

Analysis of Electrocardiograms

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The electrocardiogram (ECG) representing the electrical activity of the heart is the key biosignal for aiding the clinical staff in disease diagnosis. ECG has been always chosen as the basic signal for diagnosing the cardiac abnormalities and detecting the patients' states. Generally the various characteristic features of ECG are extracted and used for decision making purposes. This makes the decision making and diagnosis process simpler and faster. Hence appropriate feature description and extraction becomes the most important component in cardiac health diagnostics. In this chapter various techniques for feature extraction are described.

2.1 Steps in ECG Analysis

The major steps in the analysis of the ECG signals are:

- Noise elimination from ECG using noise filtering techniques
- Cardiac cycle detection by detecting QRS complex
- Detection of significant characteristic points in ECG signal
- Formulation of characteristic feature set

Noise filter removes and reduces the noise components from various sources in the ECG signal.

Cardiac cycle detection involves detecting the QRS complex peak corresponding to each beat. QRS Complex detection is implemented using Tompkins QRS complex detection algorithm.

ECG characteristic points detection involves determining of significant points on the ECG for feature extraction. It includes the detection of QRS complex onset and offset, ST segment detection and T peak detection.

Feature set formulation includes formulation and selection of characteristic features such that they significantly relate to the abnormalities. Additional features are extracted by performing complexity analysis on the signal.

2.2 Preprocessing of ECG

The ECG consists of three basic waves, P, QRS and T. These waves correspond to the far field induced by specific electrical phenomena on the cardiac surface, namely the atrial depolarization (P wave), the ventricular depolarization (QRS complex), and the ventricular repolarization (T wave). The ECG does not look the same in all the leads of the standard 12 lead system used in clinical practice. The polarity and the shape of the ECG constituent waves are different depending on the lead that is used. A sample ECG wave measured at lead II is shown in Fig. 2.1.

In a normal cardiac cycle, the P wave occurs first, followed by the QRS complex and the T wave. The sections of the ECG between the waves and complexes are called segments. The ECG is characterized by three segments namely the PR segment, the ST segment and the TP segment. The characteristic time periods in the ECG wave are the PR interval, the RT interval, and the R-R interval.

Usually ECG signals are contaminated by various kinds of noise. Various noise contaminating the ECG are described in the following section.

Power Line Interference

Power line interference consists of 60/50 Hz pickup and harmonics that can be modeled as sinusoids and combination of sinusoids. According to Friesen *et al* [1], the frequency content of this kind of noise is 60/50 Hz with harmonics and the amplitude is 50% of peak-to-peak ECG amplitude.

Let us consider the presence of a periodic artifact with the fundamental frequency of 60 Hz and odd harmonics at 180, 300, and 420 Hz. Let the sampling frequency (f_s) be 1000 Hz, and assume the absence of any aliasing error. Zeros are then desired at 60, 180, 300, and 420 Hz, which translate to $\pm 21.6^\circ$, $\pm 64.8^\circ$,

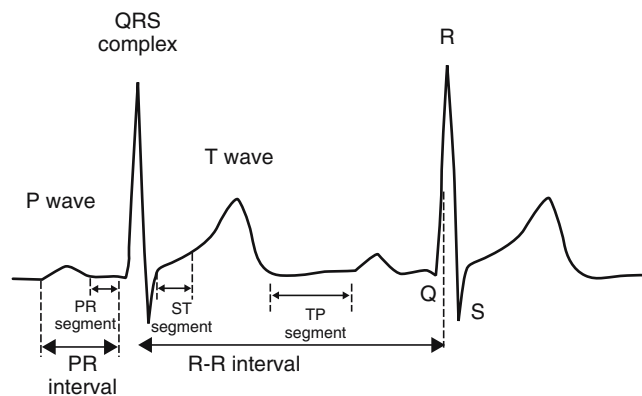


Fig. 2.1. The ECG signal

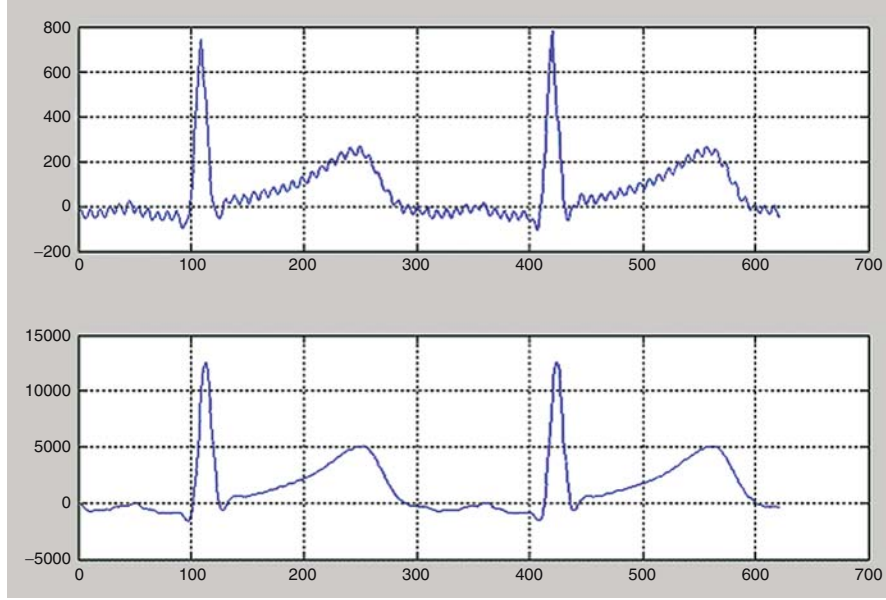


Fig. 2.2. Result of power line interference. (a) Original signal with power line interference. (b) Output of power line interference filter

$\pm 151.2^\circ$, with 360° corresponding to 1000 Hz. The coordinates of the zeros are $0.9297 \pm j0.3681$, $0.4257 \pm j0.9048$, $-0.3090 \pm j0.9510$, and $-0.8763 \pm j0.4817$. The transfer function of the filter is $H(z) = G(1 - 1.8595z^{-1} + z^{-2})(1 - 0.8515z^{-1} + z^{-2}) \times (1 + 0.6180z^{-1} + z^{-2})(1 + 1.7526z^{-1} + z^{-2})$, where G is the desired gain or scaling factor. With G computed so as to set the gain at DC to be unity, the filter transfer function becomes $H(z) = 0.6310 - 0.2149z^{-1} + 0.1512z^{-2} - 0.1288z^{-3} + 0.1227z^{-4} - 0.1288z^{-5} + 0.1512z^{-6} - 0.2149z^{-7} + 0.6310z^{-8}$. Figure 2.2 shows the performance of the power line elimination.

Electrode Contact Noise

Electrode contact noise is transient interference caused by loss of contact between the electrode and the skin, which can be permanent or intermittent. The switching action can result in large artifacts since the ECG signal is usually capacitively coupled to the system. This type of noise can be modeled as a randomly occurring rapid baseline transition that decays exponentially to the base line and has a superimposed 60 Hz component. According to Friesen *et al* [1], the duration of the noise signal is 1 sec and the amplitude is the maximum-recorded output with the frequency of 60 Hz.

Motion Artifact

Motion artifacts are transient base line changes in the electrode skin impedance with electrode motion. The shape of the base line disturbance caused by the motion artifacts can be assumed to be a biphasic signal resembling one cycle of a sine wave. The peak amplitude and duration of the artifacts are variables. The duration of this kind of noise signal is 100–500 ms with amplitude of 500% peak-to-peak ECG amplitude.

Muscle Contraction

Muscle contraction causes generation of artifactual millivolt level potentials. It can be assumed to be transient burst of zero mean band limited Gaussian noise. The variance of the distribution may be estimated from the variation and duration of the bursts. Standard deviation of this kind of noise is 10% of peak-to-peak ECG amplitude with duration of 50 ms and the frequency content being dc to 10 kHz.

Base Line Wander

The baseline wander of the ECG signals causes problems in the detection of peaks. For example, due to the wander, the T peak could be higher than R peak, and it is detected as an R peak instead. Low frequency wander of the ECG signal can be caused by respiration or patient movement. The drift of the baseline with respiration can be represented as a sinusoidal component and the frequency of respiration added to the ECG signal. The variation could be reproduced by amplitude modulation of the ECG by the sinusoidal component that is added to the base line. The amplitude variation is 15% of peak-to-peak ECG amplitude and the base line variation is 15% of ECG amplitude at 0.15 to 0.3 Hz.

These noise should be removed from ECG before extracting the characteristic features. Noise removal is accomplished by passing the cardiovascular signals through filter whose cutoff frequency is a function of the noise frequency.

To solve baseline wander, median filtering can be used. The steps involved in the implementation of baseline wander are shown in Fig. 2.3. First, the first 200 ms of samples were extracted and sorted out in ascending order, then its median was calculated. Then for every 200 ms of samples till the end of the ECG signal, the same procedure was carried out. Now, these samples are fed as input to the 600 ms window median filtering. Later, the median value is evaluated for every 600 ms of samples. Then these median values were subtracted from the original waveform to remove the baseline wander of the ECG signal. Figure 2.4 shows the result of the baseline wander filter.

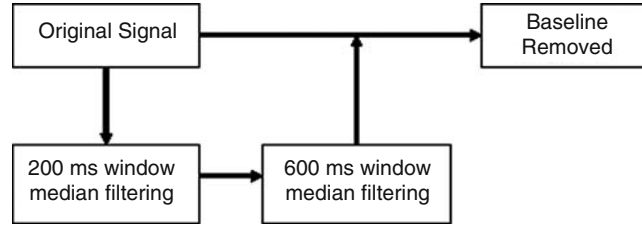


Fig. 2.3. Algorithm to remove the baseline wander

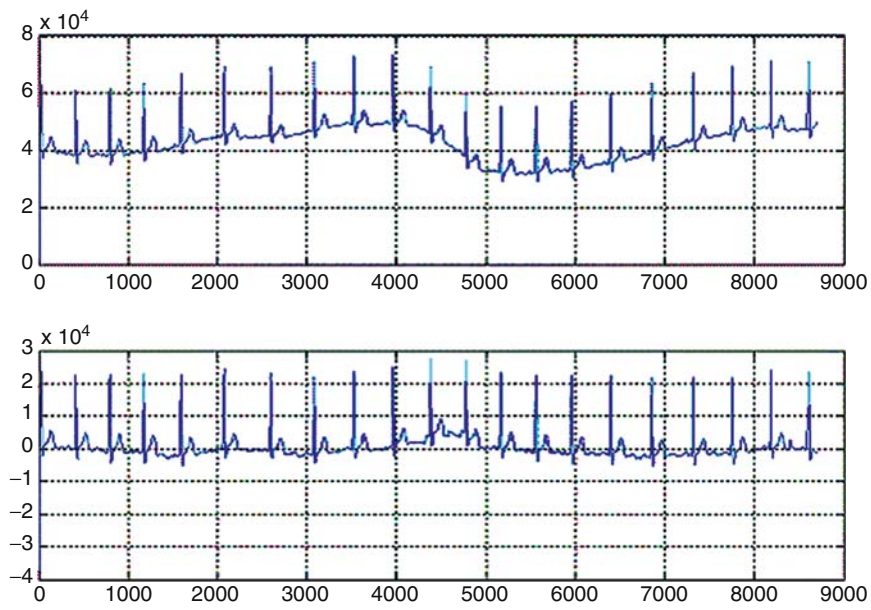


Fig. 2.4. Results of baseline wander algorithm. (a) Original signal. (b) Output of baseline wander filter

2.2.1 Noise Filtering Technique

The first step in noise filtering is determining the frequency corresponding to the significant characteristics of the ECG signal and the noises. From the Fourier transform of human ECG signal it has been found that P and T wave frequency generally lie between 0.5 and 10 Hz and QRS complex frequency ranges between 4 and 20 Hz [2]. The P or T wave sometimes coincides with the baseline noise having a low frequency range of 0–0.8 Hz. Hence it is very essential to eliminate the baseline noise from ECG signals.

In order to attenuate noise, the signal is passed through a band pass filter composed of cascaded high-pass and low-pass integer filters. The band pass

filter is designed from a special class of digital filters that require only integer coefficients. This permits the software to do the signal processing using only integer arithmetic and thereby permitting real-time processing. Since it was not possible to directly design the desired band pass filter with this special approach, the design actually consist of cascaded low-pass and high-pass filter sections. For removing the base line wander and the AC power noise, the algorithm of Alste and Schilder is implemented [3]. In this algorithm, a non recursive finite impulse response (NRFIR) filter has been used with the reduced number of taps. The basic principle behind this filtering process is that the designed frequency response has been defined with small stop band notches at 0 Hz to remove base line wander, as well as 50 Hz and its higher harmonics to remove power line interference. In this algorithm, in order to reduce the long computational time caused by the large number of multiplication involved in the filtering in the time domain the property of the discrete Fourier transform and symmetrical nature of the impulse response has been used. This is achieved by the property that the phase is the linear function of frequency that corresponds with an exact delay time. The convolution sum for the NRFIR is

$$y(nT) = \sum_{i=1}^{\frac{(M-3)}{2}} (h(i.kT) \times ((n - ki)T) + x((n - k(M - 1) + ki)T)) \\ + h\left(\frac{(M-1)}{2}kT\right) \times \left(n - k\frac{(M-1)}{2}T\right) \quad (2.1)$$

where

T = sampling interval of both the input and output signal

$k = 5$

kT = time interval between successive impulse response coefficients

$x(nT)$ = input signal

$y(nT)$ = output signal

$h(ikT)$ = filter impulse response coefficients

M = number of filter coefficients

This filter removes the baseline wander and AC power frequency noise. But some high frequency noises like muscle noise or EMG are still present in the ECG signal. These high frequency noises are eliminated by using another low pass FIR filter with a cutoff frequency higher than the frequency of the QRS complex.

2.3 QRS Complex Detection

All the required features from ECG are extracted from the filtered ECG signal. The basic and essential component for feature extraction is the detection of

the QRS complex i.e. locating the R point for each beat of the signal. Once R point is determined, all other characteristic points on the wave are determined with reference to the R point. Thus an accurate detection of the QRS complex of the ECG is an important task in ECG analysis.

2.3.1 QRS Detection Algorithm

The algorithm used to detect QRS complexes is an adaptation of the commonly used real-time QRS detection algorithm developed by Pan *et al* [4] and further described by Hamilton *et al* [5]. It recognizes QRS complexes based on analysis of the slope, amplitude and width.

Figure 2.5 shows the various processes involved in the analysis of the ECG signal. In order to isolate the portion of the wave where QRS energy is predominant, the signal is passed through a band pass filter composed of cascaded high-pass and low-pass integer filters. Then the signal is subjected to differentiation, squaring, time averaging and finally peak is detected by applying threshold.

The band pass filter is designed from a special class of digital filters that require only integer coefficients. Since it was not possible to directly design the desired band pass filter with this special approach, the design actually consist of cascaded low-pass and high-pass filter sections.

The next processing step is differentiation, a standard technique for finding the high slopes that normally distinguish the QRS complexes from other ECG waves. To this point in the algorithm, all the processes are accomplished by linear digital filters.

The differentiated waveform is subjected to a nonlinear transformation. The nonlinear transformation involves point-by-point squaring of the signal samples. This transformation serves to make all the data positive prior to subsequent integration, and also accentuates the higher frequencies in the signal obtained from the differentiation process. These higher frequencies are normally characteristic of the QRS complex.

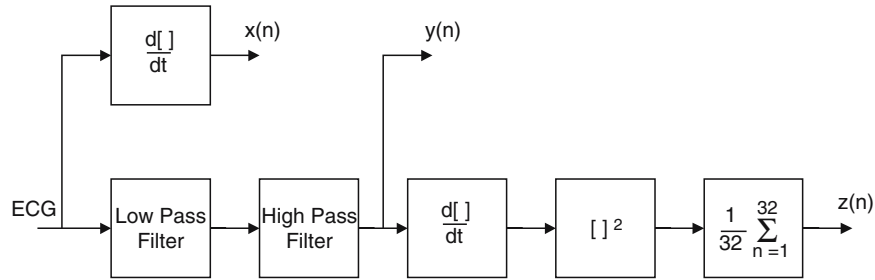


Fig. 2.5. Block diagram of the QRS detector. $z(n)$ is the time averaged signal. $y(n)$ is the band passed ECG. $x(n)$ is the differentiated ECG

The squared waveform passes through a moving window integrator. This integrator sums the area under the squared waveform over a 150 msec interval, advances 1 sample interval and integrates the new 150 msec window. The width of the window was chosen to be long enough to include the time duration of extended abnormal QRS complexes, but short enough so that it does not overlap both the QRS complex and the T wave.

Adaptive amplitude threshold applied to the band pass filtered waveform and to the moving integration waveform are based on continuously updated estimate of the peak signal level and the peak noise. After preliminary detection by the adaptive thresholds, decision processes make the final determination as to whether or not detected event was a QRS complex. A measurement algorithm calculates the QRS duration after the detection of each QRS complex. Thus two waveform features are available for subsequent analysis, RR interval and QRS duration.

Band Pass Integer Filter

The band pass filter for the QRS (heart rate) detection algorithm reduces noise in the ECG signal by matching the spectrum of the average QRS complex. Thus it attenuates T wave interference as well as noise. The pass band that maximizes the QRS energy is approximately in the 5–15 Hz range. The filter implemented in this algorithm is a recursive integer filter in which poles are located to cancel the zeros on the unit circle of the z plane. A low pass filter and a high pass filter are cascaded to form the band pass filter.

Low Pass Integer Filter

The transfer function of the second order low pass filter is

$$H(z) = \frac{(1 - z^{-6})^2}{(1 - z^{-1})^2} \quad (2.2)$$

The difference equation of this filter is

$$y(nT) = 2y(nT - T) - y(nT - 2T) + x(nT) - 2x(nT - 6T) + x(nT - 12T) \quad (2.3)$$

High Pass Integer Filter

The high pass filter is implemented by subtracting a first order low pass filter from an all pass filter with delay shown in the Fig. 2.6.

The low pass filter is an integer coefficient filter with the transfer function

$$H_{lp}(z) = \frac{Y(z)}{X(z)} = \frac{(1 - z^{-32})}{(1 - z^{-1})} \quad (2.4)$$

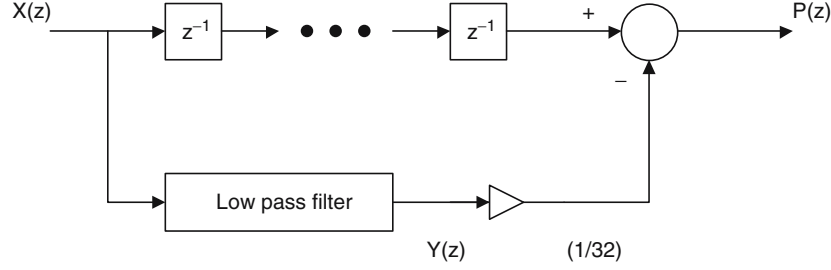


Fig. 2.6. High pass filter

The difference equation of the transfer function is

$$y(nT) = y(nT - T) + x(nT) - x(nT - 32T) \quad (2.5)$$

The high pass filter is obtained by dividing the output of the low pass filter by its dc gain and then subtracting from the original signal. The transfer function of the high pass filter is

$$H_{hp}(z) = \frac{P(z)}{X(z)} = z^{-16} - \frac{H_{lp}(z)}{32} \quad (2.6)$$

The difference equation for this filter is

$$p(nT) = x(nT - 16T) - (1/32)[y(nT - T) + x(nT) - x(nT - 32T)] \quad (2.7)$$

Derivative

After the signal has been filtered it is then differentiated to provide information about the slope of the QRS complex. A five-point derivative has the transfer function

$$H(z) = 0.1(2 + z^{-1} - z^{-3} - 2z^{-4}) \quad (2.8)$$

This derivative is implemented with the difference equation

$$y(nT) = (1/8)[2x(nT) + x(nT - T) + x(nT - 3T) - 2x(nT - 4T)] \quad (2.9)$$

The fraction 1/8 is an approximation of the actual gain of 0.1. This derivative approximates the ideal derivative in the dc through 30 Hz frequency range.

Squaring Function

The squaring function that the signal passes through is a nonlinear operation. The equation that implements this operation is

$$y(nT) = [x(nT)]^2 \quad (2.10)$$

This operation makes all data points in the processed signal positive and it amplifies the output of the derivative process nonlinearly. It emphasizes the higher frequencies in the signal that are mainly due to the QRS complex.

Moving Window Integral

The slope of the R wave alone is not a guaranteed way to detect a QRS event. Many abnormal QRS complexes that have large amplitude and long duration (not very steep slopes) might not be detected using information of the R wave only. Thus we need to extract more information from the signal to detect a QRS event. Moving window integration extracts features in addition to the slope of the R wave. It is implemented with the following difference equation

$$y(nT) = (1/N)[x(nT - (N - 1)T) + x(nT - (N - 2)T) + \dots + x(nT)] \quad (2.11)$$

where N is the number of samples in the width of the moving window. The width of the window should be approximately the same as the widest possible QRS complex. If the size of the window is too large the integration waveform will merge the QRS and T complexes together. On other hand, if the size of the window is too small, a QRS complex could produce several peaks at the output of the stage. The width of the window should be chosen experimentally.

QRS Detection Using Adaptive Thresholds

R peak is then detected using an upward and downward threshold. The thresholds are calculated using running estimates of signal peak and noise peak. Signal peaks are defined as those of the QRS complex and the noise peaks are those of the T waves, muscle noise etc. After the ECG has passed through various filter stages, its signal to noise ratio increases. Hence the thresholds can be chosen above the noise peak levels. It increases the overall sensitivity of the detector. Two sets of thresholds are used, each of which has two threshold levels. The set of thresholds that is applied to the waveform from the moving window integrator is given by

$$\begin{aligned} \text{SPKI} &= 0.125 \text{PEAKI} + 0.875 \text{SPKI} \quad \text{if PEAKI is the signal peak} \\ \text{NPKI} &= 0.125 \text{PEAKI} + 0.875 \text{NPKI} \quad \text{if PEAKI is the noise peak} \\ \text{THRESHOLD I1} &= \text{NPKI} + 0.25(\text{SPKI} - \text{NPKI}) \\ \text{THRESHOLD I2} &= 0.5 \text{THRESHOLD I1} \end{aligned}$$

where

PEAKI is the overall peak
 SPKI is the running estimate of the signal peak
 NPKI is the running estimate of the noise peak
 THRESHOLD I1 is the first threshold applied
 THRESHOLD I2 is the second threshold applied

A peak is determined when the signal changes direction within a certain time interval. Thus, SPKI is the peak that the algorithm has learned to be that of the QRS complex, while NPKI is any peak that is not related to the signal of interest. It can be seen from the above equations that the new values

of thresholds are calculated from the previous ones. In this way, the thresholds are dynamically adjusted to improve detection.

Whenever a new peak is detected it must be categorized as a signal peak or noise peak. If the peak level exceeds the THRESHOLD I1 during the first analysis of the signal, it is detected as a signal peak. A refractory pause of 200 ms is introduced after detection to minimize the detection of the same QRS complex second time.

2.4 Detection of QRS Complex Onset and Offset

The detection of QRS complex generally implies the detection of R peak of QRS complex, which can be used as the reference for extraction of various features on each beat of the ECG signal. To know the QRS complex in its entirety, recognition of the onset and offset is necessary in most types of computer based ECG analysis. QRS onset is generally defined as the beginning of the Q wave or R wave, if no Q wave is present. QRS offset is defined as the end of the S wave [6] if no S wave is visible. QRS delineation is moreover a prerequisite in certain schemes for the classification of different morphologies found. In such schemes, the features, which characterize the QRS complex, are computed with respect to the delineated interval.

Automatic detection of QRS onset and offset points with reasonable accuracy has been a difficult task. The problem is additionally complicated by the presence of power line interference and baseline wander in the original signal. Estimation of QRS onset and offset in multiple lead recordings is based on a delineation function, which is obtained by combining different leads. The function commonly employed is the spatial velocity. The recognition is done by a simple threshold or a template matching technique. Kenneth in 1982 [7] determined the onset as the intersection of the closest fit of a line having a slope of an R wave wall and the base of the wall considered with some offset from the baseline. The slope of the R wave onset and termination walls have been measured by the rule activation, which was used to detect them. This method is time consuming. Leif Sornomo [8] has determined the onset and offset using a maximum likelihood procedure based on the statistical models for the low frequency and high frequency segments of the ECG. A commercially available software product [9] determines the onsets and offsets by an analysis of the simultaneous slopes in all 12 leads. That is, the QRS duration is measured from the earliest onset in any lead to the latest deflection in any lead. Lin *et al* [10] detected onset and offset based on a thresholding technique. This method may be sensitive to noise mainly the baseline noise, which cannot be eliminated without distorting P waves.

In this chapter, we have detected edges as the point with zero slope when there is a sudden change and by a minimum distance method otherwise. The edges are assumed to lie within a window length of 50 samples taken symmetrically around the R peak. 50 samples correspond to the maximum possible

edge distance from the peak, which has been computed from the physiological study of ECG and the sampling frequency of the ECG signal. To find whether a beat has a sharp change or not, the signal values were converted to a three-pulse code train after finding the finite differences. If $[y_1, y_2, y_3, \dots, y_i, \dots, y_n]$ are the filtered signal samples defined at time t_1, t_2, t_3, \dots , etc. then the finite differences are defined as

$$dy_i = y_{i+1} - y_i. \quad (2.12)$$

For easy analysis purpose the signal samples were then converted into a train of three-pulse code train,

$$sl = \begin{cases} 1, & \text{if } dy_i > 0 \\ 0, & \text{if } dy_i = 0 \\ -1, & \text{if } dy_i < 0 \end{cases} \quad (2.13)$$

Presence of sharp changes was detected as change from -1 and 0 to 1 or vice versa (i.e. change in sign). A sharp change is defined as a point with sudden change to zero or negative slope is considered as an edge. But if no sharp changes were present in the signal, edge is detected as the minimum distance from the projected origin. The projected origin is the point of intersection of vertical projection from the peak on to the time axis and the horizontal projection from the edges of the window on the vertical projection. For onset, the edge of the window is taken as the beginning of the window whereas finding offset is taken as the end of the window. If this point is defined as (p_x, p_y) , the distance matrix comprising of distance of all signal points within the window length to the projected origin can be calculated as

$$dis_i = \text{sqrt}((t_i - p_x)^2 + (y_i - p_y)^2). \quad (2.14)$$

The edge is then defined as $[y_i, t_i]$ with minimum dis_i . The validity of the edge as a true edge was checked by using angle criteria. The angle is found between the points at which edge is detected and the fifth sample from that point. The edge was declared as true edge if the angle is less than 8 degrees. In case of false detection the minimum distance method was repeated with this point (point at which angle is found to be greater than 8 degrees) as the end of the window. By detecting the onset and offset of QRS complex, QRS duration is determined.

2.5 ST Segment Analyzer

The isoelectric period (ST segment) following the QRS is the time, at which the entire ventricle is depolarized and roughly corresponds to the plateau phase of the ventricular action potential. The ST segment is important in the diagnosis of ventricular ischemia or hypoxia because under those conditions, the ST segment can become either depressed or elevated.

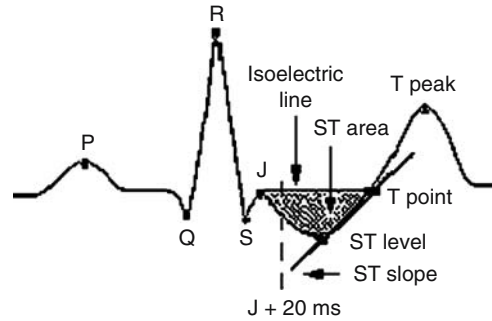


Fig. 2.7. ECG signal indicating ST area

The J point (shown in Fig. 2.7) is the first inflection point after the S point or may be the S point itself in certain ECG waveforms. The T wave peak is the maximal absolute value, relative to the isoelectric line between $J + 80$ ms and $R + 400$ ms. The onset of the T wave, the T point, is found by looking for a 35 ms period on the R side of the T wave which has values within one sample unit of each other. The T point is among the most difficult features to identify. If it is not detected, it is assumed to be $J + 120$ ms.

Having identified various ECG features, ST segment measurements are made using a window search method. Two boundaries, the $J + 20$ ms and the T point, define the window limits. The point of maximal depression or elevation in the window is then identified.

ST segment length is defined as the distance between the J point and the T point. In addition to the ST segment length, several other parameters are calculated. The ST segment deviation can be expressed as the polarity of change relative to the isoelectric line. The ST slope is defined as the amplitude difference between the ST segment point and the T point divided by the corresponding time interval. The ST area is calculated by summing all sample values between the J and T points after subtracting the isoelectric line value from each point. RT interval is defined as the time between the R peak and the corresponding T peak.

2.6 Complexity Analysis of ECG Signal

Physiological signals such as ECG have a wide variety of forms. To describe them, traditional features discussed previously using amplitude and frequency information is not sufficient. This is because the signals of different bandwidth cannot be compared. In addition such measures do not allow comparison within the same subject groups. The absolute frequency of rhythms may differ within the same subject group due to various reasons. Hence some other features are also determined.

When visually inspecting the ECG signals, one of the first impression they give to the observer is the complexity. Some beats appear at random while

others seem to demonstrate a reappearance of certain patterns at various intervals. In medical research, signal variability or system complexity has been correlated with physiological signal conditions. Direct assessment of signal complexity thus offers certain advantages in clinical research. First complexity is an intuitive description and thus eases the interpretation of measurement results. Second, as mentioned, invariant measures allow comparison across different patient population as they are insensitive to absolute measurements of amplitude and frequency.

ECG being nonlinear, non-stationary signal, a number of measures of this complex time series have been developed based on the concepts of nonlinear dynamics like Lypanov exponents, correlation dimension etc, to classify normal/abnormal beats. In this chapter, two measures of clustering the beats in terms of their complexity is used. One of these measures is defined in frequency domain and the other is defined in time domain. Complexity in frequency domain is known as spectral entropy whereas in time domain it is known as temporal complexity.

ECG signal is analyzed in a beat wise manner. Once the boundary of QRS complex is known each beat is analyzed in two groups, one containing the QRS complex and other containing the P & T segments.

2.6.1 Spectral Entropy

Spectral entropy quantifies the spectral complexity of the time series. A variety of spectral transformations exist. Of these the Fourier transformation (FT) is most probably the well-known transformation method from which the power spectral density (PSD) can be obtained. The PSD is a function that represents the distribution of power as function of frequency. Thus normalization of PSD with respect to the total spectral power will yield a probability density function. Application of Shannon's channel entropy gives an estimate of the spectral entropy of the process where entropy is given by

$$H = - \sum_f p_f \log \left(\frac{1}{p_f} \right) \quad (2.15)$$

where p_f is the pdf value at frequency f . Heuristically the entropy has been interpreted as a measure of uncertainty about the event at f . Thus entropy H may be used as a measure of system complexity. This spectral entropy H is computed for the two groups of each beat.

2.6.2 Temporal Complexity

Lempel and Ziv define temporal complexity for a string length of width n as

$$c(n) = \frac{h \cdot n}{\log_k n} \quad (2.16)$$

where k denotes the number of different characters used to represent the string length and h denotes the normalized source entropy, expressed as

$$h = (-1/\log n) \sum_i p_i \log p_i. \quad (2.17)$$

Thus h is determined by the probability p_i for each state i . In finding the temporal complexity for each of the components of the individual beats, the string length is defined with width equal to length of the corresponding components. The string length was defined using binary digits with two characters 1 and 0. For a string length within the boundary of QRS complex originally defined as x_1, x_2, \dots, x_n with

$$x_m = (1/n) \sum_i x_i. \quad (2.18)$$

After the binary transformation, it is defined as s_1, s_2, \dots, s_n , where s_i is obtained as

$$s_i = \begin{cases} 1, & \text{if } x_i \geq x_m \\ 0, & \text{if } x_i < x_m \end{cases} \quad (2.19)$$

The probability p_i for each state is defined as

$$p_i = (1/n) \sum_i s_i, \quad \text{for } s_i = 1. \quad (2.20)$$

Temporal complexity $c(n)$ was computed in a similar manner for signal length consisting of P and T wave.

2.7 Sample Results and Discussion

The various signal-processing techniques for extracting characteristic features of ECG have been discussed. These characteristic features are used to represent significant characteristics of the signal for detection and diagnosis of cardiac abnormalities. The effectiveness of the techniques is demonstrated in this section. For ease of discussion we have considered three cases case K1024 (Class N), K6528 (Class A) and K9956 (Class C) and the results obtained on applying various techniques of feature extraction such as Noise filtering, QRS complex detection, QRS onset and offset detection, ST segment analyzer are given in this section.

2.7.1 Noise Filtering

The first step in noise filtering involves the elimination of most commonly present noise such as the baseline wander and the AC power noise. Baseline noise falls in the frequency band of 0 Hz and AC power noise is in the region of 50 Hz and its harmonics. According to the recommendations made by American Heart Association for ECG recordings, in the lower frequency region, the frequency components above 0.5 Hz should not be removed. Hence

the cutoff frequency is chosen as 0.5 Hz to remove the baseline noise. In ECG the typical high frequency component is the QRS complex which is about 20 Hz. To remove the high frequency noises including the power noise the cut off frequency is chosen in the present study as 21 Hz. The actual and filtered output for Class N, Class A and Class C ECG's are shown below in Figs. 2.8–2.12. As seen from Figs. 2.9, 2.11, and 2.12, we can note that filter removes the baseline wander and attenuates the noise components without any significant distortion in characteristic points or the geometry of the ECG signal. From Fig. 2.12, we can note that even for Class C life-threatening ECG signals, the performance of the filter is good and is able to successfully remove most of the noise components while maintaining the morphology of the signal.

2.7.2 QRS Complex Peak Detection

The main component of ECG signal processing is the QRS complex detection. The implementation results of the QRS detection algorithm are shown in Figs. 2.13 and 2.14.

On implementation of the QRS detection algorithm the R peak is determined. Figures 2.15–2.17 shows the R peaks superimposed on the signal for Class N, Class A and Class C ECG, respectively.

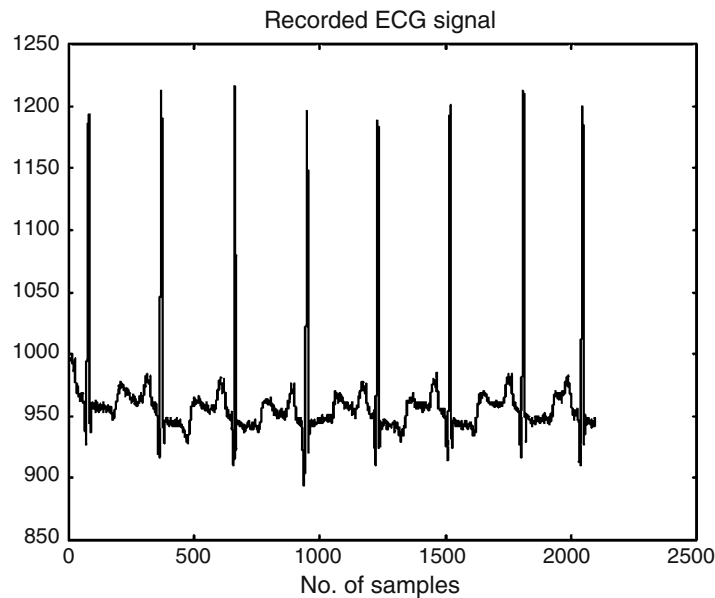


Fig. 2.8. Class N ECG signal (K1024)

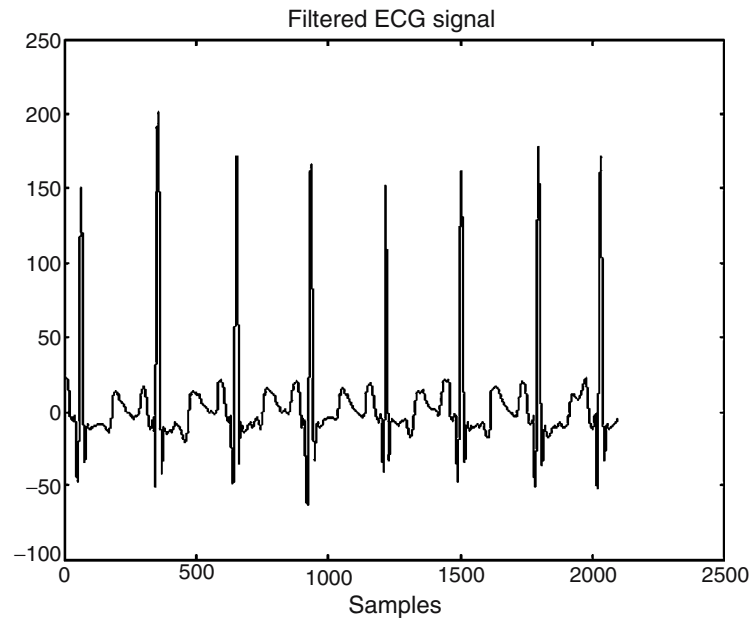


Fig. 2.9. Filtered Class N ECG signal (K1024)

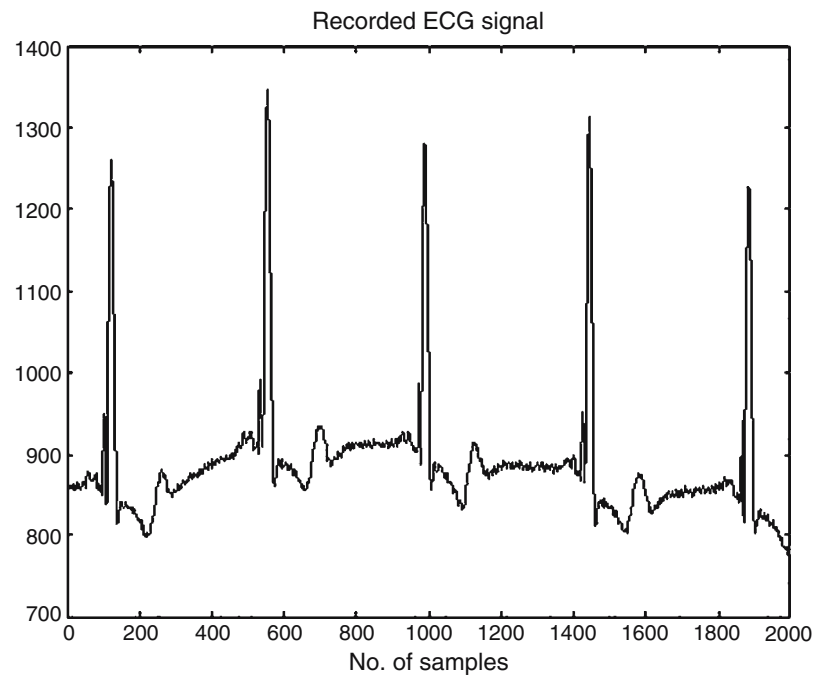


Fig. 2.10. Class A ECG signal (K6528)

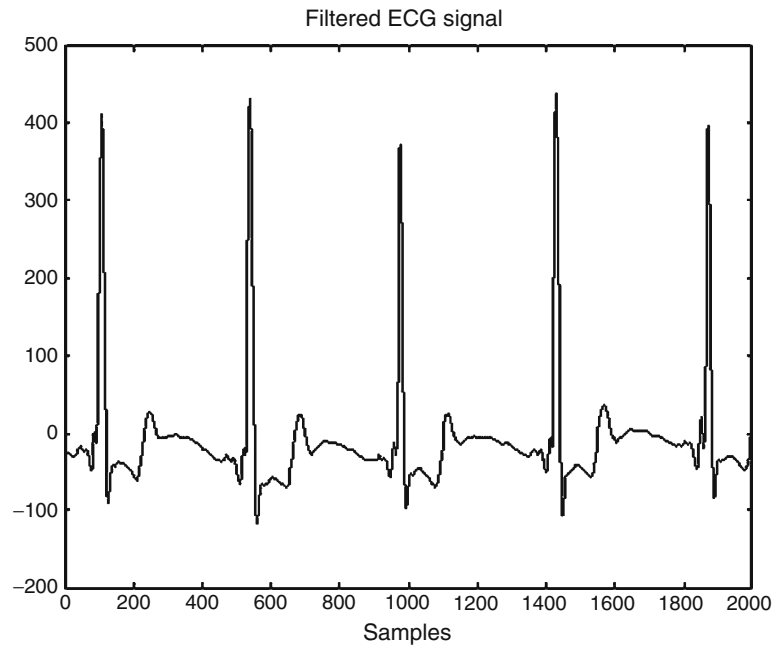


Fig. 2.11. Class C ECG signal (K9956)

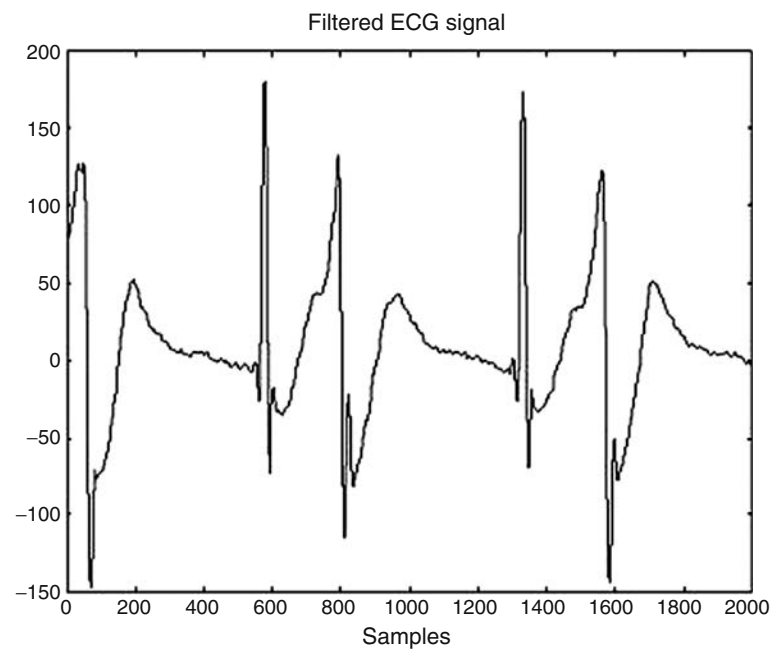


Fig. 2.12. Filtered Class C ECG signal (K9956)

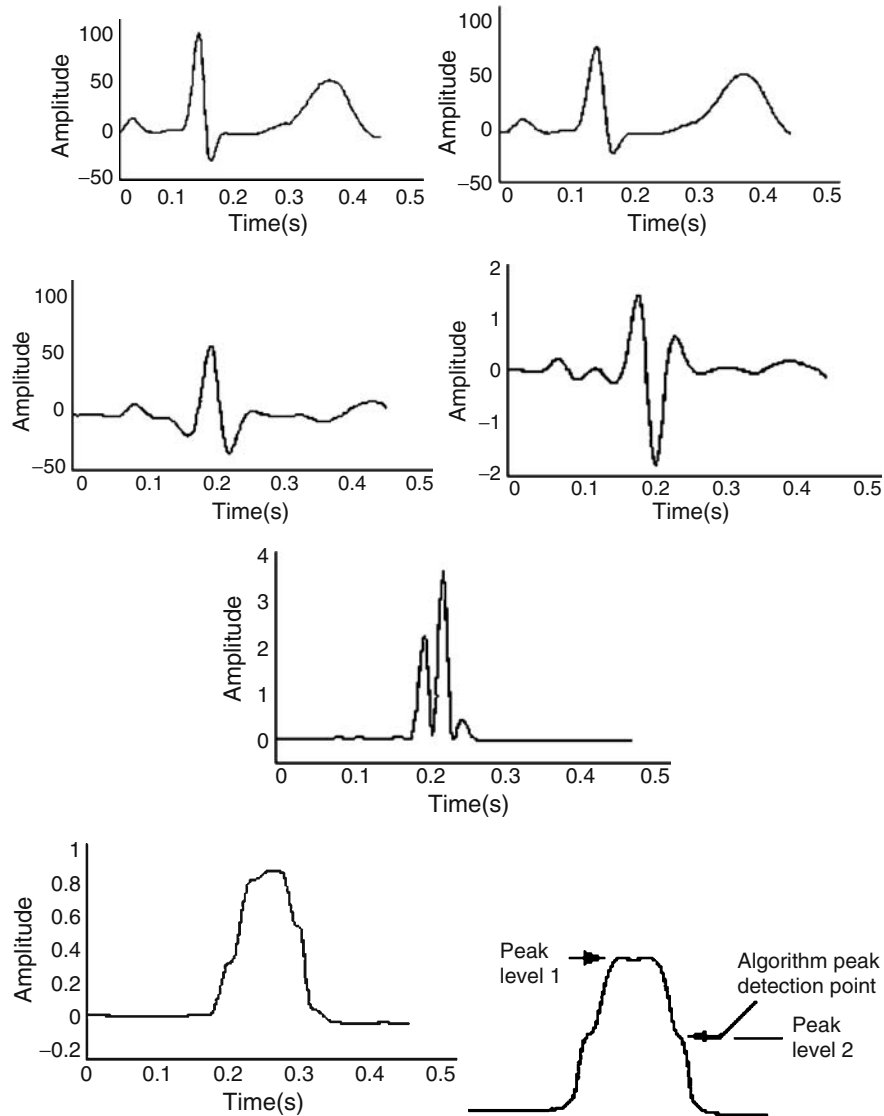


Fig. 2.13. Results of the QRS detection algorithm: (a) ECG signal showing one beat, (b) low pass filtered ECG, (c) band pass filtered ECG, (d) ECG after band pass filtering and differentiation, (e) signal after squaring function, (f) signal after moving window integration, (g) output of the moving window integrator with peak detect point

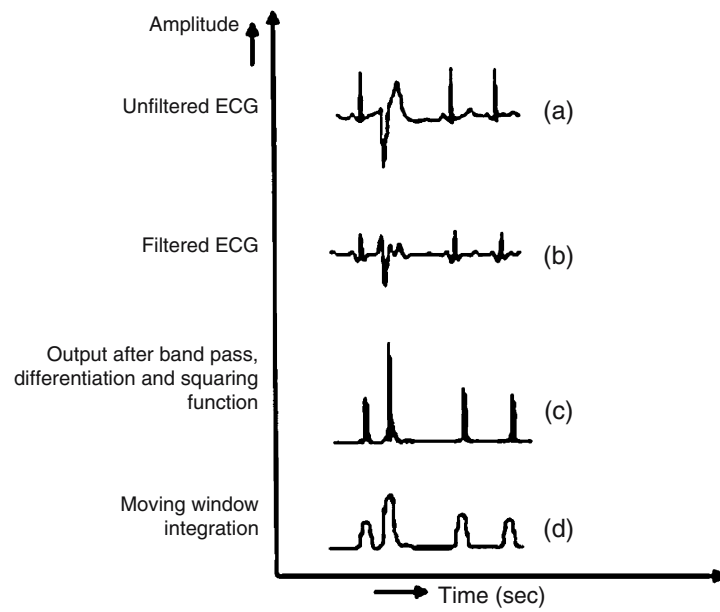


Fig. 2.14. QRS detector signals: (a) unfiltered ECG, (b) filtered ECG, (c) output after band pass, differentiation and squaring function, (d) moving window integration

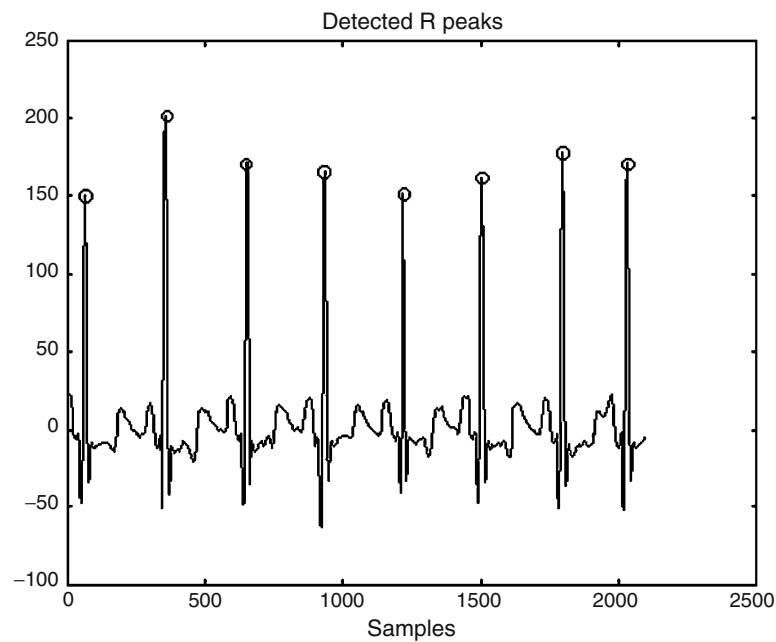


Fig. 2.15. QRS peak detection for Class N ECG signal (K1024)

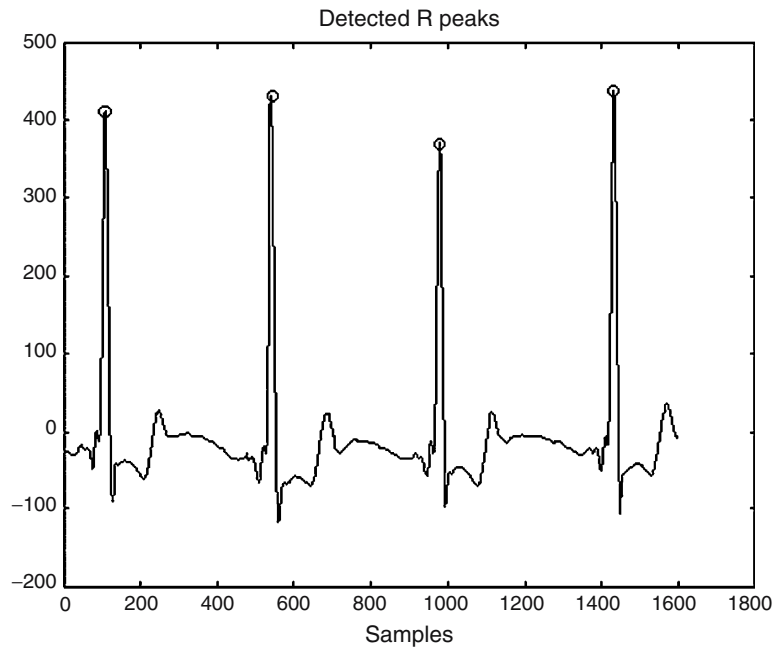


Fig. 2.16. QRS peak detection for Class A ECG signal (K6528)

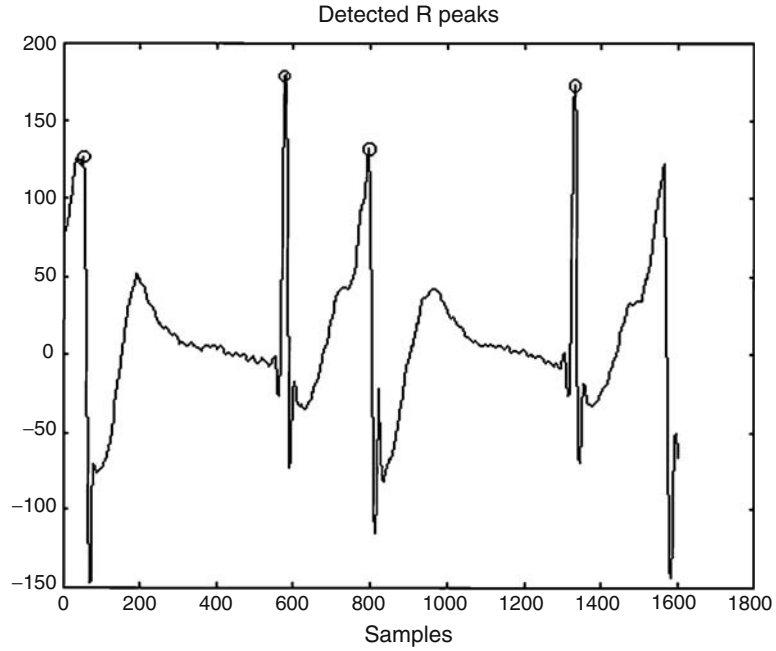


Fig. 2.17. QRS peak detection for Class C ECG signal (K9956)

Once R peak is detected the R-R interval is determined. R-R interval is the time interval between the two consecutive R peaks. The heart rate is determined from the R-R interval as

$$\text{Heart Rate} = (360/R - \text{R interval in samples}) * 60 \text{ beats/min} \quad (2.21)$$

2.7.3 Detection of QRS Complex Onset and Offset

Once R peak is known, the next task is to find the QRS complex in its entirety for further analysis. This also helps to determine the irregularity of the QRS complex. Figures 2.18–2.20 shows the onset and offset of QRS complex in Class N, Class A and Class C ECG signals, respectively. Once the onset and offset points of the QRS complex is detected, QRS width can be determined. QRS width is the time interval between QRS onset and QRS offset. The onset and offset points are also used as the boundary points of the QRS complex for complexity analysis.

2.7.4 ST Segment Detection

The ST segment detection process was discussed in Sect. 2.5. This method detects the start and end points of ST segment that provide useful information

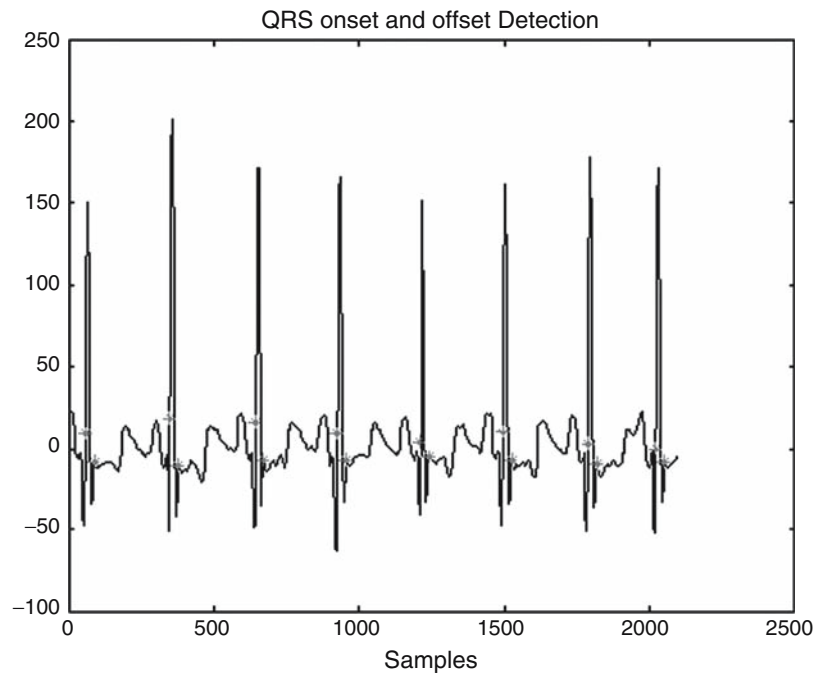


Fig. 2.18. Onset and offset of QRS complex in Class N ECG signal (K1024)

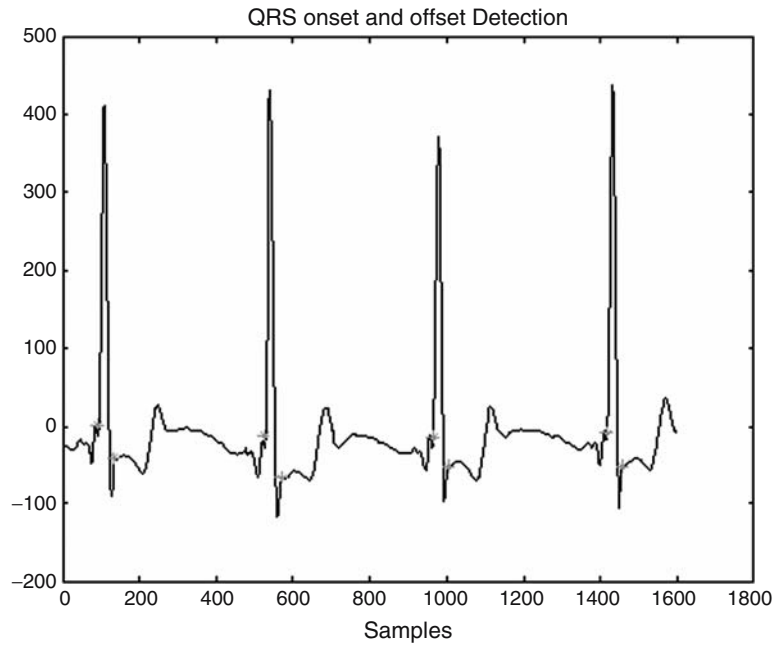


Fig. 2.19. Onset and offset of QRS complex in Class A ECG signal (K6528)

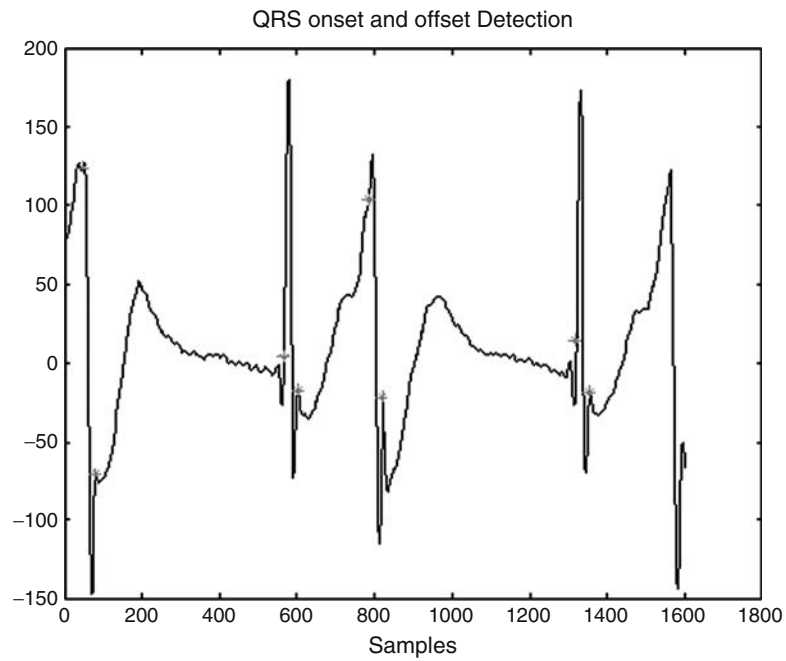


Fig. 2.20. Onset and offset of QRS complex in Class C ECG signal (K9956)

for ECG analysis. Figures 2.21–2.23 show the start and end points of the ST segment superimposed on the ECG signal. Once the start and end points of the ST segment are determined, the characteristic features of the ST segment such as ST segment width, ST segment slope, ST segment deviation, ST segment region area are determined.

2.7.5 T Peak Detection

The peak of the T wave in ECG is determined to find the RT interval. RT interval is the time interval between the R peak and the T peak of the same beat of ECG signal. The detected T peaks superimposed on the signal for Class N, Class A and Class C ECG signals are shown in Figs. 2.24–2.26.

The thirteen characteristic features obtained from each beat of the ECG signal can be used for classification purposes. The thirteen characteristic features are

- a. HR – Heart Rate
- b. ΔHR – Change in Heart Rate
- c. ω_{qrs} – QRS complex width
- d. h_{qrs} – Normalized source entropy for QRS complex
- e. h_p – Normalized source entropy for ST wave
- f. c_{qrs} – Complexity parameter for QRS complex

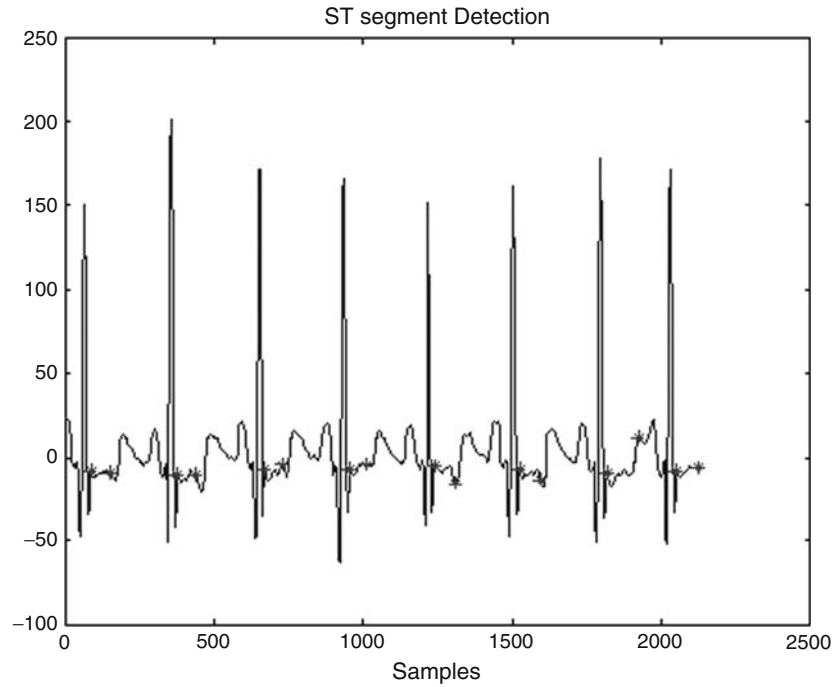


Fig. 2.21. ST segment detection for Class N ECG signal (K1024)

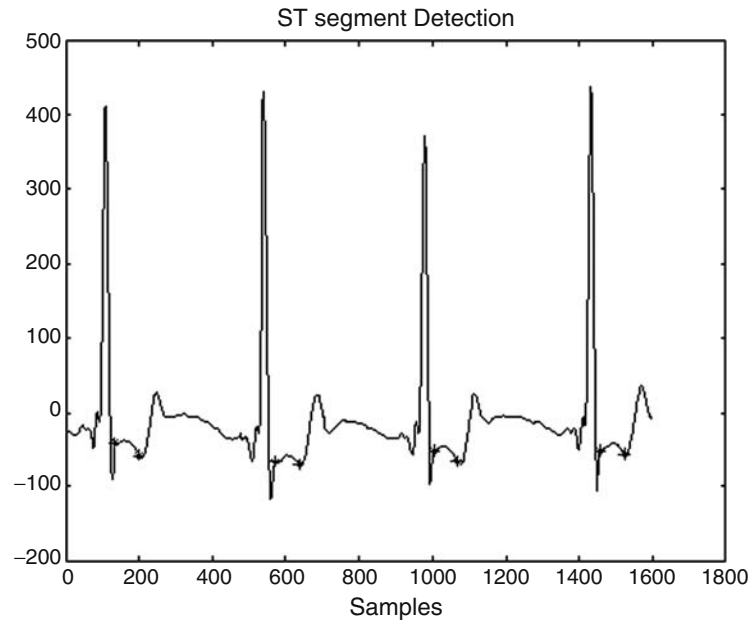


Fig. 2.22. ST segment detection for Class A ECG (K6528)

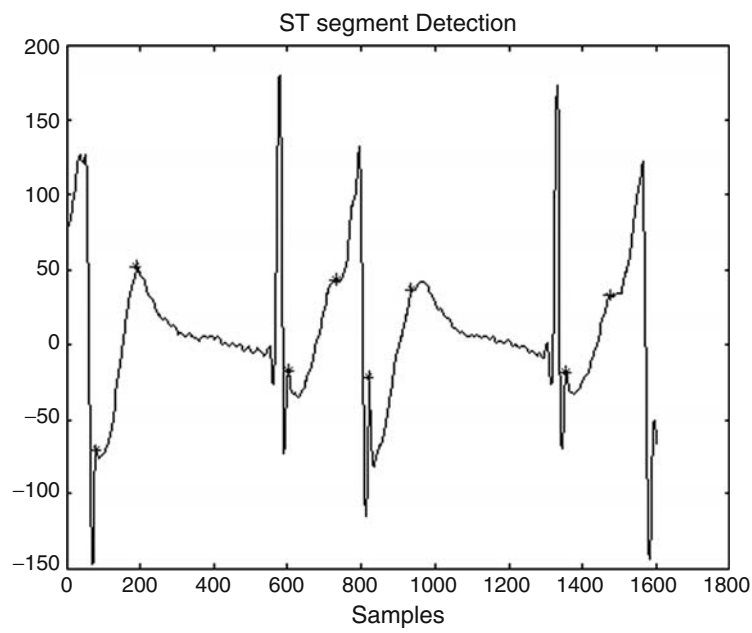


Fig. 2.23. ST segment detection for Class C ECG (K9956)

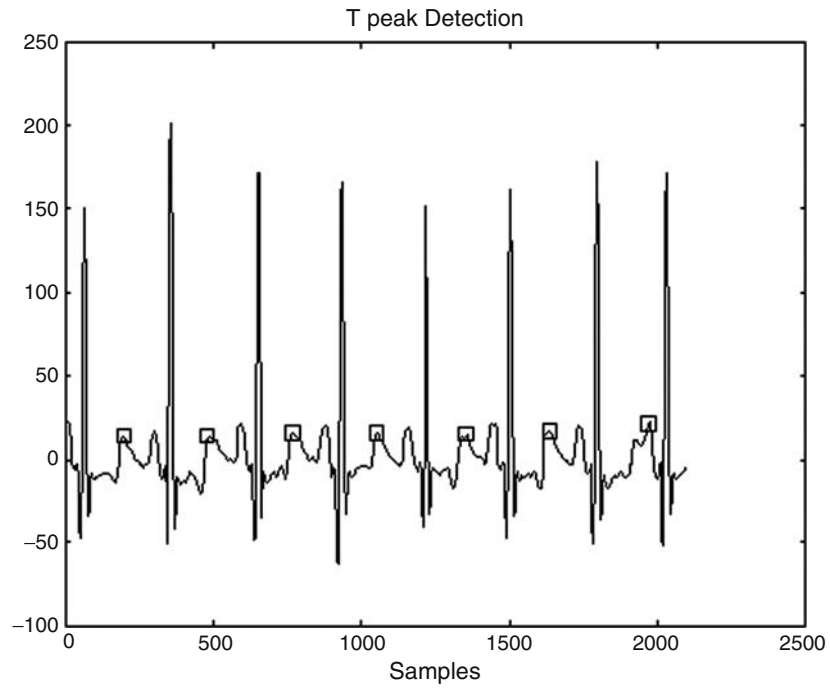


Fig. 2.24. T peak detection for Class N ECG signal (K1024)

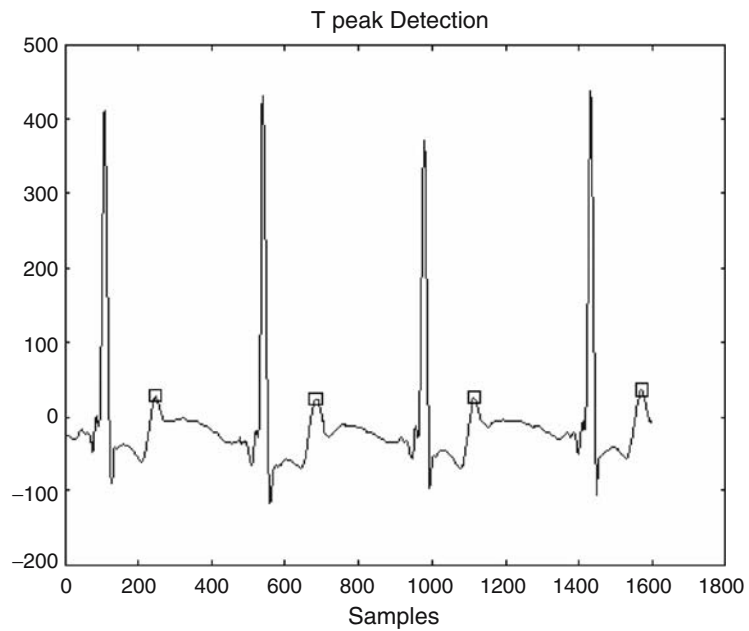


Fig. 2.25. T peak detection for Class A ECG (K6528)

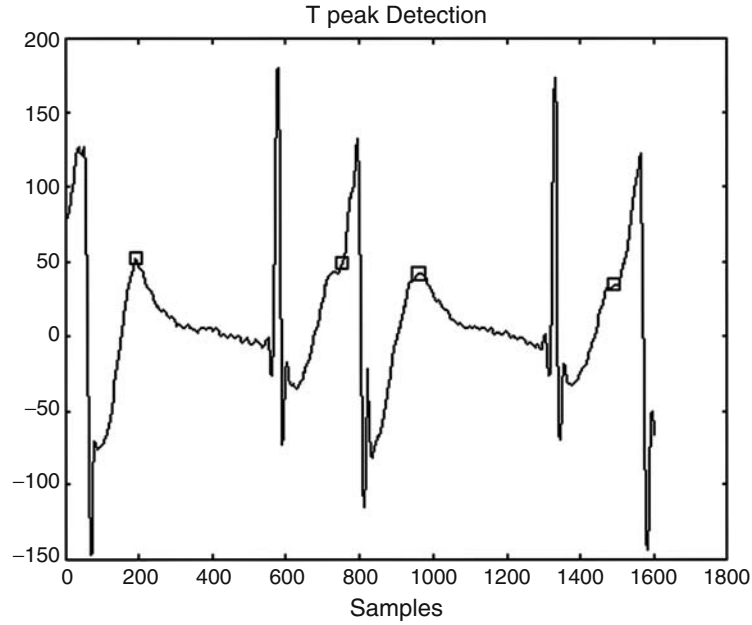


Fig. 2.26. T peak detection for Class C ECG (K9956)

- g. c_{st} – Complexity parameter for ST wave
- h. H – Spectral entropy
- i. τ_{RT} – RT interval
- j. ρ_{ST} – ST segment length
- k. ϕ – ST segment deviation
- l. θ – ST segment angle of deviation and
- m. A – ST segment area.

These features can be fed to neural network, fuzzy logic or any other classifier and diagnostic decisions can be made. These features can be extracted from lead II ECG and are very helpful in diagnostics using portable ECG recording instruments.

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