of mammals, the electro-mechanical function of their cardiac system closely resembles that of a human heart and vascular system. Thus, many experimental studies are conducted on rats for exploring the answers to key questions arising from studying the human heart. Beside many similarities, some differences can be seen between human and rat hearts which are detected during the measurement of some signals. For instance, the heart rate of a rat is approximately 5.5 times greater than the human heart rate. Also, in rats, the time distance between the offset location of the QRS-complex and the onset location of a T-wave is almost zero, while this distance can be easily distinguished in the human ECG (Table 4).

5.3. Computational burden determination of the proposed algorithm

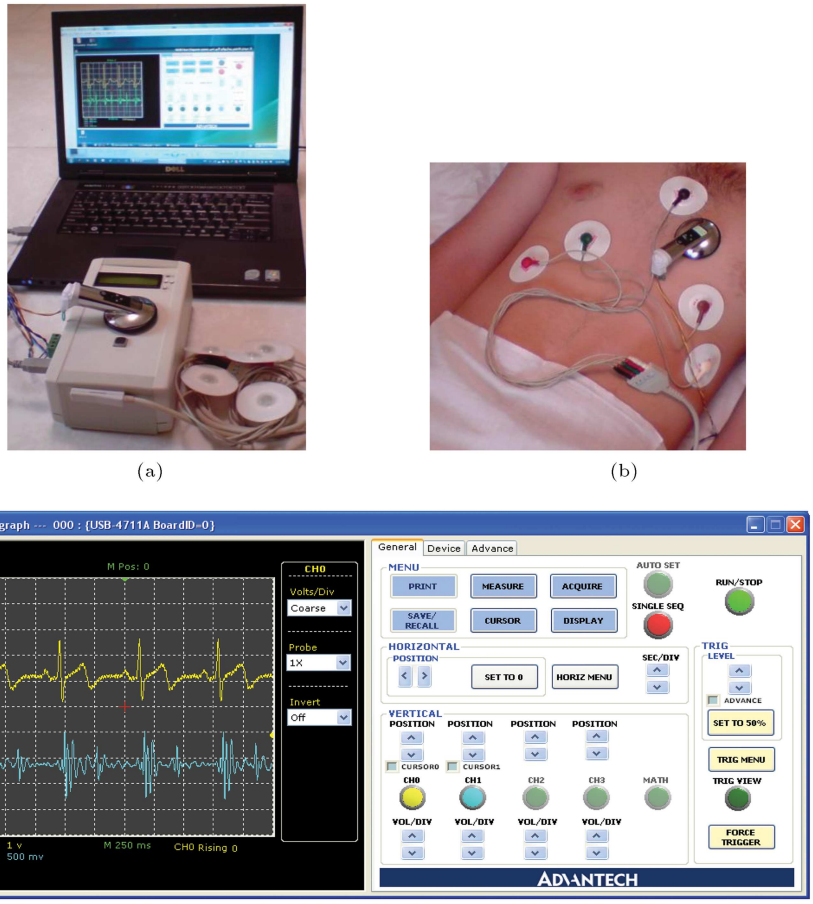
Suppose that an ECG signal is acquired from a human or animal (e.g., rat) at sampling frequency 500 Hz. If the duration of the record is 24 hours, the number of samples is, consequently, 43,200,000. If a C++/MEX wavelet-based detection-delineation technique is implemented on a fast computer (Intel Core, Quad CPU 4 GHz, 2 GB of Ram, and 4 MB Cache Memories), the total elapsed time will be approximately 270 sec [15,30]. By doing some simple calculations, the required com-

Table 3. Performance evaluation of delineation algorithms on QTDB (NR: Not Reported, NA: Not Applicable, LE: Location Error).

Method	Accuracy parameters	P_{ON}	P_{peak}	P_{OFF}	QRS_{ON}	QRS_{events}	QRS_{OFF}	T_{ON}	T_{peak}	T_{OFF}
This study	Se (%)	99.71	99.71	99.71	99.97	99.97	99.97	99.94	99.94	99.94
	P+ (%)	99.30	99.30	99.30	99.93	99.93	99.93	99.92	99.92	99.92
	LE ($\mu \pm \sigma$) (msec)	0.6±2.4	0.5±2.2	-0.5±2	0.5±2	0.5±2	0.5±2	-0.2±1.5	0.1±1.2	0.3±1.5
Homaeinezhad et al. [12]	Se (%)	99.69	99.69	99.69	99.97	99.97	99.97	99.93	99.93	99.93
	P+ (%)	99.21	99.21	99.21	99.95	99.95	99.95	99.92	99.92	99.92
	LE ($\mu \pm \sigma$) (msec)	-1.1±3.4	3.4±6.3	-0.1±3.1	-0.6±3.3	-0.7±1.9	-0.1±5.4	-1.0±3.7	-0.2± 2.6	-0.1±5.2
Ghaffari et al. [5]	Se (%)	99.64	99.64	99.64	99.97	99.97	99.97	99.93	99.93	99.93
	P+ (%)	99.00	99.00	99.00	99.95	99.95	99.95	99.92	99.92	99.92
	LE ($\mu \pm \sigma$) (msec)	-1.1±4.7	3.6 ±7.7	-0.2±3.4	-0.6±4.9	0.7±2.4	-0.1±5.9	-1.1±4.1	-0.2±3.1	-0.1±6.8
Ghaffari et al. [8]	Se (%)	99.46	99.46	99.46	99.94	99.94	99.94	99.87	99.87	99.87
	P+ (%)	98.83	98.83	98.83	99.91	99.91	99.91	99.80	99.80	99.80
	LE ($\mu \pm \sigma$) (msec)	-1.2±6.3	4.1±10.5	0.7±6.8	-0.6±8.0	1.1±2.8	0.3±8.8	-1.4±5.7	0.3±4.1	0.8±10.9
Martinez et al. [9]	Se (%)	98.87	98.87	98.75	99.97	NR	99.97	NR	99.77	99.77
	P+ (%)	91.03	91.03	91.03	NA	NR	NA	NR	97.79	97.79
	LE ($\mu \pm \sigma$) (msec)	2.0±14.8	3.6±13.2	1.9±12.8	4.6±7.7	NR	0.8±8.7	NR	0.2±13.9	-1.6±18.1
Laguna et al. [28]	Se (%)	97.7	97.7	97.7	99.92	NR	99.92	NR	99.0	99.0
	P+ (%)	91.17	91.17	91.17	99.91	NR	NA	NR	97.74	97.71
	LE ($\mu \pm \sigma$) (msec)	14.0±13.3	4.8±10.6	-0.1±12.3	-3.6±8.6	NR	-1.1±8.3	NR	-7.2±14.3	13.5±27.0
Vila et al. [29]	Se (%)	NA	NA	NA	NA	NR	NA	NR	92.6	92.6
	P+ (%)	NA	NA	NA	NA	NR	NA	NR	NR	NR
	LE ($\mu \pm \sigma$) (msec)	NA	NA	NA	NA	NR	NA	NR	-12±23.4	0.8±30.3

Table 4. Quantitative comparison between normal ECG fundamental parameters of human and rat.

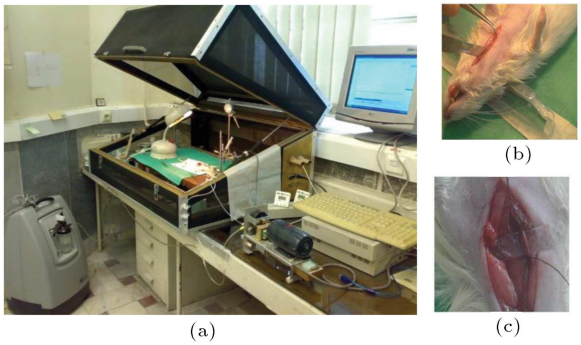
Quantity < dimension >/mamumal	Human	Male rat
RR-interval < msec>	810 ± 40	150 ± 15
Interval between P- and R-waves <msec>	150 ± 15	40 ± 10
Interval between R- and T-waves <msec>	270 ± 10	20 ± 40
P-wave amplitude to R-wave amplitude <dimensionless>	0.13 ± 0.10	0.13 ± 0.10
T-wave amplitude to R-wave amplitude <dimensionless>	0.18 ± 0.05	0.16 ± 0.05
P-wave duration to R-wave duration <dimensionless>	1.48 ± 0.20	1.10 ± 0.20
T-wave duration to R-wave duration <dimensionless>	2.13 ± 0.35	2.05 ± 0.35



(a) (b)

(c)

Figure 6. (a) The electro-phono cardiogram system designed for acquisition of the electrocardiogram and phonocardiogram signals. (b) Attachment of lead wires and the electronic stethoscope to the chest surface of the patient. (c) Simultaneous acquisition of the electrocardiogram and phonocardiogram signals and their representation at a virtual oscilloscope system.



(a) (b) (c)

Figure 7. (a) The experimental set including the surgery desk, ventilation (artificial respiration) system, humidity supplier and electronic acquisition apparatus. (b) Performing surgery for opening the chest of the male rate. (c) Finding arterial appendage and coronary artery.

putational power in this case is about $270 \times 4 \times 4 \times 10^9/43,200,000 = 100,000$ clock/sample (elapsed time × number of CPU cores × each core CPU clock rate/number of processed samples), which is about 640 times greater than the computational power of a mobile phone (the computational speed of an ordinary mobile phone is about 1400 clock/sample). Also, a Matlab code associated with the Hilbert transform-based algorithm will take about 600 sec only for the detection of QRS complexes.

During each test, the clock/sample (process time) of the computer program was estimated for rendering the usefulness of the proposed algorithm for application by a PDA or mobile. For example, in Table 5, the results obtained from application of the C++/MEX computer program of the algorithm to some records of the SCDDB, including the speed of the algorithm, is presented.

5.4. *Noise robustness assessment of the proposed algorithm*

In this step, the noise robustness property of the proposed algorithm is examined. To this end, a clean ECG segment, which includes about 1,000 QRS complexes, was chosen from SCDDB. Then, the algorithm was applied to this segment and the locations of Q-, R- and D-waves were determined and saved. Afterwards, the

Table 5. Information associated with some selected records from the SCDDB and obtained results by application of the proposed detection-delineation and analysis techniques. The CPU time also is presented in terms of clock/sample and samples/sec.

Record code	30	31	32	34	35	36	46
Gender/age	M/43	F/ 72	Unknown/62	M/34	F/72	M/75	F/unknown
Sampling frequency	250	250	250	250	250	250	250
Number of samples	22,099250	12,580,000	2,190,000	6,380,000	22,380,000	18,320,000	3,827,500
Number of beats	136,727	66,751	141,751	28,089	126,219	78,816	21,319
RR-interval mean	161.63	188.46	154.47	227.13	177.31	232.44	179.53
RR-interval std	38.15	37.85	45.94	52.75	82.94	46.38	78.43
T-wave alternans mean	0.152	0.271	0.117	0.078	0.126	0.187	0.187
T-wave alternans std	0.018.9	0.0511	0.0056	0.0043	0.0244	0.0129	0.0328
P-wave alternans mean	0.153	0.193	0.151	0.131	0.1585	0.185	0.1692
P-wave alternans std	0.0134	0.0238	0.007	0.106	0.0305	0.0213	0.0308
FN	63	26	59	13	57	29	11
FP	71	44	83	21	66	52	19
Process time (clock/sample)	1307	1280	1301	1330	1304	1261	1310

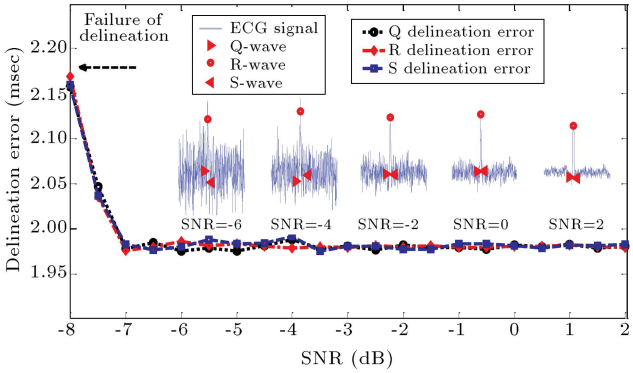


Figure 8. Variation of delineation error versus noise power (SNR).

SNR of the signal was decreased from 10 dB to −10 dB, with −0.5 dB step size. During each evaluation round, the algorithm was applied to the signal and the delineation error was calculated by taking the root-mean-square (RMS) from the delineation errors for Q-, R- and S-waves. In Figure 8, the delineation RMS error versus the SNR value for the mentioned ECG segment is shown. Assessments show that the stability margin of the algorithm is −7 dB.

6. Conclusions

Although up to now, very efficient ECG-detection algorithms have been proposed by authors. However, an everlasting question is whether it is possible to apply those algorithms to a very long duration holter ECG using a PDA, an ordinary PC or a mobile phone central processor with outstanding accuracy. The paper described the structure of a computer program to be implemented on an ordinary PC or PDA for detecting very long duration ECG PQRST events with a processing complexity less than 1300 clock/samples and an accuracy of more than 99.86%. The constitutive methods applied in this study are mainly based on human thinking models. For detection and delineation of QRS complexes, a noise-robust instantaneous concavity analysis was applied. For detection and delineation of P- and T-waves, the analysis of local extremum of the QRS-eliminated signal was used. The proposed method was applied to several databases (more than 1,000,000 beats; normal or abnormal) with different sampling frequencies and bit-rates. Also, the method was applied to 100,000 beats obtained from some male rats during ischemia and reperfusion tests. The accuracy of the method was evaluated as 99.86%, with a very slight dependency of the algorithm parameters on acquisition conditions.

Acknowledgement

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Nomenclature

List of Acronyms

PC	Personal Compute
PDA	Personal Digital Assistant
ECG	Electrocardiogram

EKG	Electrocardiogram
CPU	Central Processing Unit
LAD	Left Anterior Descending coronary artery
DT	Double-Threshold
UB	Upper Bound
LB	Lower Bound
WLS	Weighted Least Square
QTDB	QT Database
ACLDB	Animal Catheter Laboratory Database
BR	Bit-Rate
Se	Sensitivity
FP	False Positive
TP	True Positive
FN	False Negative
TN	True Negative
HR	Heart Rate
EP	Electrophysiological
MITDB	MIT-BIH Arrhythmia Database
TWADB	T-Wave Altenans Database
PAFDB	Paroxysmal Atrial Fibrillation Database
SCDDB	Sudden Cardiac Death Database
DAYDB	DAY general hospital holter database
SF	Sampling Frequency

Variables and parameters

$x(t)$	Signal
$x_{\mathrm{DT}}(t)$	Double-threshold comparison
Δt	Time increment
WL	Window length
R_k	kth R-wave
$u(t)$	Absolute concavity of original signal
$s(t)$	Original signal
q_k	Q-wave search start point
s_k	S-wave search end point
Fs	Sampling frequency
$u_w(t)$	Weight measure
σ	Standard deviation
$u_{\mathrm{thrs}}(t)$	Threshold curve
K_G	Gain coefficient for obtaining thresholds
$u_{\mathrm{std}}(t)$	Signal
μ	Sample-mean of signal
$\tau_{\mathrm{QS}}(t)$	Threshold for detecting Q and S-wave locations
$W_{\mathrm{LS}}(t)$	Least squares weights

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Biography

Mehrdad Javadi received a BS degree in Mechanical Engineering from Sharif University, Tehran, Iran, an MS degree in Mechanical Engineering from Tehran University, Tehran, Iran, and a PhD degree from the Islamic Azad University, Science and Research Branch, Tehran, Iran, where he is currently head of the Mechatronics Department. His research interests include mechanical-electrical interfaces.