QRS Complex Detection using Empirical Mode Decomposition based Windowing Technique

Saurabh Pal
Dept. of Applied Electronics and Instrumentation Engg.
Haldia Institute of Technology
Haldia, India
spal76@gmail.com

Madhuchhanda Mitra
Dept. of applied Physics
University of Calcutta
Kolkata, India
madhuchhanda94@rediffmail.com

Abstract— **In this work an Empirical Mode Decomposition based QRS complex detection algorithm is proposed. Other decomposition techniques use some predetermined basis function for transformation and hence may not be applicable for all kind of signals. Being a fully data driven adaptive technique, the present method depends on selection of proper and optimum set of IMFs to generate an intermediate signal. Some simple mathematical operations are performed on that signal to highlight the R peak. Then the Q and S points are detected by windowing technique. Only second and third IMFs are required for QRS complex detection. The proposed method is tested with PTB diagnostic database and MIT-BIH Arrhythmia database. The R peak detection success rate is 98.67%. Sensitivity and specificity of QRS complex detection is 98.88% and 99.04% respectively.**

Keywords— **adaptive, ECG, empirical mode decomposition (EMD), intrinsic mode function (IMF), QRS complex**

I. INTRODUCTION

Automatic analysis of ECG and disease identification is a major field of research for last few decades. The purpose of automation is to reduce the time required for interpretation of ECG as well as human effort. Specially in Holter monitoring, the long term continuous ECG signals are first digitized and then compressed and stored in a hard storage device. This data are later uncompressed and analyzed by medical personals to detect abnormalities. The analysis of this data takes a substantial time and the automation in the analysis considered to be a promising one. Computer based feature extraction is the primary step for automatic analysis. The Electrocardiogram represents the electrical activity of the heart. It is characterized by a number of waves P, QRS, T related to the heart activity. The QRS complex is the most prominent waveform within the electrocardiographic (ECG) signal, with normal duration from 0.06s to 0.1s [1]. It reflects the electrical activity within the heart for total ventricular muscle depolarization. Various temporal and spatial features provide valuable information about the current state of the heart. Because of its specific shape, the QRS complex serves as an entry point for almost all automated ECG analysis algorithms and detection of the QRS complex is the most important task in automatic ECG signal analysis [2]. The duration, the amplitude, and the complex QRS morphology are used for the purpose of diagnosis of myocardial infarction, cardiac arrhythmias, conduction abnormalities, ventricular hypertrophy etc. Various techniques are adopted for detection of QRS complex. Design of a bandpass filter to suppress other waves and different noises and extract QRS region is a very common practice for the same. But this method suffers from errors if the frequency band for QRS complex varies from subject to subject or for different beats of same subject (as in the case of Premature Ventricular Contraction, APC, Bundle Branch Blocks etc.).Other approaches such as algorithms using artificial neural network [3], fuzzy hybrid neural network [4], genetic algorithm [5] or wavelet based techniques [6] are adopted to enhance the quality of QRS detectors. In most cases better performance is associated with larger analysis time and higher cost of processor. All the methods including wavelet based approach are non adaptive in nature and hence not globally applicable. Basically due to dynamic changes in the behavior of heart and related organs, the ECG signals may exhibit time-varying as well as non-stationary responses. Hence a fully adaptive approach to extract the features can perform better in almost all cardiological conditions. Huang et al. [7] have proposed the Hilbert-Huang transform method (HHT) as a new tool for the analysis of nonlinear and non-stationary data. Unlike the Fourier or wavelet transform, which is predicated on a priori selection of basis functions that are either of infinite length or have fixed finite widths, Empirical Mode Decomposition (EMD) decomposes a signal into finite basis functions called the intrinsic mode functions. Then the intrinsic mode functions (IMFs) of interest are combined in a definite predetermined manner to extract the information of interest from the signal. In biomedical domain EMD is mostly used for denoising or to remove unwanted components from the bio signals as in [8]. In the present work a selective IMF based approach is proposed for QRS detection.

II. EMPIRICAL MODE DECOMPOSITION (EMD)

EMD is a general nonlinear, nonstationary signal processing method. The EMD method was initially proposed for the study of ocean waves and then the technique is efficiently used in different signal processing and analysis applications. The adaptive nature of this transform lies in the fact that the basis functions are directly derived from the signal under test unlike Fourier or Wavelet Transforms.

978-1-4244-7138-6/10/$26.00 ©2010 IEEE

According to the principle of EMD, it decomposes a signal into a sum of oscillatory functions, namely intrinsic mode functions (IMFs). IMFs have two basic features such as, 1) they have the same numbers of extrema and zero-crossings or differ at most by one, and 2) they are symmetric with respect to local zero mean.

The steps of Empirical Mode Decomposition of any signal $x(t)$ are as follows:

(1) All the local maxima of the signal are connected by a cubic spline interpolation as the upper envelope.

(2) The procedure is repeated for the local minima to produce the lower envelope.

(3) The mean m_1 of upper and low envelope value is calculated and the difference d_1 between the signal $x(t)$ and m_1 is computed, i.e.

$$x(t) - m_1 = d_1(t) \qquad (1)$$

If d_1 is an IMF as per the two conditions mentioned above, then d_1 is the first component of $x(t)$.

(4) If d_1 is not an IMF, then the steps (1), (2), (3) are repeated on d_1. Thus d_{11} is calculated as,

$$d_1 - m_{11} = d_{11} \qquad (2)$$

in which m_{11} is the mean of upper and low envelope value of d_1. Let after k cycles of operation, d_{1k} becomes an IMF, that is

$$d_{1(k-1)} - m_{1k} = d_{1k} \qquad (3)$$

Then, it is designated as $c_1 = h_{1k}$, the first IMF component from the original data.

(5) Subtracting c_1 from $x(t)$, r_1 is calculated as

$$r_1 = x(t) - c_1 \qquad (4)$$

which is treated as the original data. Repeating the above process for n times n no. of IMFs are obtained along with the final residue r_n. The decomposition process can be stopped when r_n becomes a monotonic function from which no more IMF can be extracted. By summing up, we finally obtain

$$x(t) = \sum_{j=1}^{n} c_j + r_n \qquad (5)$$

Residue r_n is the mean trend of $x(t)$. The IMFs c_1, c_2, . . ., c_n include different frequency bands ranging from high to low. The frequency components contained in each frequency band are different and they change with the variation of signal $x(t)$, while r_n represents the central tendency of signal $x(t)$.

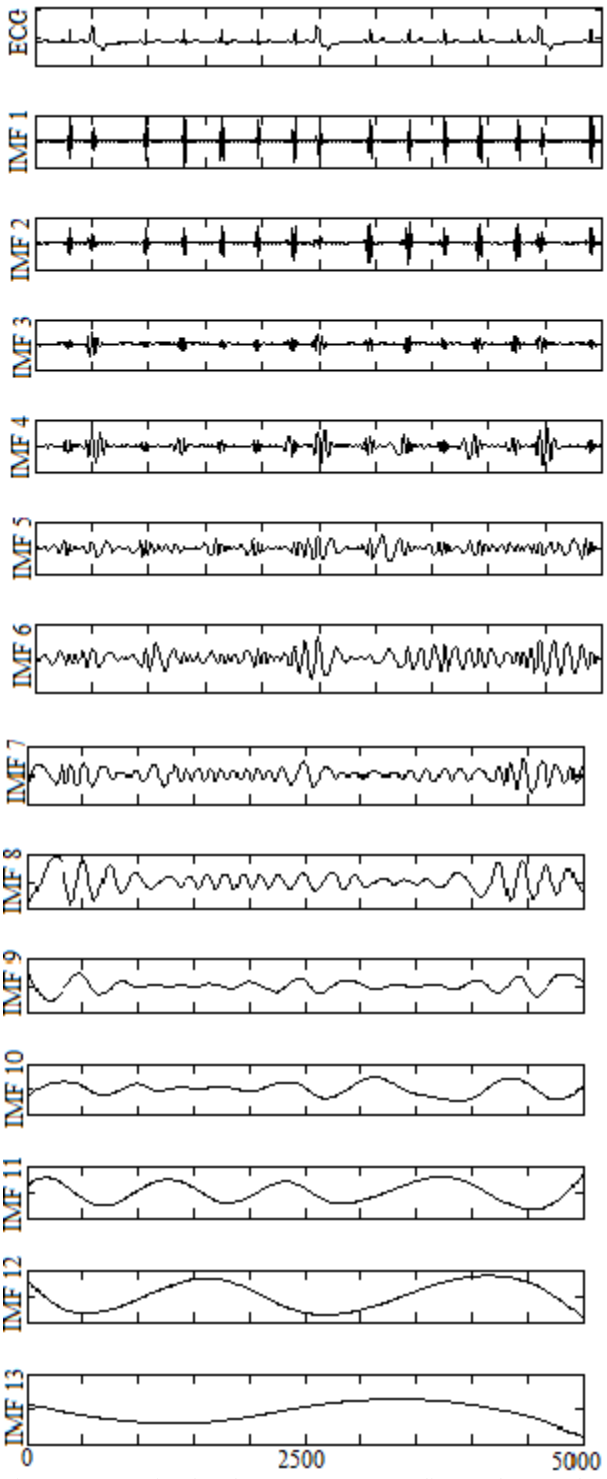

Figure 1. ECG signal and 13 IMFs corresponding to the record 119 of MIT-BIH database

Basically IMFs represents the oscillatory modes of a signal. The lower order IMFs represents the fast or high frequency oscillations whereas upper order IMFs correspond to slow or low frequency oscillations. As per the characteristics of ECG, QRS complex is the high frequency component and P and T waves are the low frequency components of the signal. Hence lower order IMFs can be combined together to reconstruct the signal which highlights QRS region over the other waves and low frequency noises like baseline drift due to respiration etc. Figure 1 shows the original ECG (record 119) and first six IMFs and figure 2 shows the rest seven IMFs.

III. SIMULATION AND IMPLIMENTATION

A. R peak Detection

In most of the cases R wave is the highest amplitude and smallest duration wave in the ECG signal. Being the high frequency part of the mother wave, it must be represented by the lower order IMFs as discussed earlier. Earlier studies [9], [10] shows that QRS region is better captured in first three IMFs. But from figure 1, it is seen that some high frequency noises are also present in first IMF along with the required QRS information. Hence here an approach is made to extract the required information with only second and third IMFs. Initial thresholding is done by subtracting mean amplitude of each IMF from the IMF itself as,

$$b_1(t) = c_j(t) - mean(c_j(t)) \qquad (6)$$

where b1(t) is the output and j takes the values 2 & 3 as the case may be.

Attained signal samples from each IMF were then squared to obtain

$$b_2(t) = b_{1\,j}^2(t) \qquad (7)$$

where $b_2(t)$ is the output and j is the IMF number. It enhances the high amplitude transitions of the signal even if R peaks are deformed or inverted.

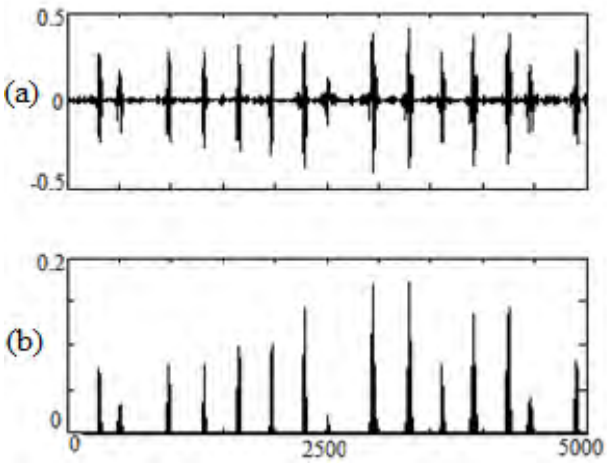

Figure 2. (a) : IMF 2 after initial thresholding (record 119)
(b): IMF 2 after squaring(119)

The signals after squaring for second and third IMF are shown in figures 2 and 3 respectively. Then the product of output from two squared IMFs (second and third IMF) is found as

$$b_3(t) = b_{1,2}^2(t) \times b_{1,3}^2(t) \qquad (8)$$

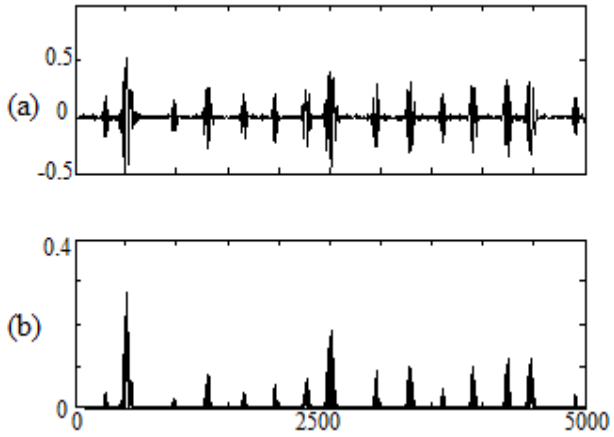

Figure 3. (a) : IMF 3 after initial thresholding (record 119)
(b): IMF 3 after squaring(119)

A statistically determined threshold value is calculated using the maximum amplitude within a stipulated interval in which the R peak is under search. Other values of the amplitude are deliberately made equal to zero. This is useful for eliminating noises if any. The maximum value of the amplitude within the required time interval starting from the first nonzero value is calculated. It is identified as the first R peak. The next R peaks are identified by the same way with different time interval upto the end of the signal. In figure 4, the original ECG signal and the product of two squared IMF are shown.

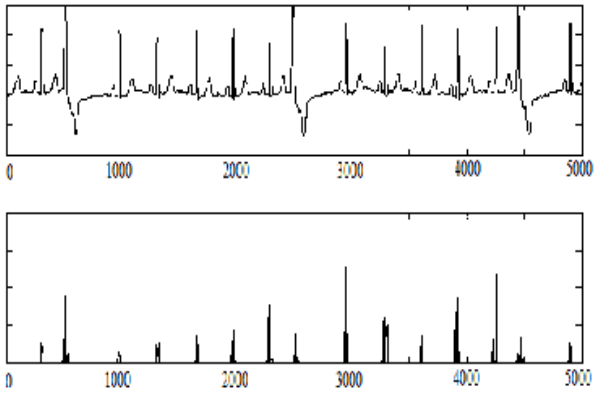

Figure 4.Original signal (record 119) and the product of the square of IMF 2 and IMF 3

B. Q and S point Detection

Q point and S points are the onset and offset point of QRS complex. These two points are obtained by adaptive windowing method. Most of the windows for ECG wave boundary detection are of fixed length. This may lead to a problem for QRS detection in some beats having abnormality like premature ventricular contraction (PVC) where QRS region is of larger length than normal beats.

These beats require windows of larger length. But for other beats this window can include unwanted parts of the wave as QRS region. To eliminate this problem, an adaptive window length is computed. Within a given time interval the maximum amplitude is expected to be the R peak. Q and S points are the minimum potential points on left and right side of R peak respectively as shown in figure 5. Window is selected to have a magnitude spectrum so that a predefined fraction of maximum amplitude for that time interval is obtained. So for larger QRS duration that particular fraction of maximum amplitude will occur in wider interval. Second and third IMFs are used for Q and S point detection.

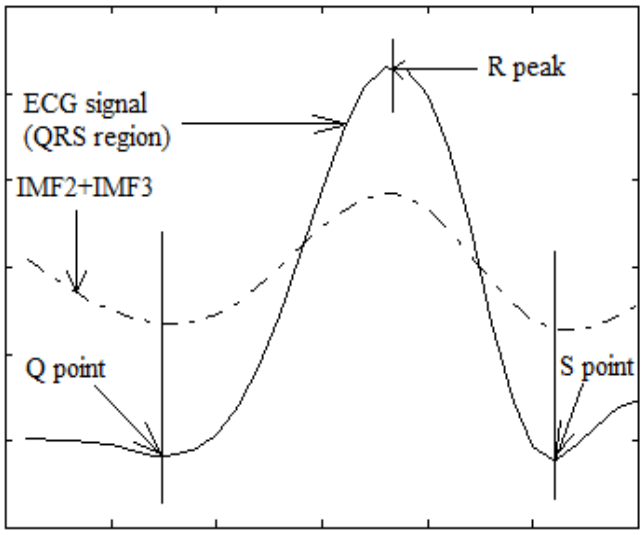

Figure 5.Detection of Q and S points

The Q and S points are the two local minima of the signal comprising of second and third IMF on either side of the previously detected R peak. There is a possibility to make a mistake in determining Q and S points in case of bundle branch block beats where there is a conjugate R peak. The crest between the two may be treated as the Q or S point. To eliminate this problem, the Q and S window is truncated for a region surrounding R peak, which includes the sub R peak, if any.

IV. RESULT AND ANALYSIS

The proposed method is tested with MIT-BIH arrhythmia database and physionet PTB diagnostic database [11]. More than 500 beats of different records from both the databases are tested. Present method shows 0.57% false positive (FP) and 0.76% false negative (FN) R peaks with a total detection failure of 1.33% as indicated in table 1.

TABLE I. RESULT FOR R PEAK DETECTION

No. of beats	*FP beats*	*FN beats*	*Failed detection beats*	*Failed detection rate*
525	3 (0.57%)	4 (0.76%)	7	1.33 %

Measured QRS durations are compared with manually measured values and in view of this, two performance indexes are used as follows:

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

$$\text{Specificity (\%)} = \frac{TP}{TP+FP}\times 100$$

where TP stands for true positive, it indicates the beats properly detected. FP stands for false positive which indicates presence of a beat when there is no beat actually. FN stands for false negative which means the algorithm fails to detect a real beat. Table 2 shows the performance values:

TABLE II. PERFORMANCE PARAMETERS FOR QRS DETECTOR

Sensitivity	*Specificity*
98.88	99.04

Figure 6 graphically represents the results achieved. Plot (a) is the ECG signal of record 119. Here beat 1 and 2 represents normal and PVC beats respectively. Sum of IMF2 and IMF3 is depicted in plot (b). Q and S points are two minimum potential points on either side of R peaks within the calculated interval. Plot (c) and (d) are the detected QRS complexes for normal and PVC beats. It proves that change in QRS morphology does not affect the QRS detection by this method.

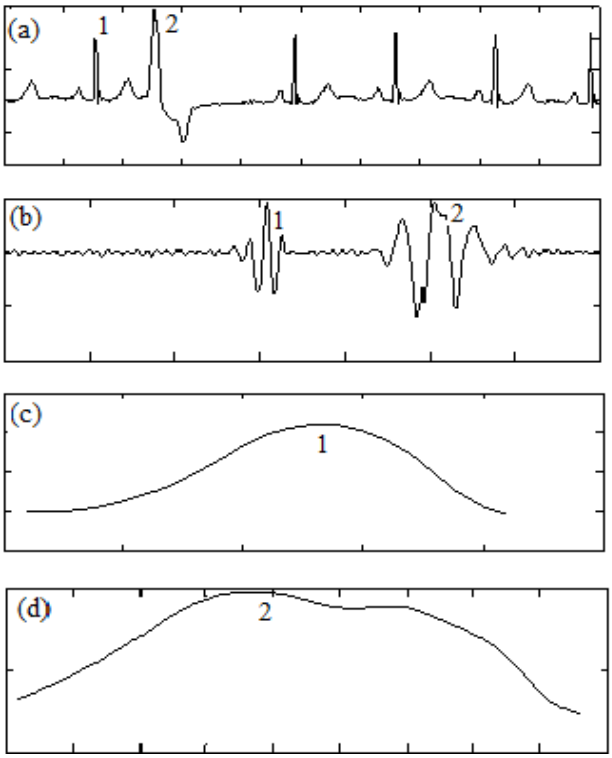

Figure 6. QRS complex representation (a) ECG data for 6 beats (record 119); (b) Plot of IMF2+IMF3; (c) Detected QRS complex for normal beat; (d) Detected QRS complex for PVC beat

V. CONCLUSION

Detection of QRS region is of great importance for cardiological diagnosis. Here an Empirical Mode Decomposition based algorithm is proposed for QRS detection. In Wavelet Transform, the basis function is predetermined and so study and analysis is required on the applicability of a particular wavelet for a specific application. In case of Empirical Mode Decomposition technique the basis function is derived from the signal data and so it is a data driven method. Being a fully adaptive decomposition technique, EMD is applicable for any kind of nonlinear and nonstationary signals. Thus there is a possibility to use this method for information extraction from ECG signal subjected to almost all kind of cardiac abnormalities. As QRS region is a part of higher oscillation in the ECG signal, lower order IMFs are retained and higher order IMFs are disregarded for detection. In the proposed method only two IMFs (second and third) are required for QRS detection. This reduces the probability of misdetection. This method has got good sensitivity, accuracy and specificity as indicated in the results. The algorithm is performs well for both normal beats and PVC beats where QRS complex morphology is abruptly changed.

REFERENCES

[1] M. Goldman, "Principle of Clinical Electrocardiography", 11th ed, , Los Altos, California 94022, Lange Medical Publication, Drawer L.

[2] C. Li, C. Zheng, C. Tai, "Detection of ECG characteristic points by wavelet transforms", IEEE Trans. on Biomedical Engineering, vol. 42, no. 1, pp 21-28, 1995.I.

[3] Y.H.Hu, W.J.Tompkins, J.L. Urrusti, V.X. Afonso, "Applications of artificial neural network for ECG signal detection and classification", Journal of Electrocardiology, vol. 26 (suppl.), pp. 66-73, 1993.

[4] S.Osowski, L.T. Hoai, "ECG beat recognition using fuzzy hybrid neural network", IEEE Trans. on Biomedical Engineering, vol. 48, no. 11, pp. 1265-1271, 2001.

[5] R. Poli, S. Cagnoni, G. Valli, "Genetic design of optimum linear and nonlinear QRS detectors", IEEE Trans. Biomed. Eng., vol. 42, pp. 1137–1141, 1995.

[6] S.Pal, M.Mitra, "Measurement of ECG characteristic points using multiresolution wavelet analysis based selective coefficient method", Elsevier Measurenent, vol. 43, Issue 2, pp. 255–261, 2010.

[7] N.E.Huang,Z.Shen, R.L.Long,M.C.Wu,H.H.Shih,Q.Zheng,N.CYen,C.C.Tung,H.H.Liu,"The empirical mode decomposition and hilbert spectrum for nonlinear and non-ststionary time series analysis", Proceedings of the royal society A:Mathematical, Physical and Engineering sciences, vol.454,no. 1971, pp.903-995,1998.

[8] Y. Zhang, Y. Gao, L. Wang, J. Chen, X. Shi, "The removal of wall components in Doppler Ultrasound Signals by using the Empirical Mode Decomposition Algorithm", IEEE Transactions in Biomedical Engineering, Vol. 54, No. 9, pp. 1631-1642, 2007.

[9] M.B. Velasco, B. Weng, K.B. Barner, "ECG signal denoising and baseline wonder correction based on the empirical mode decomposition", Comput. Bio. Med., Vol. 38, pp. 1-13, 2008.

[10] Md. Abdullah Arafat, Md. Kamrul Hasan, "Automatic detection of ECG wave boundaries using empirical mode decomposition" Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP 2009), pp. 461-464.

[11] www.physionet.org