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QRS complex detection using Empirical Mode Decomposition

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ABSTRACT

In this paper, we present a new Empirical Mode Decomposition based algorithm for the purpose of QRS complex detection. This algorithm requires the following stages: a high-pass filter, signal Empirical Mode Decomposition, a nonlinear transform, an integration and finally, a low-pass filter is used. In order to evaluate the proposed technique, the well known ECG MIT–BIH database has been used. Moreover it is compared to a reference technique, namely "Christov's" detection method. As it will be shown later, the proposed algorithm allows to achieve high detection performances, described by means both the sensitivity and the specificity parameters.

1. Introduction

The Electrocardiogram ECG represents the electrical activity of the heart. It is characterised by a number of waves P, QRS, T related to the heart activity. Another wave, called U wave is also present but its importance is not yet identified [1]. A simple model is shown in Fig. 1.

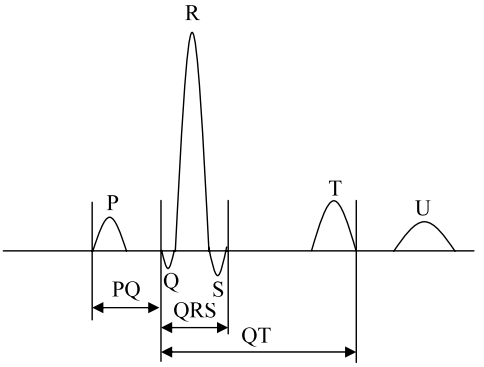

Fig. 1. A simple model of an ECG.

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The QRS complex is a major wave in any normal ECG beat. It corresponds to the depolarization of ventricles. Generally speaking, the duration, the amplitude, and the complex QRS morphology are used for the purpose of cardiac arrhythmias diagnosis, conduction abnormalities, ventricular hypertrophy, myocardial infarction, electrolyte derangements, etc.

Various signal analysis can be employed in these cases, such as Fourier or wavelet based techniques [2], algorithms using artificial neural networks [16] and genetic algorithms [17]. In 1998, a new signal analysis technique has been proposed by Huang et al. [3], called Empirical Mode Decomposition method, or Hilbert–Huang transform. The basis of this technique consists of decomposing any signal into a finite and often small number of intrinsic mode functions. Numerous applications, including the biomedical engineering field, deal with the EMD technique as a tool for analyzing nonstationary signals. For the purpose of ECG analysis, one can evoke some works such as the one proposed in [4], used for the purpose of denoising and baseline wander correction.

In this paper, the EMD is used for ECG QRS complex detection. Therefore, the algorithm consists of several steps, namely, high-pass filtering, decomposition of the ECG signal into a collection of AM–FM components (called Intrinsic Mode Functions (IMF)), nonlinear transform, integration and finally we use a first-order low-pass Butterworth filter to obtain a unique maximum for each QRS complex.

The proposed algorithm is evaluated by using the ECG MIT–BIH database [5] and is compared to "Christov's" method [6]. As we will show later, very promising results are obtained.

2. Empirical Modal Decomposition description

The EMD is defined by a process called sifting. It decomposes a given signal $x(t)$ into a set of AM–FM components, called Intrinsic Mode Functions (IMF). Therefore, K modes $d_k(t)$ and a residual term $r(t)$ [7,8] are obtained and expressed by:

$$x(t) = \sum_{k=1}^{K} d_k(t) + r(t), \quad k = 1, 2, \ldots, K. \tag{1}$$

The EMD algorithm is summarized by the following steps:

1. Start with the signal $d_l(t) = x(t)$, $k = 1$. Sifting process $h_j(t) = d_k(t)$, $j = 0$.
2. Identify all local extrema of $h_j(t)$.
3. Compute the upper (*EnvMax*) and the lower envelopes (*EnvMin*) by cubic spline lines interpolation of the maxima and the minima.
4. Calculte the mean of the lower and upper envelopes,

$$m(t) = \frac{1}{2}\big(EnvMin(t) + EnvMax(t)\big). \tag{2}$$

5. Extract the detail $h_{j+1}(t) = h_j(t) - m(t)$.
6. If $h_{j+1}(t)$ is an IMF, go to step 7, else, iterate steps 2 to 5 upon the signal $h_{j+1}(t)$, $j = j + 1$.
7. Extract the mode $d_k(t) = h_{j+1}(t)$.
8. Calculate the residual $r_k(t) = x(t) - d_k(t)$.
9. If $r_k(t)$ has less than 2 minima or 2 extrema, the extraction is finished $r(t) = r_k(t)$. Else iterate the algorithm from step 1 upon the residual $r_k(t)$, $k = k + 1$.

Fig. 2 shows the original ECG (record 219) decomposition using the EMD. IMFs are represented from high to low frequencies.

3. Description of the implemented method

Fig. 3 shows a block diagram of our QRS complex detection algorithm. This algorithm requires the following stages: High-pass filter, Empirical Mode Decomposition signal, nonlinear transform, integration and finally, a low-pass filter.

The proposed detection algorithm is evaluated on some reference ECG signals, available from the universal MIT–BIH arrhythmia database [5]. These signals are sampled at 360 Hz having a resolution of 5 μV/bit.

3.1. Baseline wander cancellation

Frequencies in the range of 0–1 Hz should be removed to reduce the influence of the baseline wander. This is achieved by the implementation of a fifth-order high-pass Butterworth filter. Fig. 4 emphasizes clearly this baseline removing, obtained from the record 222. The ECG signal after baseline wander cancellation is denoted ecg_{hp}.

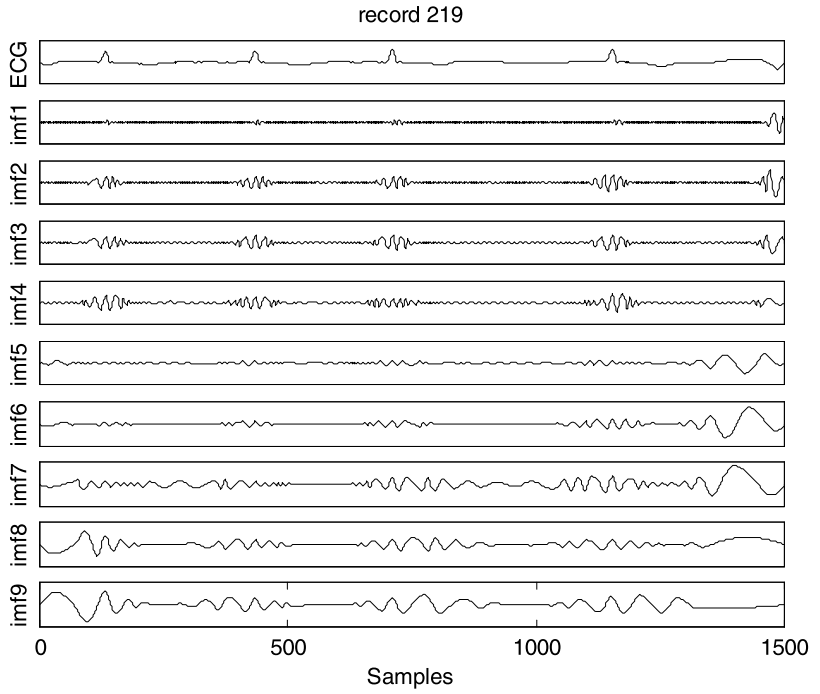

Fig. 2. The original ECG (record 219) and all the IMFs from first to ninth order obtained after Empirical Modal Decomposition.

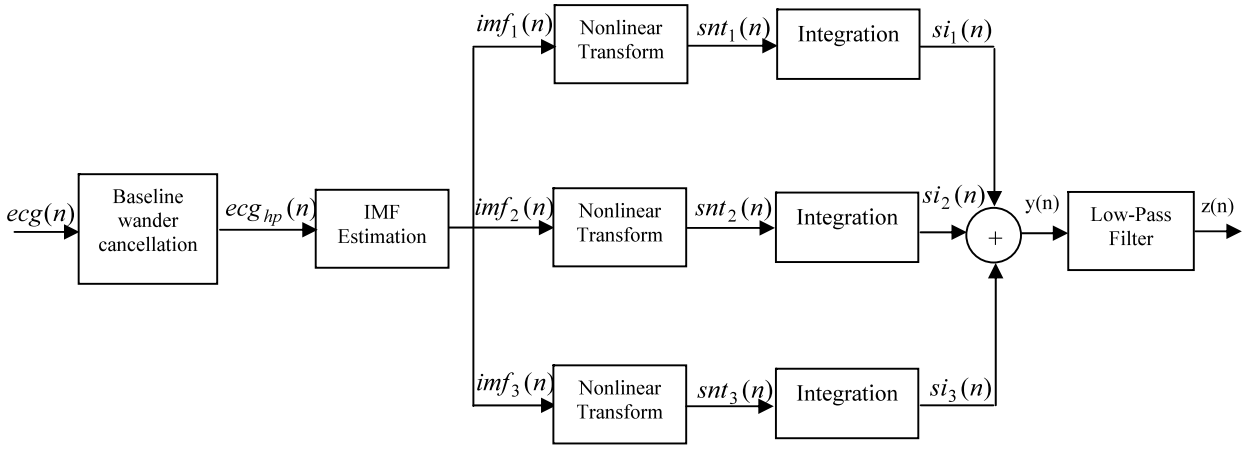

Fig. 3. Block diagram of our QRS complex detection algorithm.

3.2. IMF estimation of the ECG signal

IMF estimation can be applied to the ecg_{hp} signal. In our algorithm, we decompose the ecg_{hf} signal into a sum of three intrinsic mode functions, namely (*IMFs*), $imf_1(n)$, $imf_2(n)$ and $imf_3(n)$, as illustrated in Fig. 5, which contains enough information about the slope of the QRS complex. In the case of small-duration QRS complex, we use only two IMFs.

3.3. Nonlinear transform

After IMF estimation, we applied a nonlinear transform (see Fig. 6.c) [9,10], as follows:

$$y(n) = \begin{cases} abs(x(n) * x(n-1) * x(n-2)), & \text{if } x(n), x(n-1), x(n-2) \text{ have the same sign,} \\ 0, & \text{otherwise,} \end{cases} \tag{3}$$

where:

$$x(n) = imf_k(n) \quad \text{and} \quad y(n) = snt_k(n).$$

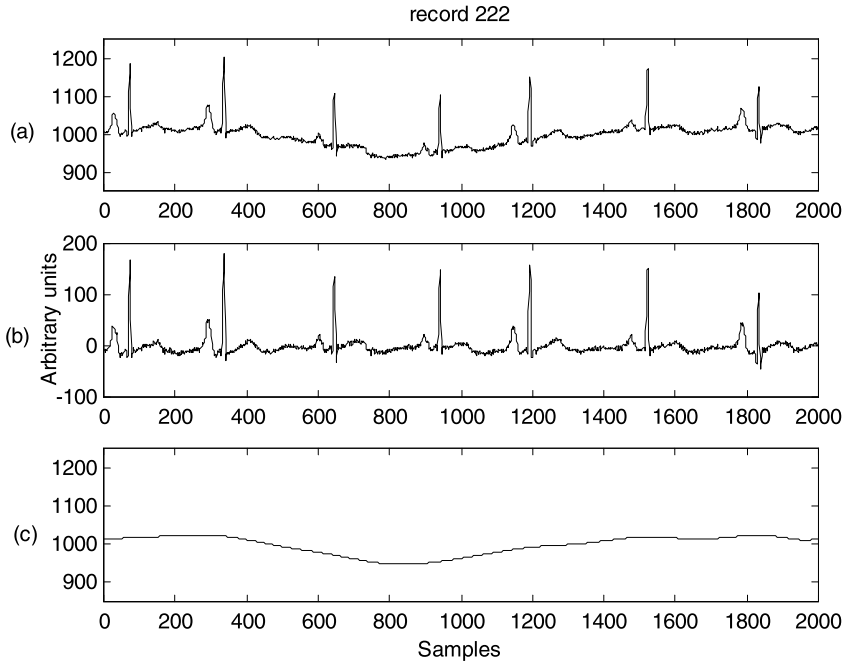

Fig. 4. (a) The original ECG signal ($ecg(n)$); (b) output of the high-pass Butterworth filter ($ecg_{hp}(n)$); (c) baseline noise separated from ECG.

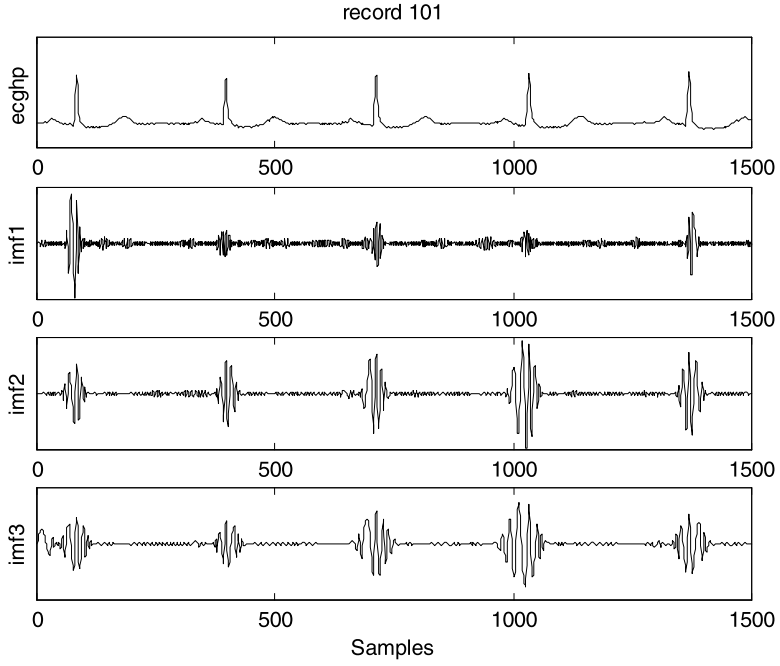

Fig. 5. IMF estimation of the ECG signal after high-pass filtering.

3.4. Integration

In order to produce a signal that includes information about the slope and the QRS with, a moving window integrator is used (see Fig. 6.d) [14,11]. This is calculated from

$$si_k(n) = \left(\frac{1}{M}\right)\big(snt_k\big(n-(M-1)\big) + snt_k\big(n-(M-2)\big) + \cdots + snt_k(n)\big), \tag{4}$$

where M is the number of samples corresponding to the integration window [14].

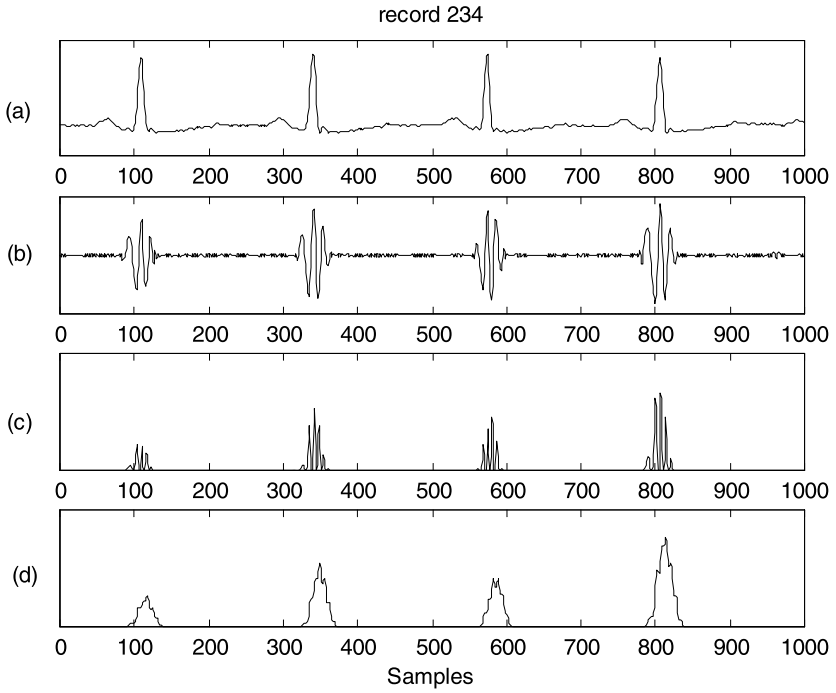

Fig. 6. Nonlinear transform and integration steps: (a) ECG signal ($ecg_{hp}(n)$); (b) one of the three IMFs (imf_1 or imf_2 or imf_3); (c) output from the nonlinear transform ($snt_k(n)$); (d) output from the moving window integrator ($si_k(n)$).

The number of samples M in the moving window is important. Generally, the width of the window should be approximately the same as the widest possible QRS.

Next, we calculate $y(n)$, that is:

$$y(n) = \sum_{k=1}^{3} si_k(n). \tag{5}$$

3.5. Low-pass filter and R-position definition

In order to obtain a unique maximum for each QRS complex, we use a first-order low-pass Butterworth filter [12,13] (see Fig. 7.c). The cut-off frequency at -3 dB is about 1 Hz or 2 Hz. The resulting signal $z(n)$, contains only the R-position Rp.

4. Experimental results and discussion

We used the MIT–BIH arrhythmia database to evaluate our algorithm [5]. Table 1 summarizes the detection performance of our algorithm compared to "Christov's" method [6]. The results are: sensitivity Se = 99.84% and specificity Sp = 99.92%. The sensitivity Se and the specificity Sp are normally computed by:

$$\mathrm{Se} = 1 - \frac{\mathrm{FN}}{\mathrm{TP}+\mathrm{FN}} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}, \tag{6}$$

$$\mathrm{Sp} = 1 - \frac{\mathrm{FP}}{\mathrm{TP}+\mathrm{FP}} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}. \tag{7}$$

A false positive (FP) indicates that the algorithm detects a beat when no beat is present; whereas, a false negative (FN) indicates that the algorithm failed to detect a real beat. TP (true positive) stands for the beat, properly detected.

Consequently, based on the obtained results, the proposed technique outperforms "Christov's" method.

About the execution time, the "Christov's" method performs better than our algorithm. In fact, the number of calculations to decompose an ECG signal by the EMD quickly increases with its size, which involves a considerable computation time. In order to solve this problem, we implement the EMD algorithm in C language with Matlab interface [15].

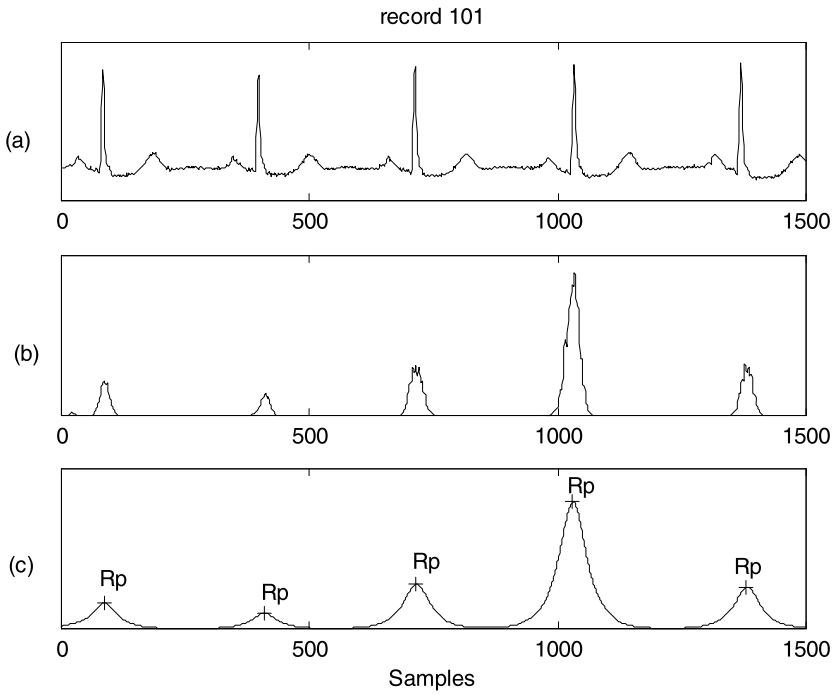

Fig. 7. R-position definition: (a) ECG signal (record 101); (b) $y(n)$ signal ($y(n) = si_1(n) + si_2(n) + si_3(n)$); (c) output of the first-order low-pass Butterworth filter ($z(n)$).

Table 1
Results of evaluation of our QRS detection algorithm using MIT/BIH database.

Record (No.)	Total (No. of beats)	Our method		Christov's method			
		FP	FN	Algo. 1		Algo. 2	
				FP	FN	FP	FN
100	2273	0	0	0	0	0	0
101	1865	0	1	4	1	4	1
102	2187	0	0	0	0	0	0
103	2084	0	0	54	2	58	0
104	2230	1	0	1	0	1	0
105	2572	15	09	35	2	36	2
106	2027	3	1	0	1	0	1
107	2137	0	2	0	2	0	0
108	1763	8	34	40	2	42	1
109	2532	0	2	1	11	0	5
111	2124	0	0	0	0	0	0
112	2539	0	0	0	0	0	0
113	1797	0	0	0	0	0	0
114	1879	0	0	0	0	0	0
115	1953	0	0	4	0	4	0
116	2412	0	16	2	22	2	19
117	1535	0	0	0	0	0	0
118	2275	0	0	0	0	0	0
119	1987	0	0	0	0	0	0
121	1863	0	0	0	0	0	0
122	2476	0	0	0	0	0	0
123	1518	1	1	0	2	0	2
124	1619	0	0	0	2	0	0
200	2601	15	10	39	9	41	6
201	1963	16	25	0	60	0	60
202	2136	0	5	0	6	0	6
203	2978	2	36	13	71	27	62
205	2656	0	2	0	4	0	4
207	1862	0	3	0	2	0	1
208	2954	0	5	7	14	7	11
209	3004	0	0	1	0	1	0

Table 1 (*continued*)

Record (No.)	Total (No. of beats)	Our method		Christov's method			
		FP	FN	Algo. 1		Algo. 2	
				FP	FN	FP	FN
210	2647	7	17	1	56	1	44
212	2748	0	0	0	0	0	0
213	3251	0	0	0	3	0	1
214	2262	1	0	1	1	1	4
215	3362	0	0	0	0	0	0
217	2208	1	1	0	3	0	2
219	2154	0	0	0	1	0	1
220	2048	0	0	0	0	0	0
221	2427	0	0	0	1	0	1
222	2484	0	0	0	2	0	0
223	2605	1	0	0	10	0	5
228	2053	4	0	0	0	1	0
230	2256	0	0	0	0	0	0
231	1886	0	0	0	0	0	0
232	1767	9	3	12	0	12	0
233	3076	0	1	0	3	0	2
234	2753	0	0	0	0	0	0
Total	110 050	84	174	215	294	239	240
		Se = 99.84 Sp = 99.92		Se = 99.69 Sp = 99.65		Se = 99.74 Sp = 99.65	

5. Conclusion

In this paper, an EMD based technique is used for the purpose of QRS complex detection. As we have seen previously, the proposed scheme uses, various stages, including, pre-processing, conditioning and post processing. Obtained results, using all ECGs from the MIT/BIH database as an evaluation set, show that more interesting performances compared to "Christov's" method, are obtained.

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