A Novel Technique for QRS Complex detection in ECG Signal based on Hilbert Transform and Autocorrelation

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Abstract- This paper proposes an algorithm for QRS complex detection technique based on Hilbert transform and autocorrelation method. In the proposed method, the period of the ECG signal is calculated first using autocorrelation method and then the R-peaks are detected using Hilbert transform. This method allows R-peaks to be differentiated from large peaked T and P waves with a high degree of accuracy and minimizes the problems associated with baseline drift, motion artifacts, and muscular noise. The performance of the algorithm is evaluated using the records of the MIT-BIH arrhythmia database. A detection error rate of 0.12%, a sensitivity of 99.95% and a positive prediction of 99.94% are achieved for the proposed method. Experimental result shows that the performance of proposed method is better as compared to the other two established techniques like Pan-Tompkins method and the technique which uses only Hilbert transform method.

Keywords- ECG signal; MIT-BIH Arrhythmia database; Hilbert transform; Autocorrelation ; QRS complex detection

I. Introduction

Electrocardiogram (ECG) is a diagnosis tool that records the electrical activity of heart recorded by skin electrode. Any disorder of heart rate or rhythm, or change in the morphological pattern, is an indication of cardiac arrhythmia, which could be detected by analysis of the recorded ECG waveform. Accurate detection of QRS complex is essential in computer-based ECG signal analysis. To detect the QRS complex more accurately it is necessary to identify the exact R-peak location from the recorded data. Morphological differences in the ECG waveform increase the complexity of QRS detection, due to the high degree of heterogeneity in the QRS waveform and the difficulty in differentiating the QRS complex from tall peaked P or T waves [1].

Several techniques [2]-[5] are reported to improve the accuracy of QRS complex detection from ECG signal because the exact detection of QRS complex is difficult, as the ECG signal is added with different types of noise like electrode motion, power-line interferences, baseline wander, muscles noise etc. [4]. Pan and Tompkins [2] reported a technique where, the detection of QRS complex was achieved by linear filtering, non-linear transformation and decision rule algorithm. In another method [3] the QRS complex of ECG signal was found out using multi rate signal processing and filter banks. As reported in [4] the QRS complex can be found after finding the R-peak by differential operation in ECG signal. The first differentiation of ECG signal and its Hilbert transform is used in [5] to find the location of R-peak in the ECG signal.

In this paper, a novel QRS complex detection algorithm is proposed using Hilbert transform (HT) and autocorrelation. Autocorrelation method is used successfully to find out primary heart sounds in phonocardiogram signal [6]. In the proposed method, the first differential of the ECG signal and its HT data is used to find regions of high probability where the R peaks are located in the ECG waveform. In this work, the autocorrelation technique is used to calculate the period of one cardiac cycle which helps to detect the QRS complex in ECG signal. A second stage detection algorithm uses these initial estimations to locate the real R peaks in the ECG wave. The advantages of proposed method are (i) the unwanted effects of large peaked T and P waves are minimized and (ii) the proposed algorithm performs with 99.88 percent accuracy in presence of significant noise contamination.

II. Hilbert transform

The Hilbert transform of the real function *k(t)* is defined as

$$\hat{k}(t)=H\left[k(t)\right]=\frac{1}{\pi}\int_{-\infty}^{+\infty}k(\tau)\frac{1}{t-\tau}\partial\tau=\frac{1}{\pi t}*k(t) \qquad (1)$$

The Hilbert Transform can be interpreted from this relation as a convolution between $k(t)$ and $\frac{1}{\pi t}$.
Applying the Fourier transform to (1), we have

$$F\left\{\hat{k}(t)\right\}=\frac{1}{\pi}F\left\{\frac{1}{t}\right\}F\left\{k(t)\right\} \qquad (2)$$

Since,

$$F\left\{\frac{1}{t}\right\}=\int_{-\infty}^{+\infty}\frac{1}{k}e^{-j2\pi f k\partial k}=-j\pi\,\mathrm{sgn}\,f \qquad (3)$$

where,

$$\mathrm{sgn}\,f=\begin{cases}+1; & f>0\\ 0; & f=0\\ -1; & f<0\end{cases}$$

then the Fourier transform of the Hilbert transform of *k(t)* is given by (2) as

$$F\left\{\hat{k}(t)\right\} = -j\,\mathrm{sgn}\; f\; F\left\{k(t)\right\} \qquad (4)$$

In the frequency domain, the result is then obtained by multiplying the spectrum of the *k*(*t*) by *j* (+90) for negative frequencies and –*j* (-90) for positive frequencies. The time domain result can be obtained performing an inverse Fourier transform. Therefore, the Hilbert transform of the original function *k*(*t*) represents its harmonic conjugate.

The pre-envelope of a real signal *k*(*t*) can be described by the expression :

$$y(t) = k(t) + j\hat{k}(t) \qquad (5)$$

The envelope *B*(t) of y(t) is defined by

$$B(t) = \sqrt{k^2(t) + \hat{k}^2(t)} \qquad (6)$$

The envelope determined using (6) will have the same slope and magnitude of the original signal *k*(*t*) at or near its local maxima. From (6) it can be observed that *B*(*t*) is always a positive function. Hence the maximum contribution to *B*(*t*) at points where *k*(*t*)=0 is given by the Hilbert transform.

III. Methodology

A new approach to QRS detection using the Hilbert transform and autocorrelation function is proposed. The block diagram of the proposed method is shown in the Fig.1.

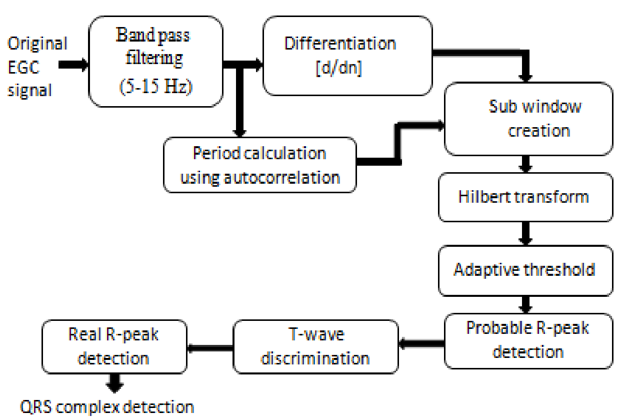

Fig.1. Block diagram of the proposed method for detection of QRS complex.

The detail description of the proposed method is given bellow

A. Filtering: The main function of the stage is to increase the signal to noise ratio of ECG signal by emphasizing the QRS complex. A band pass FIR Butterworth filter of pass band frequencies of 5-15 Hz is used to remove the power-line interference and high frequency noises from the original signal. The approximate popular pass band to maximize the QRS energy is 5-15Hz [2].

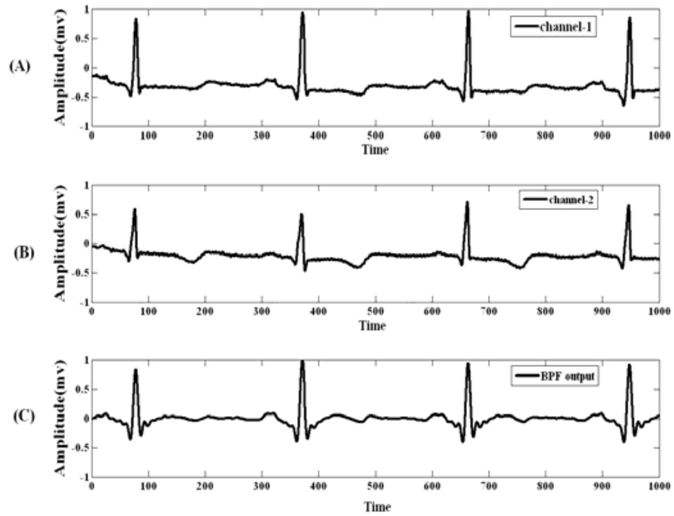

Fig.2. ECG signal in the database MIT-BIH tape #100 in the range (0-1000) samples. (A) channel-1output, (B) channel-2output, (C) band pass filter output.

B. Differentiation: The first order differentiation of filtered ECG signal is taken to remove motion artifacts and baseline drifts. The main function of first order differentiation is to indicate high slope points which show that the rising of signal from Q to R is the maximum slope and the falling of signal from R to S is the minimum slope of ECG signal. Therefore R peak is the zero crossing between these two positive and negative peaks, which is shown in Fig.3.

The first differential of the given ECG signal in discrete domain can be obtained by,

$$z(n) = \frac{1}{2\Delta t}\left[k(n+1) - k(n-1)\right],\;\; n = 0,1,2,\ldots,m-1 \qquad (7)$$

where, m is the total number of samples and Δt is the sampling time.

The initial condition is specified by *k*(–1) when *n=0*, and the final condition *k(m)* when *n*=*m*–1.The error at the boundaries is minimized by these conditions.

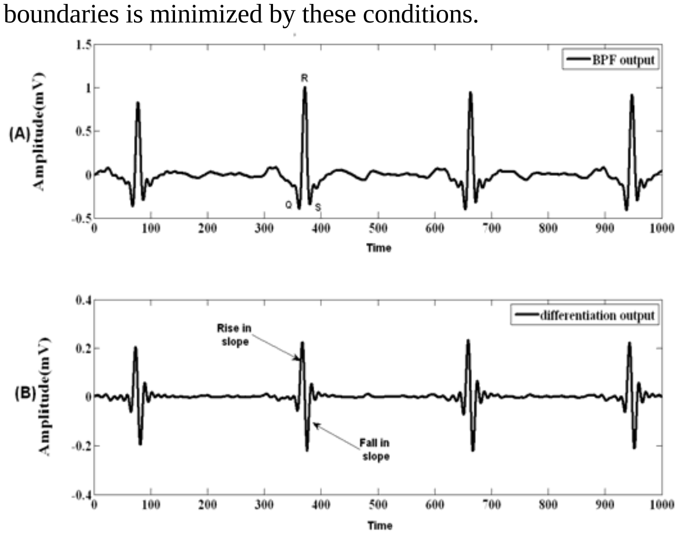

Fig.3. Sample beats from ECG signal of tape #100 in MIT-BIH database (A) band pass filter output, (B) derivative output..

C. Period calculation using autocorrelation: In the proposed method 5s duration of ECG signal is extracted from the filtered ECG signal to find the exact duration of one cardiac cycle in that particular ECG signal. The approximate R-R interval between two cardiac cycles is 0.4s to 1.2s [4], [7]. So an array *lag_sec* is created by taking a fixed length signal of 5s duration whose sampling frequency (f_s) =360 Hz. The array length is lies in between the range 0.4s to 1.2s with a time lag 0.02s. The number of samples corresponding to each *lag_sec* is found out by multiplying the sampling frequency (f_s) and store these values in an array *lag_index* as illustrated in (8).

$$lag\_index(i) = floor(lag\_\sec(i) * f_s) \qquad (8)$$

Then the autocorrelation of ECG signal is determined by the following algorithm:

Algorithm 1: Period calculation of one cardiac cycle in ECG signal using autocorrelation

1. Take an ECG signal of length 5s and denote it as *X(t)*
2. Assign an array *lag_sec* in the range o.4s to 1.2s with step size 0.02s
3. *lag_index* = *lag_sec***f_s* ;
4. Find autocorrelation
For *j*=1:length(*lag_index*) do:
For *i*=1:(length(*X*)-*lag_index*(*j*)) do:
sum(*j*)=*sum*(*j*)+abs(*X*(*i*))*abs(*X*(*i*+*lag_index*(*j*)));
End for.
sum(*j*)=*sum*(*j*)/((length(*X*))-(*lag_index*(*j*)));
End for.
5. Find the position where the *sum* is maximum and assign it with a variable index.
6. Find the corresponding *lag_sec* value which is the period of one cardiac cycle in the ECG signal.

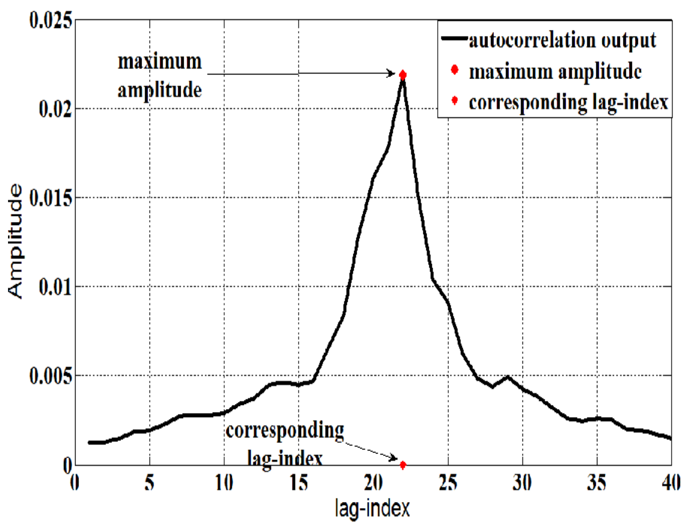

Fig.4. Autocorrelation between signal of tape #100 and its shifted version in the range (0-5)s, with a time lag of 0.02 s. The maximum amplitude shows where two signals are correlated.

D. Sub window creation: The filtered ECG signal is divided in to several sub-windows whose length equal to the one cardiac cycle duration. The one cardiac cycle duration is obtained from the output of autocorrelation. The sub window creation helps to calculate the exact number of R-peak and its position.

E. Hilbert transform: The Hilbert transform of one cardiac cycle duration length signal is calculated. The function of HT is also to locate the high probability region of ECG signal. The maximum value of the signal after taking HT in a particular window represents the probable R-peak. Thus it shows that these peaks are not the real peaks and these peaks differ from the true R- peak position by a few milliseconds.

F. Adaptive threshold: The adaptive threshold technique is used to remove the noise level from the output of HT. The adaptive threshold algorithm as follows:

Algorithm 2: Adaptive threshold technique for removing noise in HT output
1. Find equivalent RMS value of HT output 2. Find number of window and assign it with variable index *w* 3. Find maximum amplitude in a particular window and assign it as variable index max 4. For *i*=1:no. of window do: 5. If(*RMS*(*i*)>0.18*max(*i*)) then do: If((*RMS*(*i*)>max(*i*))&&(*RMS*(*i*)<max(*i*-1))) then do: *Thr*(*i*)=0.39*max(*i*); Else If((*RMS*(*i*)>max(*i*))&&(*RMS*(*i*)>max(*i*-1))) *Thr*(*i*)=0.39*max(*i*-1); End if. 6. Else If(*RMS*(*i*)<0.18*max(*i*)) then do: *Thr*(*i*)=1.6**RMS*(*i*); End if. 7. End for.

G. T wave discrimination: After finding the probable R-peaks search back technique is used to discriminate the T wave. The maximum amplitude within a 200ms window length is set to find the real R-peaks from probable R-peaks.

H. Second stage detector: A second stage detector is used to locate the Q & S point in ECG. A ±10 sample of window width from the location of the R-peak is selected in the original ECG waveform to locate these points.

IV. RESULTS AND DISCUSSION

The proposed algorithm was tested using MIT-BIH Arrhythmia database [8]. The database contains 48 records (normal cases (100-124) & abnormal cases (200-234)), each having 30 min. duration of two channel long ECG signal. The continuous recording signal was sampled at a sampling rate of 360Hz, with 11-bit resolution over ±5 mV range. The data base also contains annotation for timing information as well as beat class information verified by independent expert [9]. The algorithm is able to detect the QRS complex more accurately as shown in the Fig.7. The total performance is shown in the form of tabulation in Table I. The performance is analyzed using the following parameters [5], [10].

1. Sensitivity (Se): This indicates the percentage of true beats that were correctly detected by the algorithm.

$$Sensitivity\,(\%) = \frac{TP}{TP + FN} \qquad (9)$$

2. Positive Predictivity (+p): It gives the percentage of heart beat detection which are reality true beats.

$$Positive\ predictive\,(\%) = \frac{TP}{TP + FP} \qquad (10)$$

3. Detection error rate (%):

$$Detection\,error\,rate\,(\%) = \frac{FP + FN}{Total\ number\ of\ QRS\ complex} \qquad (11)$$

Where, TP=Number of true positive beat detected

FP= Number of false positive beat

FN= Number of false negative beat

TABLE I

THE RESULT OF THE PROPOSED METHOD FOR THE SIGNALS IN MIT-BIH DATABASE

MIT-BIH Record	TP	FP	FN	FP + FN	Se (%)	+p (%)	Detection error rate (%)
100	2273	0	0	0	100	100	0.00
101	1865	2	1	3	99.95	99.89	0.16
102	2187	3	1	4	99.95	99.86	0.18
103	2084	0	0	0	100	100	0.00
104	2230	2	1	3	99.96	99.91	0.13
105	2572	3	7	10	99.73	99.88	0.39
106	2027	2	2	4	99.90	99.90	0.20
107	2137	2	4	6	99.81	99.91	0.28
108	1763	6	0	6	100	99.66	0.34
109	2532	2	3	5	99.88	99.92	0.20
111	2124	0	1	1	99.95	100	0.05
112	2539	0	0	0	100	100	0.00
113	1795	0	0	0	100	100	0.00
114	1879	2	1	3	99.95	99.89	0.16
115	1953	0	0	0	100	100	0.00
116	2412	5	1	6	99.96	99.79	0.25
117	1535	0	1	1	99.93	100	0.07
118	2275	0	1	1	99.96	100	0.04
119	1987	1	0	1	100	99.95	0.05
121	1863	0	1	1	99.95	100	0.05
122	2476	0	0	0	100	100	0.00
123	1518	0	0	0	100	100	0.00
124	1619	0	0	0	100	100	0.00
Total	**47645**	**30**	**25**	**55**	**99.95**	**99.94**	**0.12**

The detector achieves very good performance on the studied MIT-BIH arrhythmia database for signal with noise even in the presence of pronounced muscular noise and baseline artifacts. The QRS detector attains Se=99.95%, +P=99.94%, and detection error rate of 0.12%. The proposed method is compared with Hilbert transform and Pan-Tompkins method as shown in Table II. In Hilbert transform method the Se=99.94%, +p=99.93 and detection error rate=99.87 was achieved against MIT-BIH arrhythmia database. The proposed algorithm deploying Hilbert transform and autocorrelation works well than the earlier reported technique which is based on HT method [5] and PT method [2].

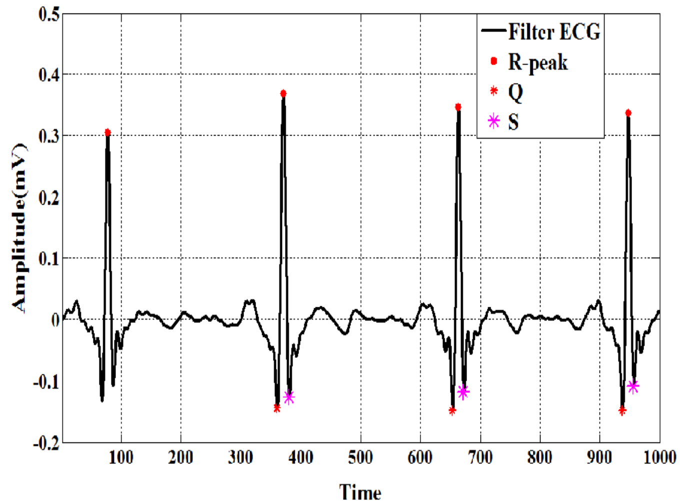

Fig.7. The detected QRS point of signal tape #100

TABLE II

THE COMPARISON OF THE PROPOSED METHOD WITH THE HILBERT TRANSFORMS (HT) AND PAN-TOMPKINS (PT) METHOD

MIT-BIH Record	TP	Proposed method			HT method			PT method		
		FP	FN	Detection error rate (%)	FP	FN	Detection error rate (%)	FP	FN	Detection error rate %
100	2273	0	0	0.00	0	0	0	0	0	0
101	1865	2	1	0.16	3	1	0.21	5	3	0.43
102	2187	3	1	0.18	1	2	0.14	0	0	0
103	2084	0	0	0.00	0	0	0	0	0	0
104	2230	2	1	0.13	12	5	0.76	1	0	0.04
105	2572	3	7	0.39	7	3	0.39	67	22	3.46
106	2027	2	2	0.20	1	0	0.05	5	2	0.35
107	2137	2	4	0.28	1	7	0.37	0	2	0.09
108	1763	6	0	0.34	-	-	-	199	22	12.54
109	2532	2	3	0.20	1	7	0.32	0	1	0.04
111	2124	0	1	0.05	1	1	0.09	1	0	0.05
112	2539	0	0	0.00	0	0	0	0	1	0.04
113	1795	0	0	0.00	0	0	0	0	0	0
114	1879	2	1	0.16	1	0	0.05	3	17	1.06
115	1953	0	0	0.00	0	0	0	0	0	0
116	2412	5	1	0.25	0	0	0	3	22	1.04
117	1535	0	1	0.07	1	1	0.13	1	1	0.13
118	2275	0	1	0.04	1	0	0.04	1	0	0.04
119	1987	1	0	0.05	1	0	0.05	1	0	0.05
121	1863	0	1	0.05	0	1	0.05	4	7	0.59
122	2476	0	0	0.00	0	0	0	1	1	0.08
123	1518	0	0	0.00	1	0	0.07	0	0	0
124	1619	0	0	0.00	0	0	0	0	0	0
Total	**47645**	**30**	**25**	**0.12**	**30**	**28**	**0.13**	**292**	**101**	**20.03**

V. CONCLUSION

This paper proposes a novel QRS detection algorithm using the properties of Hilbert transform and autocorrelation. The algorithm shows the accuracy over 99.88% for QRS complex detection even in the presence of significant noise contamination. The result of the proposed method is compared with the Hilbert transform (HT) method and Pan-Tompkins (PT) method. The experimental shows that the proposed method performs better as compared to above two methods and allows a reliable and accurate detection of the QRS complexes.

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