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Detection of QRS Complexes in ECG Signals Based on Empirical Mode Decomposition

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Detection of QRS Complexes in ECG Signals Based on Empirical Mode Decomposition

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Abstract - Arrhythmia is one kind of diseases that gives rise to the death and possibly forms the immedicable danger. The most common cardiac arrhythmia is the ventricular premature beat. The main purpose of this study is to develop an efficient arrhythmia detection algorithm based on Empirical Mode Decomposition (EMD). This algorithm requires the following stages: band-pass Butterworth filters, Empirical Mode Decomposition, sum the first three Intrinsic Functions Mode (IMFs), and take its absolute value, retain the amplitudes, find the position of the maximum. The excellent performance of the algorithm is confirmed by a sensitivity of 99.82 % (204 false negatives) and a positive predictivity of 99.89% (114 false positives) against the MIT-BIH arrhythmia database.

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I. Introduction

The Electrocardiogram signal which represents the electric activity of the heart is characterized by a periodic behaviour or quasi periodical. It is typically composed of three called significant waves; P wave, QRS complex and T wave (see fig.1). The detection of the R-peaks and consequently of the QRS complexes in an ECG signal provides information on the heart rate, the conduction velocity, the condition of tissues within the heart as well as various other abnormalities and, thus, it supplies evidence to support the diagnoses of cardiac diseases. For this reason, it has attracted considerable attention over the last three decades.

The algorithms in the relevant bibliography adapt a range of different approaches to yield a procedure leading to the identification of the waves under consideration. These approaches are mainly based on derivative-based techniques [1], [2], *classical* digital filtering [3]–[5], adaptive filtering [6], [7], Tompkins method [8],wavelets [9], Christov's algorithm [10], genetic algorithms [11], Hilbert Transform [12] and zero-crossing-based identification techniques [13].

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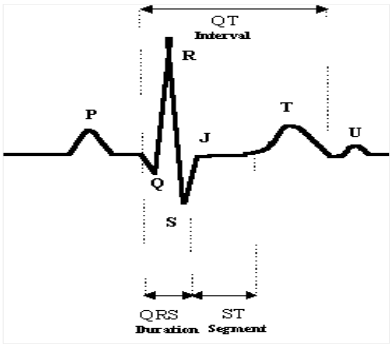


Fig.1 : An ECG bit with typical parameter values.

The Empirical Mode Decomposition (EMD) is a new method designed by N. E. Huang for nonlinear and non-stationary signal analysis [14]. The key part of this method is that any complicated data set can be decomposed into a finite and often small number of Intrinsic Mode Functions (IMFs) that admits well behaved Hilbert transforms. This decomposition method is adaptive, and, therefore, highly efficient. Since the decomposition is based on the local characteristic time scale of the data, it is applicable to nonlinear and non-stationary processes.

The major advantage of the EMD is that the basis functions are derived from the signal itself. Hence, the analysis is adaptive, in contrast to the wavelet method where the basis functions are fixed. In this paper, a detection method based on the EMD approach is proposed. The EMD is based on the sequential extraction of energy associated with various intrinsic time scales of the signal starting from finer temporal scales (high frequency modes) to coarser ones (low frequency modes). The total sum of the IMFs matches the signal very well and therefore ensures completeness.

In this paper, the EMD is used for ECG QRS complex detection. Therefore, the algorithm consists of several steps, namely, band-pass Butterworth filter, decomposition of the ECG signal into a collection of AM–FM components (called Intrinsic Mode Functions (IMF)), sum the first three Intrinsic Functions Mode (IMFs), and take its absolute value, retain the amplitudes, find the position of the maximum.

The proposed algorithm is evaluated by using the ECG MIT–BIH database [15] and is compared to

other methods. As we will show later, very promising results are obtained.

II. Empirical Mode Decomposition

A new non-linear technique, called Empirical Mode Decomposition method, has recently been developed by N.E.Huang *et al* for adaptively representing non-stationary signals as sums of zero mean AM-FM components. EMD is an adaptive, high efficient decomposition with which any complicated signal can be decomposed into a finite number of Intrinsic Mode functions (IMFs). The IMFs represent the oscillatory modes embedded in the signal, hence the name Intrinsic Mode Function.

The starting point of EMD is to consider oscillations in signals at a very local level. It is applicable to non-linear and non-stationary signal such as ECG signal.

An Intrinsic Mode function is a function that satisfies two conditions:

i. The number of extrema and the number of zero crossings must differ by at most 1.
ii. At any point the mean value of the envelope defined by maxima and the envelope defined by minima must be zero.

a) Sifting Process

The basic principle of this method is to identify the intrinsic oscillatory modes by their characteristic time scales in the data empirically and then decompose the data.

A systematic way to extract the IMFS is called the Sifting Process and is described below:

1. Identify all the extrema (maxima and minima) of $x(t)$.
2. Find the upper envelope $e_{\max}(t)$ of the $x(t)$ by passing a natural cubic spline through the maxima, and similarly, find the lower envelope $e_{\min}(t)$ of the minima.
3. Compute the average:

$$m(t) = [e_{\min}(t) + e_{\max}(t)]/2 .$$

4. Get an IMF candidate from $h(t) = x(t) - m(t)$ (extract the detail).
5. Check the weather properties $h_i(t)$ is an IMF. If $h_i(t)$ is not an IMF, repeat the procedure from step 1. If $h_i(t)$ is an IMF, then set $r = x(t) - h_i(t)$ and then $h_i(t) = c_i$.

The procedure from step 1 to step 5 is repeated by sifting the residual signal. The sifting processing ends when the residue r satisfies a predefined stopping criterion. The $h_i(t)$ $(i = 1.....n)$ are being sorted in descending orders of frequency. Finally, the original $x(t)$ can be reconstructed by a linear superposition as given in equation 1.

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{1}$$

In practice, after a certain number of iterations, the resulting signals do not carry significant physical information. To prevent this, we go for some boundary conditions. We can stop the sifting process by limiting the normalized standard deviation (SD).

The SD is defined as:

$$SD = \sum_{t=0}^{T} \frac{\left|h_{1(k-1)}(t) - h_{1k}(t)\right|^2}{h_{1(k-1)}^2(t)} \tag{2}$$

The SD is set between 0.2 and 0.3 for proper results [14]. When the SD is smaller than a threshold, the first IMF component from the data, designated as

$$c_1(t) = h_{1k}(t) \tag{3}$$

is obtained. Then $c_1(t)$ is separated from $x(t)$ to obtain

$$x(t) - c_1(t) = r_1(t) \tag{4}$$

Since the residue, $r_1(t)$ still contains information of longer period components, it is treated as the new data and subjected to the same sifting process as described above. This procedure can be repeated on all the subsequent $r_i(t)$, and the result is

$$r_{i-1}(t) - c_i(t) = r_i(t), \quad i = 1,....., N \tag{5}$$

where $r_0(t) = x(t)$ and $c_i(t)$ is the ith IMF of $x(t)$. The whole procedure terminates either when the component $c_n(t)$ or the residue $r_n(t)$ becomes very small or when the residue $r_n(t)$ becomes a monotonic function. Combining equation 4 and equation 5 yields the EMD of the original signal.

The sifting process was applied on an ECG signal to obtain the various IMFs. This has been represented in Fig.2 and Fig.3. The EMD method is a powerful tool for analyzing ECG signal. It is very reliable as the base functions depend on the signal itself. EMD is very adaptive and avoids diffusion and leakage of signal.

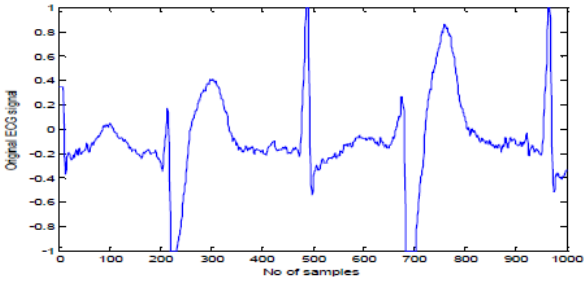


Fig.2 : An ECG signal (201 of MIT-BIH database) containing 1000 samples.

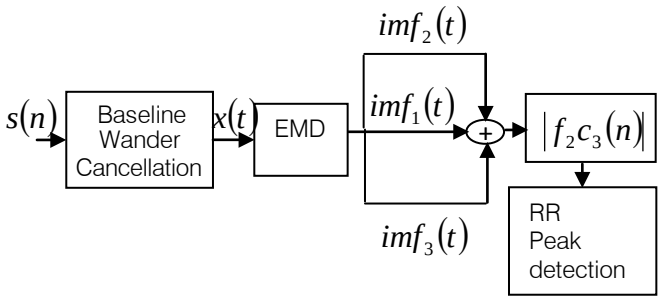


Fig.3 : The various IMFs of the ECG signal.

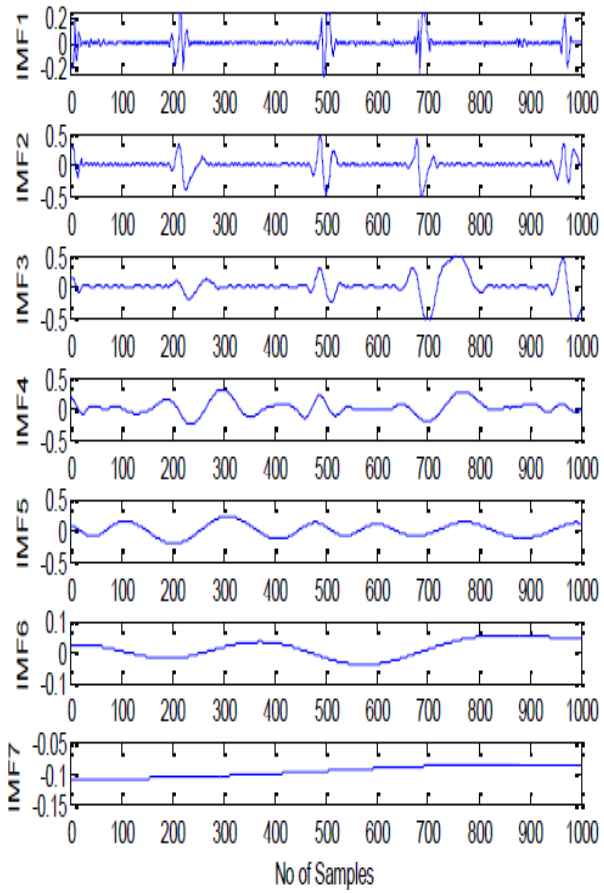


Fig.4 : Block diagram describing the structure of our QRS complex detection.

III. Description of the Implemented Method

Fig.4 illustrates a block diagram describing the structure of our QRS complex detection algorithm. It consists of three blocs: Band-Pass Filter, Empirical Decomposition signal, sum the first three Intrinsic Functions Mode IMFs, take its absolute value, retain the amplitudes, and finally, find the position of the maximum.

a) Preprocessing

We first apply a moving average filter of order 5 to the signal. This filter removes high frequency noise like interspersions and muscle noise. Then, drift suppression is applied to the resulting signal. This is done by a high pass filter with a cut off frequency of 1Hz. Finally, a low pass Butterworth filter with a limiting frequency of 30 Hz is applied to the signal in order to suppress needless high frequency information even more. Fig.5 illustrates respectively; noisy ECG signal (record 101) $s(n)$, and the resulting filtered ECG signal $s_r(n)$.

b) Decomposing ECG into IMFs

The primary EMD is applied on $x(t)$ and the IMFs are obtained to locate the fiducial points in the ECG signal. The EMD of $x(t)$ (equation 1) is given by [14], where $c_i(t)$ is the *i*th IMF and $r_n(t)$ is the residue.

The IMFs are obtained by applying EMD on the filtered ECG signal $x(t)$. These IMFs and the ECG signal are then used to determine the fiducial points of the ECG signal.

c) R Peak Detection

Since the R wave is the sharpest component in the ECG signal, it is captured by the lower order IMFs which also contain high frequency noise. Past analysis using the EMD of clean and noisy ECG indicates that the QRS complex is associated with oscillatory patterns typically presented in the first three IMFs [16].

In our analysis, we have also found similar results. We denote the sum of first three IMFs as fine to coarse three, $f_2c_3(t)$ given by

$$f_2c_3(t) = \sum_{i=1}^{3} c_i(t) \qquad (6)$$

The oscillations associated with QRS complex in $f_2c_3(t)$ are much larger than those due to noise. Fig. 6 shows $f_2c_3(t)$ with $x(t)$ for a single ECG beat. It reveals that the R-peak in the ECG signal is detected by the peak of $f_2c_3(t)$.

Therefore, the R-peak detection comprises the following steps which are also illustrated in Fig. 7 for a series of ECG beats.

(I) Sum the first three IMFs to get $f_2c_3(t)$ and take its absolute value as $a(t)$.

(II) Retain the amplitudes of $a(t)$ larger than a threshold, T, where T is statistically selected to be half of the maximum value of $a(t)$ and make others zero. This eliminates the noise.

(III) Find the position of the maximum of a segment of time duration t_R starting from the first non zero value of $a(t)$ (Fig. 7). This is the first R-peak position. Similarly, find all other R-peak positions until the end of $a(t)$ is reached.

According to the width of QRS complex which is normally 100 ms with variation of $\pm$20 ms [6], we select t_R to be about 200 ms. We have considered the absolute value of $f_2c_3(t)$ since R-wave, and thus $f_2c_3(t)$, give a negative peak in some ECG leads.

After finding the R-peak position, t_0, we can find whether the peak is positive or negative from the value of $f_2c_3(t_0)$. If $f_2c_3(t_0)$ is positive, then the R-peak is positive since the base of $f_2c_3(t)$ is zero.

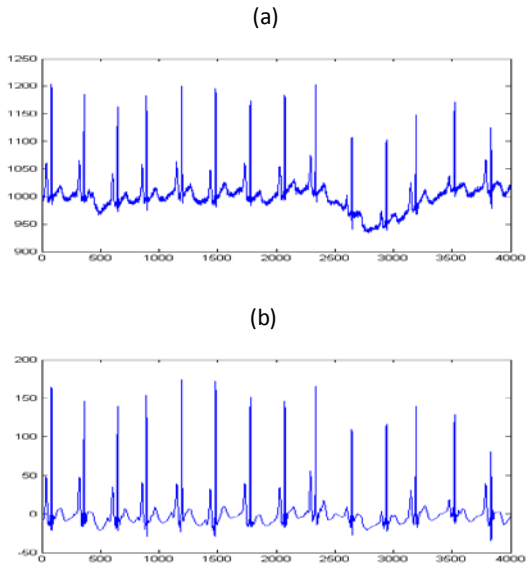


Fig.5 : (a) original ECG signal 222; (b) output of the band-pass Butterworth filter.

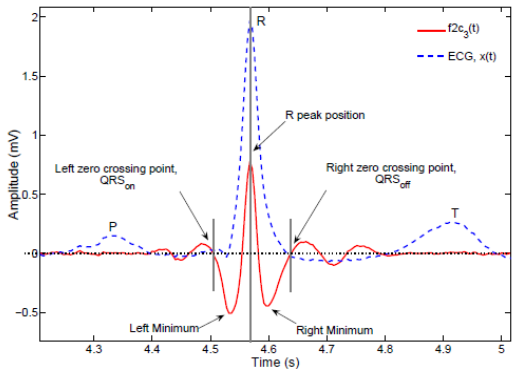


Fig.6 : Illustration of the QRS complex detection.

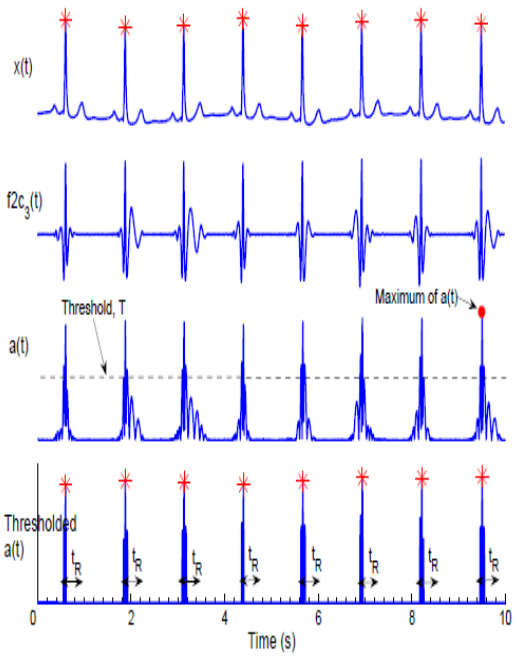


Fig.7 : steps for the R-peak detection.

IV. Results and Discussion

The algorithm was tested against a standard ECG database, i.e. the MIT-BIH Arrhythmia Database. The database consists of 48 half-hour ECG recordings and contains approximately 109,000 manually annotated signal labels. ECG recordings are two channel, however for the purpose of QRS complex detection only the first channel was used (usually the MLII lead). Database signals are sampled at the frequency of 360 Hz with 11-bit resolution spanning signal voltages within $\pm$5 mV range.

QRS complex detection statistic measures were computed by the use of the software from the Physionet Toolkit provided with the database. The two most essential parameters we used for describing the overall performance of the QRS complex detector are: sensitivity Se and positive predictivity +P.

The sensitivity and positive predictivity of the detection algorithms are computed by

$$Se = \frac{TP}{TP + FN} \quad (7)$$

$$+P = \frac{TP}{TP + FP} \quad (8)$$

where TP is the number of true positives, FN the number of false negatives, and FP the number of false positives [17]. The sensitivity reports the percentage of true QRS complexes that were correctly detected. The positive predictivity reports the percentage of detected QRS complexes which were in reality true QRS complexes.

Table.1 shows he results of the algorithm for all the records of the MIT-BIH. Figures 8, 9, 10, 11, and 12 give detection examples performed over tapes from MIT-BIH database. The exact QRS complexes are almost found correctly.

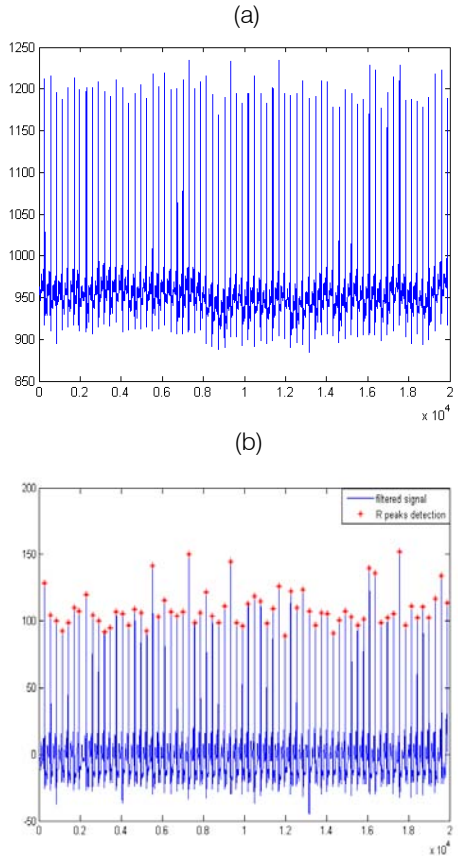
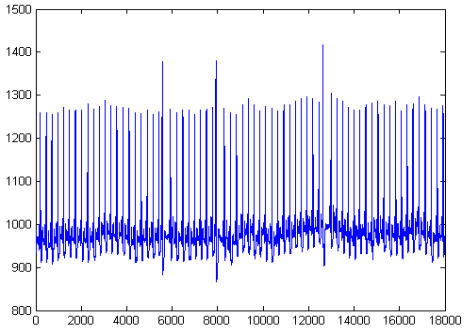


Fig.8 : (a) original ECG signal 100; (b) output of the band-pass Butterworth filter (in blue) and QRS detected (in red).

Record No.	Total (No. of beats)	FP	FN	Se	P
100	2273	0	0	100	100
101	1865	0	0	100	100
102	2187	0	1	99.95	100
103	2084	0	0	100	100
104	2230	2	1	99.96	99.91
105	2572	0	3	99.88	99.61
106	2027	5	2	99.90	99.75
107	2137	0	0	100	100
108	1763	7	14	99.21	99.60
109	2532	0	2	99.92	100
111	2124	0	1	99.95	100
112	2539	0	0	100	100
113	1795	0	0	100	100
114	1879	0	0	100	100
115	1953	0	0	100	100
116	2412	0	14	99.42	100
117	1535	1	0	100	99.93
118	2275	0	0	100	100
119	1987	0	0	100	100
121	1863	0	1	99.95	100
122	2476	2	0	100	99.92
123	1518	0	0	100	100
124	1619	0	1	99.94	100
200	2601	2	10	99.62	99.92
201	1963	0	15	99.24	100
202	2136	1	2	99.91	99.95
203	2982	2	29	99.03	99.93
205	2656	0	7	99.74	100
207	1862	14	26	98.60	99.24
208	2956	0	10	99.66	100
209	3004	8	1	99.97	99.73
210	2647	4	15	99.4	99.85
212	2748	1	0	100	99.96
213	3251	2	3	99.91	99.94
214	2262	4	3	99.87	99.82
215	3363	6	1	99.9	99.82
217	2208	1	1	99.95	99.95
219	2154	3	10	99.54	99.86
220	2048	2	0	100	99.90
221	2427	15	1	99.96	99.39
222	2484	0	5	99.80	100
223	2605	1	11	99.58	99.96
228	2053	14	2	99.90	99.32
230	2256	2	5	99.78	99.91
231	1886	0	0	100	100
232	1780	5	1	99.94	99.72
233	3079	0	1	99.97	100
234	2753	0	5	99.82	100
Total	109809	114	204	99.82	99.89

Table.1 : Performance of the algorithm using MIT/BIH database.

(a)



(b)

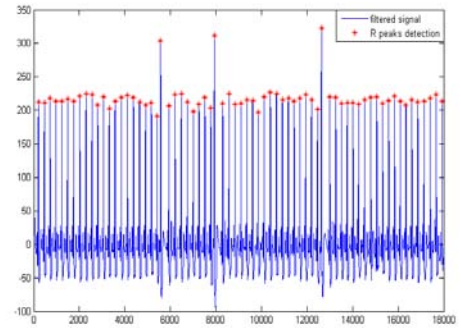
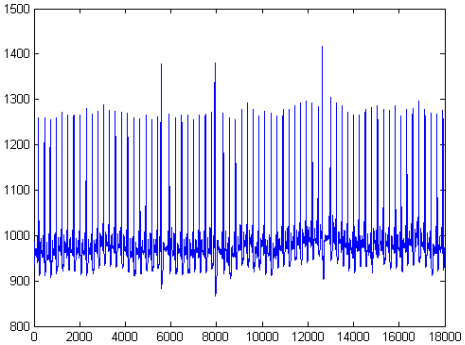


Fig.9 : (a) original ECG signal 105; (b) output of the band-pass Butterworth filter (in blue) and QRS detected (in red).

(a)



(b)

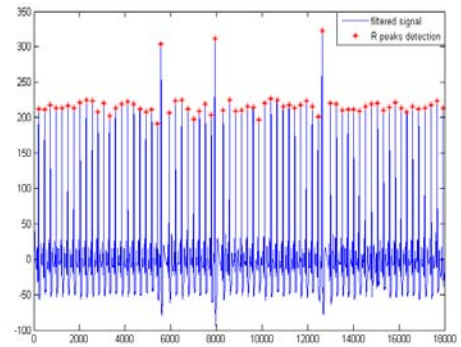
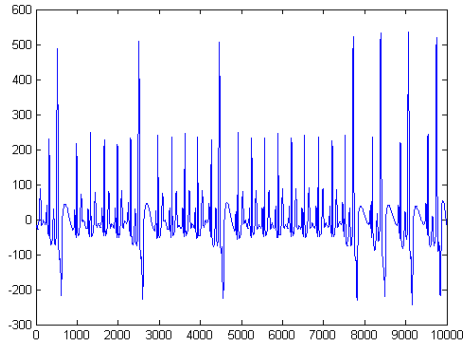


Fig.10 : (a) original ECG signal 108; (b) output of the band-pass Butterworth filter (in blue) and QRS detected (in red).

(a)



(b)

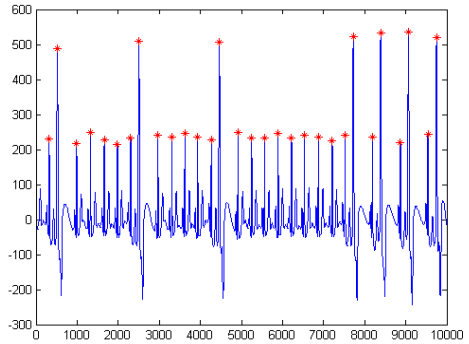
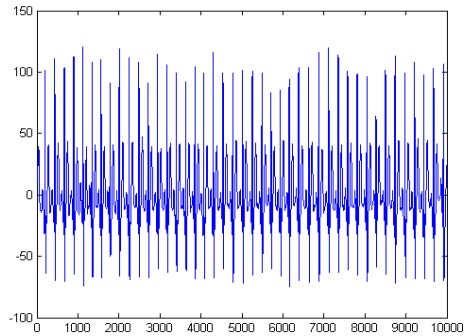


Fig.11 : (a) original ECG signal 119; (b) output of the band-pass Butterworth filter (in blue) and QRS detected (in red).

(a)



(b)

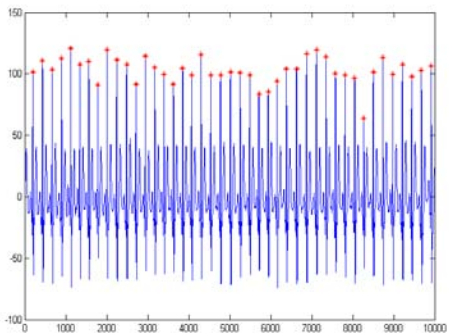


Fig.12 : (a) original ECG signal 219; (b) output of the band-pass Butterworth filter (in blue) and QRS detected (in red).

The average sensitivity of the algorithm is 99.82% and its positive predictivity is 99.89 %. The EMD method is found to have a good sensitivity and predictivity. Moreover this method is much more evolved than others. It is because the fast oscillatory QRS complex is highly detectable in the lower order IMFs irrespective of other characteristic wave amplitude.

Algritms	P (%)	Se (%)
Proposed Algorithm	99.89	99.82
Kohler [13]	88.70	99.57
Pan [8]	99.07	98.55
Zheng [9]	98.07	94.18
Christov's [10]	99.65	99.74
Martineze [18]	99.86	99.80
Madeiro [19]	98.96	98.47

Table.2 : Comparison of the performance.

Comparing the sensitivity and predictivity of the different methods in Table. 2 we find that EMD is a better choice for R peak detection.

V. Conclusion

We have developed a new algorithm based on the EMD for the automatic detection of QRS complex. The algorithm is evaluated for all of records obtained from the MIT-BIH. The proposed algorithm exhibits better performance than the threshold based technique and achieves high sensitivity Se=99.82 % and predictivity P=99.89 % for the QRS complex detection. The EMD method works not only for lead II but also for other leads. Only three lower order IMFs are needed to completely identify the QRS complex in the ECG signal.

References Références Referencias

1. X. Afonso, W.J. Tompkins, and T.Q. Nguyen, S. Luo, "ECG beat detection using filter banks," IEEE Trans. Biomed. Eng. vol. 46, pp. 192–202, 1999.
2. J. Fraden, M.R. Neumann, "QRS wave detection," Med. Biol. Eng.Comput. vol. 18, pp. 125–132, 1980.
3. S.E. Fischer, S. A. Wickline, and C. H. Lorenz, "Novel real-time R wave detection algorithm based on the Vectorcardiogramfor accurate gated magnetic resonance acquisitions," Magn. Reson. Med., vol. 42, no. 2, pp. 361–70, 1999.
4. L. Keselbrener, M. Keselbrener, S. Akselrod, "Nonlinear high pass filter for R-wave detection in ECG signal," Med. Eng. Phys., vol. 19, no. 5, pp. 481–484, 1997.
5. J. Leski, E. Tkacz, "A new parallel concept for QRS complex detector," Proc. 14th Annu. Int. Conf. IEEE Engineering in Medicine and Biology Society, Part 2, Paris, France, pp. 555–556, 1992.
6. A. Kyrkos, E. Giakoumakis, and G. Carayannis "Time recursive prediction techniques on QRS detection problem," Proc. 9th Annu. Conf. IEEE Engineering in Medicine and Biology Society, Boston MA, pp. 1885–1886, 13-16 Nov 1987.
7. K.P. Lin, W.H. Chang, "QRS feature extraction using linear prediction," IEEE Trans. Biomed. Eng., vol. 36, pp.1050–1055, 1989.
8. J. Pan, Tompkins, WJ, "A Real-Time QRS Detection Algorithm," IEEE Transactions on Biomedical Engineering. 1985:32, 230-236.
9. Li C, Zheng C, C. Tai, "Detection of ECG Characteristic Points Using Wavelet Transforms," IEEE Transactions on Biomedical Engineering. 1995:42, 21-28.
10. Ivaylo I. Christov, "Real time electrocardiogram QRS detection using combined adaptive Threshold," BioMed.Eng.Online 3 (2004) 28, ttp://www. biomedical-engineering-online.com/content/3/1/28.
11. R. Poli, S. Cagnoni, and G. Valli, "Genetic design of optimum linear and nonlinear QRS detectors," IEEE Trans. Biomed. Eng., vol. 42, pp. 1137–1141, 1995.
12. S.K. Zhou, J.T. Wang, and J.R. Xu, "The real-time detection of QRS complex using the envelop of ECG," (New Orleans, LA), p. 38, in Proc. 10th Annu. Int. Conf., IEEE Engineering in Medicine and Biology Society, New Orleans, LA, 1988.
13. B.U. Kohler, C. Hennig, R. Orglmeister, "The principles of software QRS detection," Engineering in Medicine and Biology Magazine,IEEE, vol. 21, pp. 42 – 57, Jan.-Feb. 2002.
14. N. E. Huang, Z. Shen, and S. R. Long, M. C. Wu, Shih H. H., Zheng Q., Yen N. C., Tung C. C., Liu H. H., "The empirical mode decomposition and hilbert spectrum for nonlinear and nonstationary time series analysis," Proc.R. Soc. Lond., pp. 454:903{995, 1998.
15. MIT–BIH Arrhythmia Database Directory, Harvard University–Massachusetts Institute of Technology Division of Health Sciences and Technology, July 1992.
16. M. B. Velasco, B. Weng, and K. E. Barner, "ECG signal denoising and baseline wander correction based on the empirical mode decomposition," Comput.Bio. Med., 38:1-13, 2008.
17. (ANSI/AAMI EC57), "Testing and reporting performance results of cardiac rhythm and ST segment measurement algorithms," (AAMI Recommended Practice/American National Standard), 1998.
18. J.P. Martinez, R. Almeida, and S. Olmos, A. Rocha, Laguna P., "Awavelet-based ECG delineator: evaluation on standard databases," IEEE Trans Biomed Eng, 51:570–81, 2004.
19. Joào P.V. Madeiro , Paulo C. Cortez, Francisco I. Oliveira, Robson S. Siqueira., "A new approach to QRS segmentation based on wavelet bases and adaptive threshold technique," IEEE Trans Medical Engineering & Physics 29, pp. 26–37, 2007.