

R Peak Detection with Diagnosis of Arrhythmia using Adaptive Filter and Hilbert Transform

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Abstract - R peak of electrocardiogram (ECG) signal detected with good accuracy by combining adaptive filter and Hilbert transform. In proposed algorithm adaptive filter reduces the mean square error to an extent and estimates the fundamental signal even in nonappearance of prior data about statistical properties of the signal and noise, and gives improved detection outcomes. All pass characteristic of Hilbert transform eliminates unnecessary signal distortion and exhibit the property of time dependency. Arrhythmia happened due to irregular heart rhythm which diagnosed by extracting numerous ECG features such as RR interval, Heart rate, QRS width, PR interval. A graphical user interface (GUI) also developed which is a convenient way to represent output waveform, features and type of abnormalities in a single window screen with more simplicity, consistency and familiarity. The signal has been taken from MIT-BIH arrhythmia database. Sensitivity of 99.22% and positive predictivity of 99.34% achieved by proposed methodology.

Key Words: Electrocardiogram, adaptive filtering, Hilbert transform, features, GUI, arrhythmia.

1. INTRODUCTION

Electrocardiogram (ECG) also abbreviated as EKG signal. For diagnosis electrocardiogram remains the reference standard in spite of the development of many other diagnostic procedures. EKG signal comprises six wave i.e. P wave, QRS complex (Q wave, S wave and peak R wave), T wave and U wave. P wave generated due to depolarization of atria, QRS complex indicates the depolarization of left and right ventricles, R wave has peak amplitude in QRS complex which is a point of interest in detection process and contains most of the important clinical information regarding heart [1], PR interval estimated from beginning of P-wave to the starting of QRS complex, RR interval is the difference between two successive R peaks, also named as Inter-beat- interval (IBI). Electrocardiography is an important tool used for diagnosing heart condition. Deviation from normal sinus rhythm (normal heart cycle) are the symptoms of arrhythmia that denotes some form of cardiovascular disease (CVD) [2]. Cardiac arrhythmia displays a situation of abnormal electrical movement in the heart which is a danger to humans [3]. The heart produces miniature electrical impulses which spread over the heart muscle to make the heart contract. These impulses can be identified by the ECG machine. The electrocardiogram signal and heart rate reveals the cardiac health of human heart. Any disorder in

heart rate or rhythm or variation in the morphological pattern of this signal is a sign of cardiac arrhythmia. It is detected and diagnosed by scrutiny of the recorded waveform. The amplitude and duration of the P-QRS-T-U wave holds beneficial information about the nature of disease associated to heart. An electrocardiogram (EKG) is completed to determine the heart electrical activity, to check exactly how rapid your heart is beating and to find the reason of symptoms of heart disease like shortness of breath, dizziness, unbalances heartbeat [1]. Various noise or artifacts such as power line interference, baseline wandering, motion artifacts, and electrode contact noise distort the signal quality, frequency resolution, which generates signals with large amplitude that can be analogous to PQRST waveforms and masks miniature features that are essential for clinical diagnosis and monitoring [4]. Elimination of these artifacts is a significant task for better diagnosis. For that purpose wavelet denoising used in proposed work. R-Peak is the most noticeable part during signal examination which relates to the contraction of the ventricles for the duration of a heartbeat. QRS complex detected more accurately with presented algorithm that escalates detection sensitivity by processing the RR interval as compared to some previous methods such as wavelet Transform method in which accuracy throws down to 77.3% for large muscle artifact signals [5], Template matching technique [6], Wavelet Transform with histogram, moving average and two thresholds technique [7], Wavelets and artificial neural networks based method [8]. So the main objective of this study to detect R peak with good accuracy and to extract electrocardiogram features along with arrhythmia diagnosis by using an algorithm formed with combination of adaptive filter and Hilbert transform.

2. MATERIAL AND METHODS

The processing of ECG signal involve of de-noising, baseline correction, filtering, thresholding, feature extraction and arrhythmia detection. Flow chart of proposed algorithm represented in Fig.1. The whole explanation of preprocessing steps and evaluation of performance parameters discussed here.



Fig -1: Flowchart of proposed algorithm

2.1 Original ECG signal

An offline data used for processing electrocardiogram signals that can be taken from MIT-BIH arrhythmia database available on Physionet ATM bank [9]. The raw data basically contaminated with numerous noise artifacts which needs to be eliminate to enhance detection performance. These artifacts added to the signal while recording due to movement in muscles, electrode etc.

2.2 Wavelet denoising and subtraction

Most of the signal corrupted with the baseline wandering noise which shift the signal upward or downward and affect the pattern of QRS recognition. Elimination of baseline drift is hence mandatory in the analysis of the ECG signal to decrease the fluctuations in beat morphology with no physiological equivalent [10]. Electrode impedance and respiration alters because of perspiration which is the leading sources of baseline wander in utmost types of ECG recordings. This baseline wandering can be removed without troubling the ECG waveform features. To keep baseline at the correct position firstly signal denoise using wavelet function wden(db6) and then subtracted from the original signal.

2.3 Adaptive filtering

An adaptive filter uses iterative computations to decrease the error “in forming the relationship among two signals in real time”. Basic diagram of an adaptive filter is shown below

in Fig.2. Here, the input c_1 denotes the ECG which is observed with the additive noise n . The reference signal c is either a pure noise generator or a signal associated to n . Since the n and c_1 are uncorrelated, then

$$E[e^2] = E[(n - d)^2] + E[c_1^2] \tag{1}$$

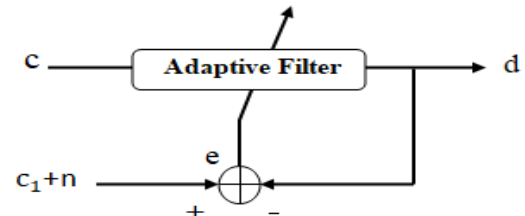


Fig -2: A general diagram of an adaptive filter

Let the N coefficients of the filter at the k^{th} iteration be represented as $W_k = [w_1(k), w_2(k), \dots, w_N(k)]^T$. For an input vector $C_k = [c(k), c(k - 1), \dots, c(k - N)]^T$,

the output will be given in equation as:

$$d(k) = \sum_{i=0}^N w_i(k) c(k - i) = W_k^T C_k \tag{2}$$

The working of filter is to adjust its weights W iteratively to decrease the mean square error (MSE) within the primary and the reference inputs [11]. Usually, LMS and RLS algorithm has been used to bring up to date the coefficients of predictor. In present work, RLS (Recursive least square) have been used for the said purpose. Upon convergence, a predictor is able to predict the gradually varying components (low frequency content) accurately i.e. producing a reduced amount of error in comparison to fast moving components (high frequency content).

2.3.1 RLS Algorithm

Recursive least square (RLS) algorithm recursively discovers the filter coefficients with an objective function of lessening the cost function of summation of weighted linear least squares linking to the input vector unlike LMS (least mean square) and other analogous variants that aim to decrease the mean square error. The RLS algorithm shows very fast convergence at the price of bigger computational complexity [2]. Eigen value spread problem also eliminated by this algorithm. Equation representing the relations for updating weights is as follows:

$$\bar{w}(n) = \bar{w}(n - 1) + \bar{k}(n) * e(n) \tag{3}$$

$$\bar{k}(n) = \frac{\lambda^{-1} * P(n-1)}{1 + \lambda^{-1} * \bar{c}} (n - 1)^T * P(n - 1) * \bar{c}(n - 1) * \bar{c}(n - 1) \tag{4}$$

$$e(n) = c(n) - \bar{c}^T(n-1) * \bar{w}(n-1) \quad (5)$$

$$P(n) = \lambda^{-1} * P(n-1) - \lambda^{-1} * \bar{k}(n) * \bar{c}(n-1)^T * P(n-1) \quad (6)$$

where $c(n)$ is desired signal value of n th sample, λ is exponential forgetting factor, $P(n)$ is a $k \times k$ matrix, $\bar{k}(n)$ is a $1 \times k$ vector, $\bar{c}(n-1)^T$ is transposed input vector, $\bar{w}(n)$, $\bar{w}(n-1)$ represent weight vectors at n th and $(n-1)$ th sample having dimension of $1 \times K$, μ and $e(n)$ are the step size parameter and the instantaneous error respectively having dimension of 1×1 , $\bar{c}(n)$ is a $1 \times K$ input signal vector containing signal values from $c(n)$ to $c(n-k)$.

2.4 Savitzky-Golay Filtering

A technique of data smoothing centered on local least squares polynomial approximation was given by Savitzky and Golay in 1964. They revealed that fitting a polynomial to a set of input samples and then estimating the resulting polynomial at a distinct point within the approximation interval is corresponding to discrete convolution with a static impulse response. The low pass filters achieved by this process are broadly known as Savitzky Golay filters. Noisy data gained from chemical spectrum analyzers smoothens and least squares smoothing decreases noise while preserving the shape and height of waveform peaks [12]. For N data points (N is odd, $N=2M+1$) a data vector X having M points on either side of x_0 :

$$X = [x_{-M}, \dots, x_{-1}, x_0, x_1, \dots, x_M]^T \quad (7)$$

Then by a polynomial of degree d , N data samples fitted in X :

$$\hat{x}_m = c_0 + c_1 m + \dots + c_d m^d; \quad -M \leq m \leq M \quad (8)$$

In this case s_i , $i=0,1,\dots,d$, is defined to have components which is a $d+1$ polynomial basis vectors:

$$s_i(m) = m^i, \quad -M \leq m \leq M \quad (9)$$

The corresponding matrix S ($N \times (d+1)$) is well-defined to have s_i as columns:

$$S = [s_0, s_1, \dots, s_d] \quad (10)$$

Then the design stages for the SG filters can be explained as follows:

$$F = S^T S \quad (11)$$

$$G = S F^{-1} \quad (12)$$

$$B = G S^T = S G^T = S F^{-1} S^T = [b_{-M}, \dots, b_0, \dots, b_M] \quad (13)$$

The steady state equation of SG filter for smoothing a noisy

sequence $x(n)$ with length N , order d as:

$$y(n) = \sum_{m=-M}^M b_0(m) x(n+m) = \sum_{m=-M}^M b_0(-m) x(n-m) \quad (14)$$

For proposed work the SG filter has order of 3 and window length of 15.

2.5 Squaring and differentiation

The strength of the signal decreased after passing through number of preprocessing steps. Hence it is required to enhance the strength of signal so that squaring performed [13]. This raises the amplitude of signal and all the information available in the positive half which added easiness in detection of correct peaks. Then the signal differentiated to acquire the slope information of QRS complex.

2.6 Hilbert transform

To detect R peaks proficiently the proposed technique is described in a very suitable manner. A real valued time function $x(t)$ i.e. differentiated ECG, and the Hilbert transform of the that signal is given by equation:

$$w(t) = H[x(t)] = \frac{1}{\pi} \int_{-\infty}^{\infty} x(\tau) \frac{1}{t-\tau} d\tau \quad (15)$$

In accordance with transformation the independent variable do not altered so that Hilbert transform shows the property of time dependency [14]. And this relation comes from the convolution calculation:

$$w(t) = \frac{1}{\pi} \times x(t) \quad (16)$$

$$F[w(t)] = \frac{1}{\pi} F\left\{\frac{1}{t}\right\} F\{x(t)\} \quad (17)$$

$$F\left(\frac{1}{t}\right) = -j\pi \operatorname{sgn}f \text{ where } \operatorname{sgn}f = \begin{cases} +1 & \text{if } f > 0 \\ 0 & \text{if } f = 0 \\ -1 & \text{if } f < 0 \end{cases} \quad (18)$$

The i/o correlation of Hilbert transform is the conversion of linear function, therefore it act like a linear filter where all the amplitudes of spectral components are lasting identical where the phases altered with $\pm 90^\circ$. The imaginary part of the analytic signal is Hilbert transform and its real part act as its input. Output waveform demonstrates the Hilbert transform of a differentiated EKG segment. The R-peaks happened due to the zero-crossings of the differentiated EKG, because the Hilbert transform is an odd filter and in the output of the transform represented as peaks. On the differentiated electrocardiogram the effects of the Hilbert transform described in terms of its signal envelope and odd symmetry property. All pass characteristic of the Hilbert transform avoids needless signal distortion, in comparison to the additional derivative technique which tends to diminish the signal at the lower frequencies. Therefore, the

essential rectification of the differentiated EKG signal delivered by the odd phase element of the filter in order to recognize the QRS peaks while the uniform magnitude of the filter confirms that essential information of the QRS complexes is preserved [15]. The Hilbert transformed output signal is stated as;

$$S(t) = x(t) + jw(t) \quad (19)$$

$$V(t) = \sqrt{x^2(t) + w^2(t)} \quad (20)$$

$$\varphi(t) = \arctan\left(\frac{w(t)}{x(t)}\right) \quad (21)$$

Where $V(t)$ is the envelop of $x(t)$ and $\varphi(t)$ is instantaneous phase angle.

2.7 R peak detection

There is need of extraction of suitable metrics from the signal. Before the extraction of these metrics from the ECG signal, the Q, R, S peaks with their position in each beat were identified. This is achieved with an algorithmic script with the following approach: The first aim is the detection of the R Peak because one time the R-Peak is detected; it can be used to notice the Q and S points effortlessly. Because of the idiosyncratic nature of the QRS complex and the typical characteristics of the R peak, this is willingly identified even in the utmost distorted ECG readings. Thus it is castoff as the basis for ECG feature computations [16]. By choosing a window of particular length, the peak with maximum value detected. A threshold also applied for better detection, distinguishing correctly detected and falsely detected peaks. Then R peaks detected on the envelope of Hilbert transformed signal represented by the small red circles as shown in Fig.4.

2.8 Feature extraction

For the resolution of diagnosis after R peak detection, there is need to extract several features from the preprocessed ECG data, comprising QRS width, RR interval, PR intervals. The deflection positional information provides the feature such as RR interval which used in medical as a pointer of Ventricular Heart Rate. Two R peaks in successive beats is calculated and their difference is figured for determining the RR interval. Electrocardiogram feature extracted on the basis of given equations:

$$PR \text{ Interval} = \frac{R_{loc(i)} - P_{loc(i)}}{f_s} \quad (22)$$

$$QRS \text{ width} = \frac{(S_{loc(i)+x}) - (Q_{loc(i)-x})}{f_s} \quad (23)$$

$$Heart \text{ Rate} = \frac{60}{RR \text{ interval}} \quad \text{bpm} \quad (24)$$

Where f_s stand for sampling frequency $R_{loc(i)}$ specify current R peak locations and $P_{loc(i)}$ indicates current P peak locations. Here variable x shows instant 5 ms, added to S_{loc} and are subtracted from Q_{loc} . S and Q peak sites represented by S_{loc} and Q_{loc} respectively [17]. Heart rate computed in beats per minutes (bpm) and for a normal person in resting state varies from 60 to 100 bpm.

2.9 Arrhythmia

Arrhythmia happened due to irregular heart rhythm and various types of arrhythmias diagnosed in this paper. With extracted features numerous cardiovascular arrhythmias are noticed as Right bundle branch block. Within the right bundle branch it act as a delay or block of conduction. An interruption of conduction reveals as incomplete right bundle branch block. Right bundle branch block occurs when QRS duration > 0.14 sec. Sinus Bradycardia occurs when heart rate is less than 60 beats per minute in resting state, though it is rarely suggestive until the rate falls below 50 beat/min. Sinus Tachycardia states to quick beating of the heart as a heart rate more than 100 beats per minute in adult. Diseases were predicted from extracted features as according to medical science condition for Tachycardia fulfilled if heart rate > 100 bpm (beats per minute) [18]. Normal range of heart rhythm is 60 to 100 bpm. When QRS width > 0.12 sec and heart rate varies from 101 to 250 bpm then Ventricular tachycardia happened. Normal range QRS width lies between 0.08 to 0.10 sec. Incomplete Bundle Branch Block occurred when QRS width between 0.10 sec to 0.12 sec and QRS width > 0.12 sec for Bundle Branch Block [16]. First degree heart block take place when PR interval > 0.2 sec.

3. ECG DATABASE

MIT-BIH arrhythmia database used in this work which available on Physionet ATM bank. This offline data firstly collected in a directory which further used for preprocessing. It consists of total 48 subjects signal including males and females. There are 25 men of age group 32-89 years and 23 women of age group 23-89 years. For estimation of arrhythmia detection this database was firstly usually accessible from the set of standard test material and has been used for that purpose as well as for elementary investigation into cardiac dynamics at larger than 500 sites worldwide [9]. These signals have voltage of 10mV, resolution of 10 bit and 360 Hz sampling frequency.

4. RESULTS

Output waveforms obtained from proposed methodology as shown in Fig.3 and Fig.4. These waveforms produced in MATLAB tool. An ECG record 102 has been taken from MIT-BIH arrhythmia database and processed as illustrated in

figures below. The duration of this signal is 10 second or 3600 samples.

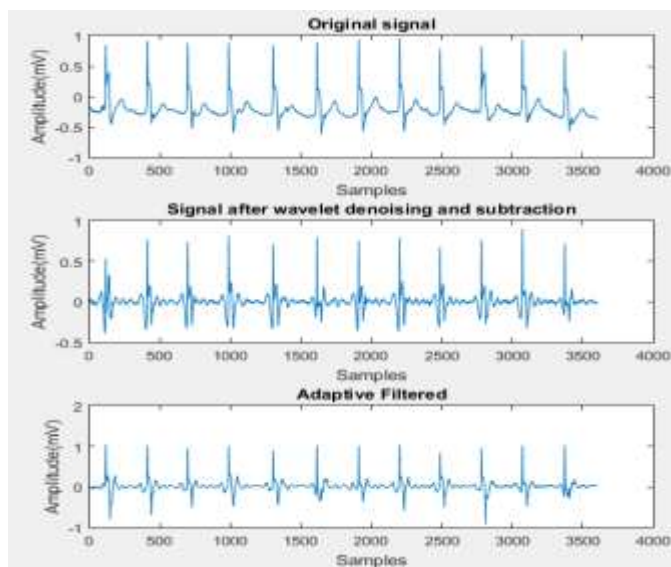


Fig -3: Output waveforms of original ECG record 102, Signal after wavelet denoising and subtraction, adaptive filtered ECG plotted in amplitude (mV) versus sample values.

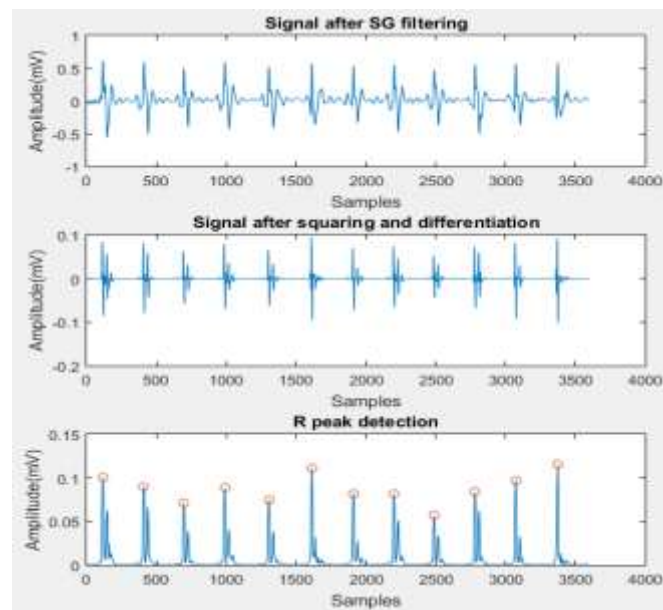


Fig -4: Noise suppression and peak detection: SG filtered ECG, Signal obtained after squaring and differentiation, R peak detected shown by red circles.

4.1 Performance measures

Four measures used for determining the performance of present algorithm. These are Total beats (TB), True positive (TP) i.e. correctly detected peaks, False positive (FP) i.e. falsely detected peaks, False negative (FN) i.e. undetected

peaks. Total number of beats corresponds to total R peak. Fidelity parameters computed by following formula:

$$\text{Sensitivity (\%)} = \frac{TP}{TP+FN} \times 100 \quad (25)$$

$$\text{Positive Predictivity (\%)} = \frac{TP}{TP+FP} \times 100 \quad (26)$$

Table -1: Performance parameters

ECG record	TB	TP	FP	FN	Se (%)	+P (%)
100	13	13	0	0	100	100
102	12	12	0	0	100	100
103	11	11	0	0	100	100
105	14	14	1	0	100	93.33
108	11	11	0	0	100	100
109	16	15	0	1	93.75	100
112	14	14	0	0	100	100
117	9	9	0	0	100	100
118	12	12	0	0	100	100
121	10	9	0	1	90	100
123	8	8	0	0	100	100
124	8	8	0	0	100	100
201	14	14	0	0	100	100
202	9	9	0	0	100	100
209	15	15	0	0	100	100
222	13	13	0	0	100	100
223	13	13	1	0	100	92.85
230	14	14	0	0	100	100
231	10	10	0	0	100	100
232	8	8	0	0	100	100
234	15	15	0	0	100	100
TOTAL	249	247	2	2	99.22	99.34

It can be stated that true positive rate termed as Sensitivity (Se) and positive predictivity (+P) defines that to how much extent a disease is predictable correctly. Se of 99.22% and +P of 99.34% has been achieved by proposed technique.

4.2 Developed GUI

Developed GUI is an effective and efficient way which represents extracted ECG feature, detected R peak wave along with arrhythmia diagnosis. Any ECG signal can be selected from the popup menu and loaded by clicking on load pushbutton. Detected R peak (shown by red circles) wave observed by corresponding R peak pushbutton. For the selected signal PR interval greater than 0.2 sec so that type

of arrhythmia diagnosed is first degree heart block as shown in Fig.5.

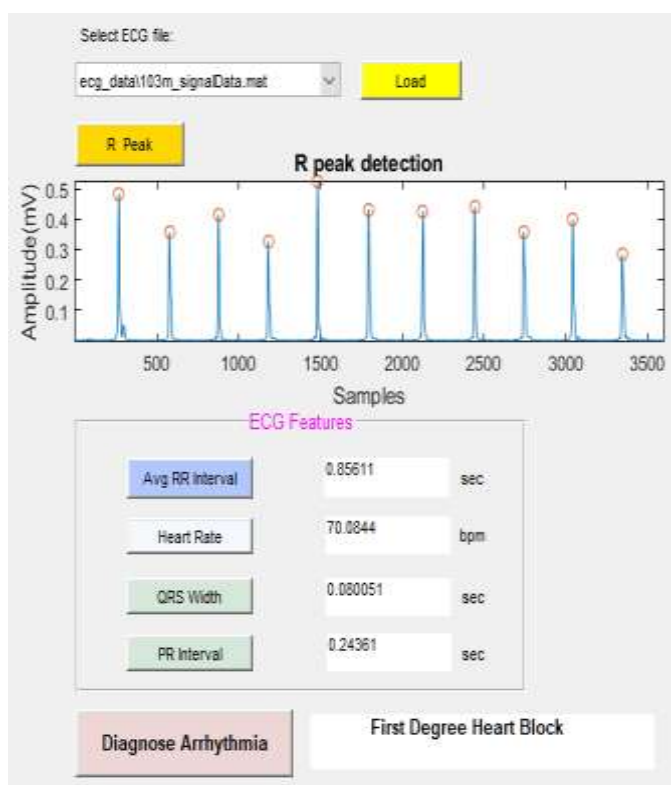


Fig -5: Developed GUI

4.3 Comparison with previous state of art methods

A quick survey of some previous studies has been provided to compare the best performance observed in the present study. Se and +P are listed in Table with methods, novelty of particular study. In this paper a new algorithm by combining adaptive filter and Hilbert transform for QRS complex detection is proposed. This method achieves good accuracy in term of sensitivity and positive predictivity in comparison with other competing methods, offering an advantage of minimized mean square error and low computational complexity. A graphical user interface also developed which provide unity, clarity, directness, alignment, integrity, comfort and charm to the user. The user interface is a single object with a certain personality to help a particular user perform a particular task.

Table -2: Comparison with previous state of art methods

Methods	Novelty	Se (%)	+P (%)
Wavelet Transform method [5]	Detect arrhythmia types by relating the extracted ECG features.	94.12	88.90
Template matching algorithm [6]	Template waveform produced using a short-term autocorrelation	95.80	98.30

	process for QRS detection.		
Wavelet Transform with histogram, moving average and two thresholds technique [7]	Two wavelet function (haar & db10) with dual thresholding for QRS detection	98.68	97.24
Second derivative method [15]	Bandpass filtering, squaring and variable thresholds comparison for QRS detection	98.08	99.18
Wavelets and artificial neural networks method [8]	Four wavelet basis functions those are appropriate in detection of QRS complexes inside dissimilar QRS morphologies in the signal.	97.20	98.52
Geometrical matching algorithm [19]	Use decision function in a confined moving-window process for QRS detection.	97.94	99.13
Presented methodology	Combination of adaptive filter and Hilbert transform for R peak detection with arrhythmia diagnosis.	99.22	99.34

5. CONCLUSION

This paper presents an improved R peak detection system that work on adaptive filtering and Hilbert transform. Type of arrhythmia also diagnosed on the basis of extracted ECG features. By adopting a wavelet function for denoising and Savitzky Golay filter for filtering occurrence of false positive and false negative beats reduced. During recording extra ventricular waveform formed due to which artifacts generated that are also removed with adaptive filtering. Presented technique achieves better-quality detection of delayed potentials. So sensitivity of 99.22% and positive predictivity of 99.34% has been attained by proposed methodology.

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