A New QRS Detection Algorithm Based on the Hilbert Transform

DS Benitez[1], PA Gaydecki[1], A Zaidi[2], AP Fitzpatrick[2]

[1] Department of Instrumentation and Analytical Science, UMIST, Manchester, United Kingdom
[2] Manchester Heart Centre, Manchester Royal Infirmary, Manchester, United Kingdom

Abstract

A robust new algorithm for QRS detection using the properties of the Hilbert transform is proposed in this paper. The method allows R waves 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 was tested using the records of the MIT-BIH Arrhythmia Database. Beat by beat comparison was performed according to the recommendation of the American National Standard for ambulatory ECG analyzers (ANSI/AAMI EC38-1998). A QRS detection rate of 99.64%, a sensitivity of 99.81% and a positive prediction of 99.83 % was achieved against the MIT-BIH Arrhythmia database. The noise tolerance of the new proposed QRS detector was also tested using standard records from the MIT-BIH Noise Stress Test Database. The sensitivity of the detector remains about 94% even for signal-to-noise ratios (SNR) as low as 6dB.

1. Introduction

Accurate determination of the QRS complex, in particular, accurate detection of the R wave peak, is essential in computer-based ECG analysis especially for a correct measurement of Heart Rate Variability (HRV).

However, this is often difficult to achieve, since various sources of noise contamination [1] are frequently encountered, such as baseline drifts, motion artifacts and muscular activity. Furthermore, 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 [2].

A new approach to QRS detection using the properties of the Hilbert transform is presented in this paper. The algorithm uses the first differential of the ECG signal and its Hilbert transformed data to locate the R peaks in the ECG waveform. This has a number of advantages, the unwanted effects of large peaked T and P waves are minimized and the new algorithm performs excellently in the presence of significant noise contamination.

1.1. The Hilbert transform

Given a real time function $x(t)$, its Hilbert transform [3,4] is defined as:

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

It can be seen from (1) that the independent variable is not changed as result of this transformation, so the output $\hat{x}(t)$ is also a time dependent function. Furthermore, $\hat{x}(t)$ is a linear function of $x(t)$. It is obtained from $x(t)$ applying convolution with $(\pi t)^{-1}$ as shown in the following relationship:

$$\hat{x}(t) = \frac{1}{\pi t} * x(t) \tag{2}$$

Rewriting Equation (2) and applying the Fourier transform, we have:

$$F\{\hat{x}(t)\} = \frac{1}{\pi}F\{\frac{1}{t}\}F\{x(t)\} \tag{3}$$

Since,

$$F\{\frac{1}{t}\} = \int_{-\infty}^{\infty}\frac{1}{x}e^{-j2\pi fxdx} = -j\pi\,\mathrm{sgn}\,f \tag{4}$$

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

The Fourier transform of the Hilbert transform of $x(t)$ given by Equation (3) may be re-expressed as:

$$F\{(\hat{x})\} = -j\,\mathrm{sgn}\,f \cdot F\{x(t)\} \tag{5}$$

In the frequency domain, the result is then obtained by multiplying the spectrum of the $x(t)$ 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 $x(t)$ represents its harmonic conjugate.

2. The new approach to QRS detection using the Hilbert transform

One of the properties of the Hilbert transform is that it is an odd function. That is to say that it will cross zero on the x-axis every time that there is an inflexion point in the original waveform (Figure 1). Similarly a crossing of the zero between consecutive positive and negative inflexion points in the original waveform will be represented as a peak in its Hilbert transformed conjugate.

Figure 1. R wave equivalences in the Hilbert transformed waveform (H[d/dt(ECG)]) of the first differential of the ECG (d/dt[ECG]).

This interesting property can be used to develop an elegant and much easier way to find the peak of the QRS complex in the ECG waveform corresponding to a zero crossing in its first differential waveform *d/dt*(ECG). The block diagram of the proposed approach is shown in Figure 2.

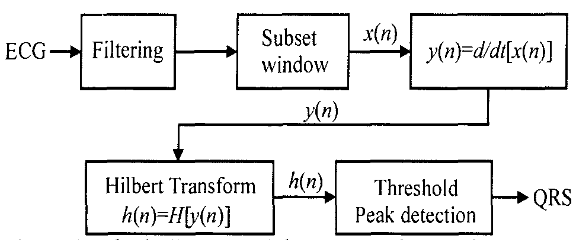

Figure 2. Block diagram of the proposed QRS detector.

As with most QRS detector algorithms, the first stage of the proposed algorithm is formed by a filtering section [5]. A band pass FIR filter, which coefficients were design using a Kaiser-Bessel window was used for this purpose. The Kaiser window was chosen because its flexibility and characteristics such as maximum flat in the band pass and side lobe reduction.

The band stop frequencies were set at 8 and 20 Hz in order to remove muscular noise and maximize the QRS complex respectively.

Since this algorithm for Hilbert transformation works well with short sequences, a moving 1024 points rectangular window is used to subdivide the input sequence $k(n)$ before obtaining its first differential and performing the Hilbert transformation. To optimize accuracy, the started point of the next window should mach the last R point located in the previous ECG subset. Then, the first differential of the resulting filtered windowed sequence $x(n)$ is performed in order to remove motion artifacts and base line drifts. The rising slope of the R wave will be represented as a maximum and the falling slope will be represented as a minimum in the first differential sequence. The peak of the R wave will be equivalent to the zero crossing between these two positive and negative peaks (see Figure 1).

So given the filtered ECG waveform subset sequence $x(n)$, its first differential ($y(t)=d/dt$(ECG)) in discrete domain can be obtained by:

$$y(n) = \frac{1}{2\Delta t}\left[x(n+1) - x(n-1)\right] \qquad (6)$$

for $n = 0, 1, 2, \ldots, m\text{-}1$

where: m is the total number of samples
Δt is the sampling frequency

The initial condition is specified by $x(-1)$ when $n = 0$, and the final condition $x(m)$ when $n = m$-1. These conditions minimize the error at the boundaries.

The Hilbert transform $h(n)$ of the sequence $y(n)$ that represents the first differential of the ECG waveform in this subset is then obtained using the following methodology:

1. Obtain the Fourier transform $F(n)$ of the input sequence $y(n)$
2. Set the DC component to zero
3. Multiply the positive and negative harmonics by $-j$ and j respectively
4. Perform the inverse Fourier transform of this resulting sequence

Because the P and T waves are minimized in relation to the relative peak corresponding to the peak of the QRS complex in the Hilbert sequence, a simple peak detector with an adaptive threshold is used to locate the peaks in the $h(n)$ sequence. The threshold must be adaptive in order to guarantee accurate detection of the R peaks. The threshold level is set as follows: First the equivalent RMS value of the Hilbert transformed sequence is determined and this value is compared with the maximum amplitude of the Hilbert transformed sequence of 1024 points, this comparison is used to determine the level of noise present in the subset under analysis, if the RMS value is equal or greater than 18% of the maximum value of the sequence, the level of noise in the segment is considered to be high and therefore the threshold level is setup at 39% of the maximum amplitude of the Hilbert sequence, if the maximum value of the sequence under study is greater than two times the amplitude of the maximum value of the previous subset of 1024 points, then the threshold is set to 0.39% of the maximum amplitude of the previous subset. When the RMS value is lower than 18% of the maximum value of the sequence, the amount of noise in the subset is considered to be low and threshold level is setup to 1.6 times the RMS value.

When two peaks in the Hilbert sequence are located very close each other (less than 200 ms), only one the peak is considered as the real R peak, the decision is made in base of the amplitude of the peak and their position in relation to the last R peak located using an adaptive time threshold based in the average inter beat length (R-R interval) of the previous R peaks located.

3. Methods

The detector was tested using entire records from the MIT-BIH Arrhythmia database [6]. Beat by beat comparison was performed according to the recommendation of the American National Standard for ambulatory ECG analysers (ANSI/AAMI EC38-1998) [7]. For purposes of comparison, the analysis was performed over the entire length of the records of the database and no learning periods were allowed. Episodes of ventricular flutter (in record 207) were excluded from the analysis. A false negative (FN) occurs when the algorithm fails to detect a true beat (actual QRS) quoted in the corresponding annotation file of the MIT-BIH record and a false positive (FP) represents a false beat detection. Sensitivity (Se) [7], positive prediction (+P) [7], and detection error rate (DER) [8] were calculated using equation 7 to 9 respectively:

$$\text{Sensitivity (\%)} = \frac{TP}{TP + FN}\% \tag{7}$$

$$\text{Positive predictivity (\%)} = \frac{TP}{TP + FP}\% \tag{8}$$

$$\text{DER (\%)} = \frac{FP + FN}{\text{Total \#of QRS complex}}\% \tag{9}$$

Where: TP (true positives) is the total number of QRS correctly located by the detector.

The noise effects in the detector were quantified by the noise stress test recommended by the ANSI/AAMI EC38-1998 standard using the records from the MIT-BIH Noise Stress Test Database [6]. This database contains 12 sample records contaminated with electrode motion artifacts and significant amount of baseline wander and muscular noise.

4. Results and discussion

The detector shows outstanding performance for noisy signals even in the presence of pronounced muscular noise and baseline artifacts. A QRS detection error rate of 0.36%, a sensitivity (Se) of 99.81% and a positive prediction (+P) of 99.83 % was achieved against the MIT-BIH Arrhythmia database. The results obtained are summarized in Table 1. The performance is comparable to other results presented in the literature. In the case of the noise tolerance test, the performance of the proposed QRS detector remains high for SNR's as low as 6 dB with high sensitivity values (about 94%) and with equally high positive predictions (above 88%). The results obtained are presented in Table 2. The sensitivity of the detector falls under 90% for SNR's lower than 6dB. The reliability of the proposed detector compares very favorably with published results for other QRS detectors especially for the difficult to analyze noisy MIT-BIH record 105 which has been extensile used through the literature to test QRS detectors and therefore comparisons are possible. The predominant features of this record are high grade of noise and artifacts. Comparative results are shown in the Table 3.

Table 1. QRS Detection Performance using the MIT-BIH Arrhythmia Database (Excluding Episodes of Ventricular Flutter)

FP	FN	DER (%)	Se (%)	+P (%)
187	203	0.36	99.81	99.83

Table 2. Noise Tolerance of the proposed QRS Detector Using the MIT-BIH Noise Stress Test Database.

Record	DER (%)	Se (%)	+P (%)
118e24	0.00	100	100
118e18	0.22	99.96	99.82
118e12	3.95	98.81	97.28
118e06	14.53	94.69	91.13
118e00	33.49	84.15	82.66
118e_6	44.78	78.45	77.16
119e24	0.05	100	99.95
119e18	0.25	99.95	99.80
119e12	5.94	99.14	95.12
119e06	16.16	95.87	88.85
119e00	30.85	89.73	81.34
119e_6	47.16	81:08	74.17

The good performance of the proposed detector can be explained by the fact that using the Hilbert transform algorithm developed, baseline wander and noise are removed from the ECG signal and the R peaks are easily identified in the Hilbert transformed of the first differential of the ECG using the adaptive method previously described. This equivalence is easily seen in the graph of the Figure 3.

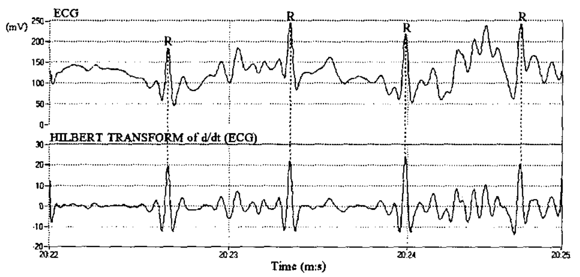

Figure 3. Equivalence of the R peaks in the Hilbert transformed of the first differential of the ECG for an excerpt of 1024 sample points from MIT/BIH database record 105 (20:22 form the beginning). Notice the great amount of noise present in the signal.

Table 3. Performance Comparison with other detectors for the noisy MIT-BIH record 105 containing 2572 QRS complex.

Method	FP	FN	DER (%)	Ref.
Proposed detector	6	3	0.35	
Neural-based adaptive filtering	10	4	0.54	[8]
Wavelet transforms	15	13	1.09	[9]
Topological mapping	41	4	1.75	[10]
Optimized filtering and dual edge thresholding	35	21	2.18	[11]
Linear adaptive filtering	40	22	2.41	[8]
Bandpass filtering and search-back	53	22	2.91	[5]
Bandpass filtering	67	22	3.46	[12]
Filter banks*	53	16	3.22	[13]

* This result reporter over 2139 beats only.

5. Conclusion

The usefulness of the properties of the Hilbert transform for QRS detection has been studied in this paper and a new QRS complex detector has been proposed. Using the MIT-BIH arrhythmia database, the algorithm developed performed highly effectively with accurate QRS peak detection, even in the presence of significant noise contamination. This robust noise rejection of the algorithm proposed is emphasized with the results obtained for the noise stress test, where high sensitivity and positive prediction rates were obtained for even high noise contaminated signals.

Acknowledgements

D. Benitez would like to express his thanks to his sponsors, Overseas Research Student Award Scheme and UMIST Graduate Research Scholarship in the U.K. and to FUNDACYT in Ecuador for their financial support and for giving him the chance to pursue his studies in the United Kingdom.

References

[1] Friesen GM, Jannett TC, Jadallah MA, Yates SL, Quint SR, Nagle HT. A comparison of the noise sensitivity of nine QRS detection algorithms. IEEE Trans. Biomed. Eng. 1990;37:85-98.

[2] Thakor NV, Webster JG, Thompkins WJ. Estimation of QRS complex power spectra for design of a QRS filter. IEEE Trans. Biomed. Eng. 1984;31: 702-5.

[3] Bracewell RN. The Fourier transform and its applications. McGraw-Hill, 1978.

[4] Oppenheim, A.V., Schafer, R.W., Discrete-*Time Signal Processing*, Englewood Cliffs, NJ, Pretince-Hall, 1989.

[5] Hamilton PS, Tompkins WJ. Quantitative investigation of QRS detection rules using the MIT/BIH arrhythmia database. IEEE Trans. Biomed. Eng. 1986;33:1157-65.

[6] MIT-BIH Database distribution, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, 1998.

[7] American National Standard for Ambulatory Electrocardiographs, publication ANSI/AAMI EC38-1998, Association for the Advancement of Medical Instrumentation, 1998.

[8] Xue Q, Hu YH, Tompkins WJ. Neural-network-based adaptive filtering for QRS detection. IEEE Trans. Biomed. Eng. 1992;39:315-29.

[9] Li C, Zheng C, Tai C. Detection of ECG characteristic points using wavelet transforms. IEEE Trans. Biomed. Eng. 1995;42:21-8.

[10] Lee J, Jeong K, Yoon J, Lee M. A simle real-time microprocessor QRS detection algorithm. In: Proceedings of the 18th Annual International Conference of the IEE eng. and Med. and Biomed. Society 1996. Amsterdam: IEEE, 1996: 1396-98.

[11] Ruha a, Sallinen S., Nissila S. A real-time microprocessor QRS detector system with a 1-ms tiing accuracy for the measurment of ambulatory HRV. IEEE Trans. Biomed. Eng. 1997;44:159-67.

[12] Pan J, Tompkins WJ. A real time QRS detection algorithm. IEEE Trans. Biomed. Eng. 1985;32:230-36.

[13] Afonso VX, Tompkins WJ, Nguyen TQ, Luo S. ECG beat detection using filter banks. IEEE Trans. Biomed. Eng. 1999;46:192-201.

Address for correspondence:
Dr. PA Gaydecki
DIAS, UMIST, PO Box 88, Manchester M60 1QD, UK
E-mail: patrick.gaydecki@umist.ac.uk