R-peak detection using Wavelet-Energy Histogram and Adaptive Thresholding

Mrs. Alka Barhatte
Department of Electronics & Telecommunication
Maharashtra Institute of Technology,
Pune, Maharashtra
alka.barhatte@mitpune.edu.in

Dr. Rajesh Ghongade
Department of Electronics & Telecommunication
Vishwakarma Institute of Information Technology,
Pune, Maharashtra
rbghongade@gmail.com

Abstract — Electrocardiogram (ECG) is a noninvasive technique used as a primary diagnostic tool for cardiovascular diseases. The QRS complex detection and extraction is the primary step in the feature extraction of ECG analysis. Denoising of a signal, high accuracy, robustness and less computational time are the key features of QRS complex detection. Here we are introducing comparatively less complex algorithm with good accuracy and computational time. The proposed algorithm is based on wavelet energy-histogram, Hilbert transform & adaptive Thresholding. The QRS complex detection with proposed algorithm is evaluated with all the 48 records from MIT-BIH Arrhythmia database with average detection accuracy 98.3%, average positive predictivity of 0.974, average sensitivity of 0.974, and detection error rate as 5.17%.

Keywords— Wavelet transform, Energy-histogram, Hilbert transform, Adaptive Thresholding, QRS complex

I. INTRODUCTION

The detection of QRS complex generally implies the detection of R peak of QRS complex which can be used for the extraction of various features on each beat of the ECG signal. Automatic detection of QRS complex with reasonable accuracy is a difficult task in presence of noise [B-1].ECG signal may be corrupted by various types of noise like power line interference, electrode contact noise, motion artifacts, muscle contraction (electromyography, EMG), baseline drift and ECG amplitude modulation with respiration, instrumentation noise generated by electronic device used in signal processing, electrosurgical noise and other, less significant noise sources [2].

A number of automated methods for the detecting of R peaks of ECG signals have been published. These are based on derivatives, filtering, wavelet transforms, Neural Network, EMD, algebraic approach etc. Numerous methods have been reported which are more sensitive to different levels of noise. By exploiting PCA or ICA or NNs, a statistical model of the ECG signal, noise is first extracted and then the in-band noise is removed by discarding the dimensions corresponding to the noise [3-4,6-9]. S. Banerjee, R. Gupta, M. Mitra et al.[3] have given a comparison of the noise sensitivity of nine QRS Detection Algorithms for a normal, single-channel lead 11, synthesized ECG corrupted with five different types of synthesized noise based on amplitude & derivative method.

The proposed algorithm is based on the wavelet transform as the preprocessing tool, energy histogram, Hilbert transform to emphasize the QRS complex & adaptive Thresholding for R-peak detection. All 48 recordings of MIT_BIH Arrhythmia database are used for experimental analysis. Each record is having duration of 30minutes & sampling frequency of 360HZ.

II. METHODS

A. Discrete Wavelet Transform

In wavelet transform, a signal is analyzed and expressed as a linear combination of the sum of the product of the wavelet coefficients and mother wavelet. A family of the mother wavelet is available having the energy spectrum concentrated around the low frequencies like the ECG signal as well as better resembling the QRS complex of the ECG signal. Therefore, for the analysis of an ECG signal at different scales, wavelet transform (DWT) is used in practice. In discrete wavelet transform (DWT), for analyzing both the low and high frequency components in a signal, it is passed through a series of low-pass and high-pass filters with different cut-off frequencies. This process results in a set of approximate (Ca) and detail (Cd) DWT coefficients, respectively [6]. The filtering operations in DWT result in a change in the signal resolution, whereas sub sampling (down sampling/up sampling) causes change of the scale. Thus, DWT decomposes the signal into approximate and detail information thereby helping in analyzing it at different frequency bands with different resolutions. Here db9 is used as a mother wavelet since it is found to be most effective.

B. Wavlet Energy-Histogram

The morphology of ECG signal represents the significant rise at QRS complex. Because of the peculiar shape of the QRS complex, it can be said that the energy of the signal is different during the existence of the QRS as compared to other parts of ECG signal. The energy change is attributed to the transition from the Q point to R point and back to S point. This energy change can be captured by decomposing the signal with DWT at a suitable level [5]. Energy histogram is obtained by processing the ECG signal for decomposition using db9 as a mother wavelet. Window size of two samples is considered for the decomposition of a signal. The energy of third level approximated segment is obtained. Then the window is moved on to next sample & procedure is repeated for every sample till the end of signal. To emphasize the energy change in the signal is further processed for first order differentiation.

C. Hilbert Transform

Hilbert transform is one of the most important and common transform used for detection of R peak of ECG signal.
The Hilbert Transform g(t) of f(t) is given by-

$$g(t) = \frac{1}{\pi} p \int_{-\infty}^{\infty} \left(\frac{f(\tau)}{t - \tau} \right) d\tau \quad \ldots\ldots (1)$$

when the integral exists. It is normally not possible to calculate the Hilbert Transform as an ordinary improper integral because of the pole at τ = t. However, the P in front of the integral denotes the Cauchy principal value which expands the class of functions for which the integral in definition exists. In the frequency domain, the signal is transformed with a filter of response

$$H(e^{j\omega}) = \begin{cases} -j, & 0 < \omega < \pi \\ j, & -\pi < \omega < 0 \end{cases} \quad \ldots\ldots (2)$$

The effects of the Hilbert Transform have been explained in terms of its odd symmetry property and envelope signal. If it is applied directly over the ECG signal or over a band-pass filtered version, the QRS fiducial point is associated to a zero-crossing on the Hilbert transformed version. The Hilbert Transform is used to obtain the related analytical signal and its squared amplitude. The envelope of the analytical signal is always a positive function and the maximum contribution to its value is at the zero crossing of the input signal. If it is applied on the differentiated ECG, the R-peaks will be represented as peaks in the output of the transform. The Hilbert Transform's all-pass characteristic prevents unnecessary signal distortion since it shifts -90^0 for positive and $+90^0$ for negative frequencies [1].

D. Adaptive Thresholding technique

Adaptive Thresholding technique is one of the important steps carried out for detection of R-peak. Using fixed threshold based algorithms it is observed that defining high values for threshold leads to lack of proper detection and defining low values causes incorrect detection of the peaks present in the respective signal [12]. In adaptive threshold structure, detection is done by using a pair of threshold limits named Upper Limited Threshold (T2) and Lower Limited Threshold (T1). The amplitude of Hilbert transformed signal is compared with these threshold levels & the numbers of peaks detected by T1 & T2 are obtained. If peaks detected by both the thresholds are same then T2 is considered as final threshold value and processed for the R-peak detection. If those are not same then T1 & T2 are changed according to equation 1 explained in section III.

III. METHDOLOGY AND ALGORITHM

Fig. 1 shows the block diagram of the proposed algorithm.

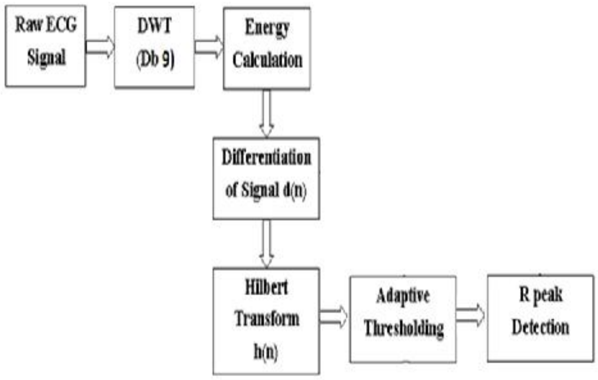


Fig. 1 Block diagram

*A. **Algorithm for R peak Detection***

1. *Initially the complete ECG signal 30 minutes is divided into a frame of 3600 samples.*

2. *For every frame following procedure is repeated for R-peak detection.*

i) Set window size of two samples& set it to the 1st sample of the frame..

ii) Perform 3 level decomposition of the signal consisting of two samples using DWT, db9 as a mother wavelet.

iii) Calculate the energy of 3rd level approximated coefficients.
iv) Move the window to the next sample & repeat the steps ii) & iii) till the end of the frame. Fig. represents the output of energy-histogram obtained for one frame.
v) Once the energy-histogram is obtained for a frame, then that energy signal is processed for the first order differentiation.
vi) Calculate the Hilbert transform H[n] of the differentiated output which leads to an enhanced envelops. Fig. represents the Hilbert transform of the differentiated signal.
vii) Set up the initial values for the Upper threshold as 20% of max(H[n]) & lower threshold as 2% of max(H[n]) represented by following formula-
T2=0.2*max(H[n]) &
T1=0.02*max(H[n])
viii) Search for the peaks/maximas in an entire array of H[n] obtained by upper threshold and lower thresholds as N1 & N2 respectively.
ix) Compare the values of N1& N2, if they are not equal then Calculate the error component as
Delta=T2-T1 multiply with the scaling factor of 0.125 ie η= (delta*w)

x) Increase the Lower threshold T1 by η & reduce the upper threshold T2 by η till the N1 becomes equal to N2.

$$T1 = T1 + \eta \ , \ T2 = T2 - \eta \quad \ldots\ldots (3)$$

xi) If N1=N2, then consider T2 as final threshold and search for the R-peaks.

xii) For R peak detection, a pulse train is generated by comparing the threshold value with the every sample of H[n]. If H[n]>T2 the next 70 samples are set to the value 1 & rest all samples will be zero. Then the ECG signal is multiplied by the pulse train. Fig.

xiii) The R-peaks are obtained from this modulated signal are shown in fig.

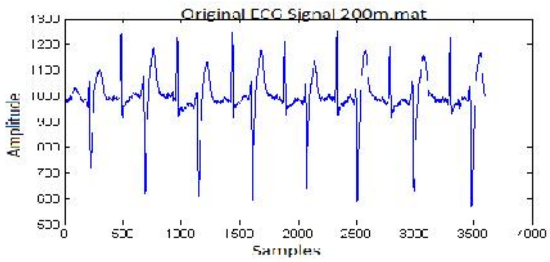
3. At the end, the whole record is scanned according to the R-peak locations obtained, if difference between two R-peaks indices is found to be less than 70 samples the next sample is skipped.

IV. RESULTS & ANALYSIS

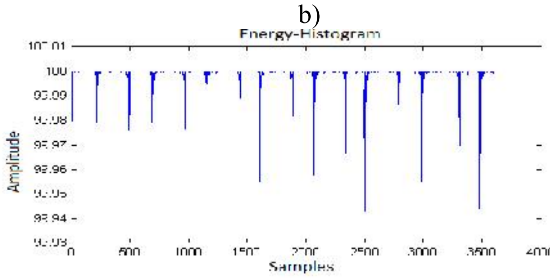
A. Results

The results obtained by the proposed algorithm are shown for ECG signal having negative R peaks –

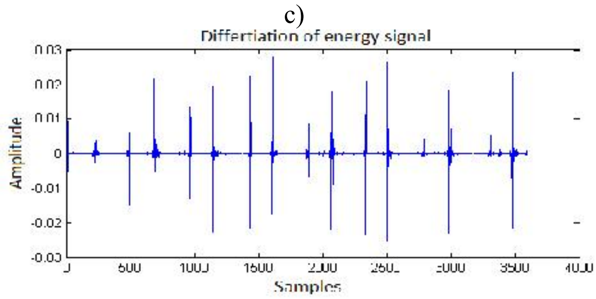
a)



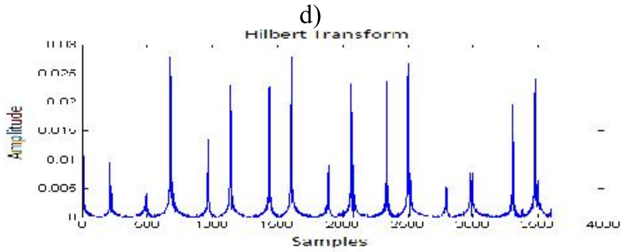
b)



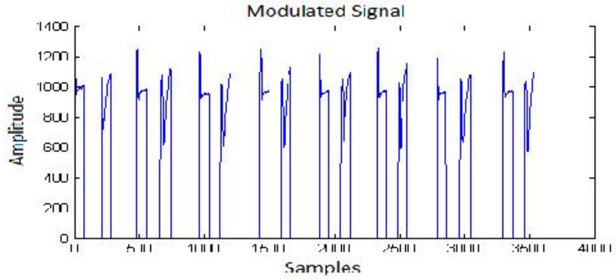
c)



d)



e)



f)

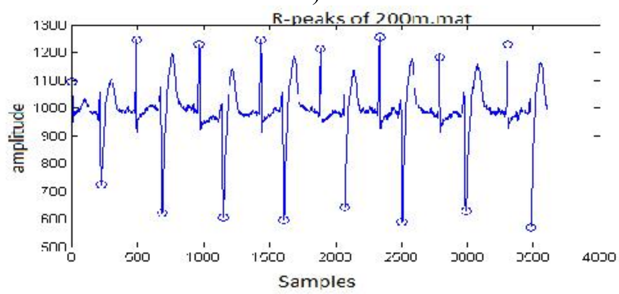


Fig. 2 a) Original Signal b) wavelet Energy –histogram of ECG signal c) Differentiation of energy signal d)Hilbert Transform of Differentiated signal e) Modulated signal for peak detection f) R-peaks located on original signal

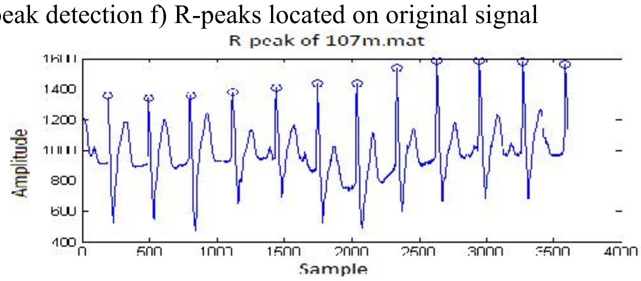


Fig. 3 R-peaks for 107m.mat ECG signal

B. Evaluation of the proposed algorithm

For evaluation of proposed all 48 ECG records of 30 minutes are used & is implemented on a 2.4GHz Intel core i3.3110M processor using MATLAB version 12. It has been observed that the average processing time for a single heart beat is 1.5ms. The R peaks detected by the proposed algorithm is compared with the annotations of R points available with MIT-BIH database. For the detected R-peak a tolerance margin of ± 25 sample is kept as compared to annotations. The result thus obtained is summarized in table no.1.

From the detected R-peak, we obtained three parameters as – i) True Positive (TP), it represents the number of R-peaks correctly detected. ii) False Negative (FN), it represents true R-peak which is missed. iii) False Positive (FP), it represents a noise is detected as R-peak.

The performance of the algorithm is evaluted based on following three paramters.

I) Detection Accuracy (DA)- It represents the percentage of beats detected correctly with respect to actual beats [eq^n 4]

$$DA = \frac{(|\, Actual\ beats - Detected\ beats\,|)}{Actual\ beats} \ \ldots\ldots(4)$$

II) Sensitivity (Se) – It represents fraction of ECG beats that are correctly detected from all ECG beats.[eq^n 5]

$$Se = \frac{TP}{TP+FN} \ \ldots\ldots\ (5)$$

III) Positive Predictivity (Pp)- It represents the fraction of real ECG beats in all detected beats. [eq^n 6]

$$Pp = \frac{TP}{TP+FP} \ \ldots\ldots\ (6)$$

The overall performance is measured in terms of the detection error rate (DER) given by

$$DER = \frac{FN+FP}{Actual\ \ beats} \ \ldots\ldots\ (7)$$

From table 1, it can be seen that the average detection accuracy obtained is 98.30%, average sensitivity is 0.9745, average positive predictivity is 0.9741 and the average detection error rate is 5.17%.

V. CONCLUSION

In this paper, the task of R peak detection is carried out using the new approach of energy-histogram. It can be observed clearly from the energy plot that the significant energy change in the signal at QRS complex. This is obtained using wavelet decomposition till the third scale. As Wavelet is acting as the denoising tool, there is no need of any preprocessing of a signal. It also eliminates the problem of base line wonder & dc shift. Hilbert transform further contribute in reducing the noise in the signal by enhancing the peak of differentiated signal. Adaptive Thresholding is the simplest algorithm which gives the better results of R-peak detection. Overall the algorithm is less complex resulting into increased computation time efficiency with good accuracy.

Table1. Performance evaluation of the proposed algorithm using MIT-BIH Arrhythmia database

Sr. No	Record No	Actual beats	Detected beats	DR	PP	SP	DER
1	100	2273	2272	99.95601	0.996928	0.99956	0.00352
2	101	1865	1852	99.30295	0.985421	0.979603	0.034853
3	102	2187	2189	99.90855	0.999086	0.999086	0.001829
4	103	2084	2078	99.71209	0.999038	0.996161	0.004798
5	104	2229	2185	98.02602	0.951487	0.931869	0.115747
6	105	2572	2537	98.63919	0.956248	0.943235	0.099922
7	106	2027	2037	99.50666	0.957781	0.958722	0.083868
8	107	2137	2129	99.62564	0.99953	0.995788	0.004679
9	108	1774	1857	95.32131	0.804028	0.832582	0.370349
10	109	2532	2512	99.21011	0.988751	0.979697	0.031201
11	111	2124	2158	98.39925	0.966172	0.979793	0.054614
12	112	2539	2560	99.1729	0.991406	0.999213	0.009453
13	113	1795	1795	100	1	1	0
14	114	1879	1881	99.89356	0.985114	0.987214	0.027674
15	115	1953	1948	99.74398	0.999487	0.996928	0.003584
16	116	2412	2362	97.92703	0.999153	0.978441	0.022388
17	117	1535	1556	98.63192	0.983933	0.997394	0.018893
18	118	2288	2293	99.78147	0.992586	0.992153	0.015297
19	119	1987	1985	99.89935	0.999496	0.99849	0.002013
20	121	1863	1982	93.61245	0.911201	0.969404	0.125067
21	122	2476	2474	99.91922	0.999596	0.998788	0.001616
22	123	1518	1513	99.67062	0.999339	0.996047	0.004611
23	124	1619	1643	98.5176	0.979915	0.994441	0.025942
24	200	2601	2572	98.88504	0.948698	0.938485	0.112265
25	201	2000	1920	96	1	0.96	0.04
26	202	2136	2204	96.81648	0.965971	0.996723	0.03839
27	203	2980	3170	93.62416	0.825552	0.878188	0.307383
28	205	2656	2652	99.8494	0.999623	0.998117	0.002259
29	207	2332	2154	92.36707	0.918756	0.848628	0.226415
30	208	2955	3103	94.99154	0.930158	0.978003	0.095431
31	209	3005	3077	97.60399	0.976601	1	0.02396
32	210	2650	2580	97.35849	0.977132	0.951321	0.070943
33	212	2748	2809	97.7802	0.975515	1	0.025109
34	213	3251	3243	99.75392	0.9963	0.993848	0.009843
35	214	2262	2319	97.48011	0.96809	0.992485	0.04023
36	215	3363	3279	97.50223	0.994815	0.999694	0.005352
37	217	2208	2200	99.63768	0.998636	0.995018	0.006341
38	219	2287	2135	93.35374	0.999532	0.9331	0.067337
39	220	2048	2045	99.85352	0.999511	0.998047	0.002441
40	221	2427	2420	99.71158	0.989256	0.988403	0.02431
41	222	2483	2501	99.27507	0.986405	0.993556	0.020137
42	223	2589	2478	95.71263	0.993543	0.946559	0.059869
43	228	2053	2081	98.63614	0.911581	0.915541	0.174866
44	230	2256	2247	99.60106	0.99911	0.998892	0.003989
45	231	1573	1567	99.61856	0.998086	1	0.001907
46	232	1780	1801	98.82022	0.985564	0.997191	0.017416
47	233	3079	3076	99.90257	0.977487	0.976174	0.04482
48	234	2753	2756	99.89103	0.998911	0.999637	0.001453
		Average Values		98.3000902	0.974177661	0.974516252	0.051757993

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