Detection of ECG beat using ensemble empirical mode decomposition

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Abstract

The electrocardiogram (ECG) is the most common non-invasive test possessing a significant clinical value to cardiac disease diagnostic. In this paper, we developed a robust ECG delineation algorithm based on Ensemble Empirical Mode Decomposition (EEMD) which has very interesting properties on pseudo periodic signals. The proposed algorithm consists to identify an optimum and appropriate set of IMFs to reconstruct a complex or wave from ECG signal. First, QRS complexes are delineated by detecting the peaks of individual waves. Then the determination of P and T wave peaks was performed. We evaluated the reliability of our method on two manually annotated databases: QT database and MIT-BIH Arrythmia database. It proves particularly effective in cases of very noisy recordings or with abnormal morphology. A comparison is also made between the proposed method and other delineation system. The results showed a better or comparable performance and accurate fiducial points detection.

1. Introduction

The ECG signal, representing the electrical activity of the heart, is the diagnosis technique of the most common heart disease. It is a non-stationary random signal structured (as shown in Fig. 1) by a succession of waveforms (P, Q, R, S, and T). The analysis of these waves allows the diagnosis of certain cardiac diseases which their detection and characterization prove to be important.

The P wave represents the contraction of the atria. It is a deflection corresponding to the depolarization of the right and left atria. This wave is often positive and of low amplitude. The QRS complex corresponds to a set of deflections due to the depolarization of the ventricles. The T wave is the rest period of the heart. It is a deflection corresponding to ventricular repolarization [1,2]. Any morphological or temporal modification of its events is pathology; changes concerning the rate or frequency are cardiac arrhythmias (fatal diseases). Therefore, extraction and identification of ECG signal parameters are an essential step for any analysis and diagnosis.

Many conventional methods exist to effectively detect fiducial points. These segmentation methods are based on derivative or differential filtering techniques [3-7] or on wavelet transform [8-10]. The wavelet transform provides a description of the signal in the time-scale domain, permitting a temporal description of ECG features at different resolutions. Thus, this technique is useful for ECG analysis, despite it is composed of waves of very different temporal characteristics [11]. The continuous wavelet transform generally contains redundant information on the signal. In practice, we employ discrete wavelet families which are less redundant, and which contain enough information for analysis. The use of DWT in the various works of literature is justified [8-10].

The disadvantage of wavelet methods mentioned above is that P and T waves tend to overlap when the heart rate increases. These waves having the same frequency components, are supposed to meet the same scale. In fact, this tool is not appropriate in this case.

Other methods as in [3,4] are based on derivative digital filtering. Noises and P and T waves are eliminated by bandpass filtering then QRS complex enhancement is performed by nonlinear transformation. With the first and second derivatives, the precise location of the QRS complex is not always guaranteed: sometimes the beginning of this complex is located and other times the end, seeing that the QRS complex frequency band changes from individual to other and for different beats of same individual.

Some segmentation algorithms have been developed to exploit all information on the different pathways as in [5]. These algorithms, based on the calculation of the normalized integral are highly sensitive to fluctuations of the baseline and to noise. As well as, in most cases, one quality derivation is disposed.

In [6], a matched filtering technique is applied to improve the performance of QRS detectors using an artificial neural network approach. The modeling of low-frequency is made by ANN based adaptive filter and for detection of QRS complex the residual signal is filtered by a matched linear filter.

The dECG signal (the derivate of ECG) as presented in [7] is used to analyze the QRS complex. This derivate suppresses P and T waves because it is based on the wave gradient which is greater in the QRS-region than in the non-QRS region. But this method remains difficult to apply in case of waves having high frequency noise.

To implement an efficient ECG delineation algorithm, the extraction of fiducial points that represent the distinctive traits of individual is still a big challenge. In this paper, we proposed a new method for ECG waves detection based on the Ensemble Empirical Mode Decomposition. In fact the EEMD is adopted to decompose the signal into a set of IMFs which are used for the singularity detection. The performance is approved using manually annotated databases: MIT-BIH Arrhythmia [12] and QT [13].

2. Ensemble Empirical Mode Decomposition

Huang et al. [14] have proposed the empirical mode decomposition method. This method addresses the problem of non-stationary signals analysis. Unlike time-frequency representations and wavelet, the EMD decomposition is intrinsic

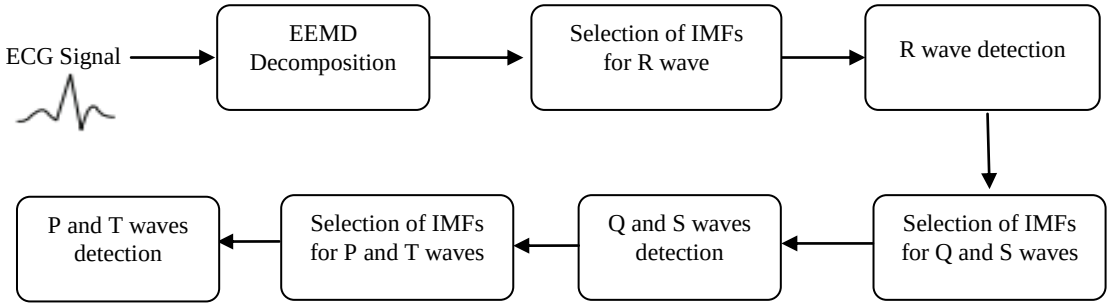

Fig. 1. Description of the adopted algorithm

to the signal. It decomposes a complex in several modes: intrinsic mode function (IMF). These IMFs are simple oscillations with zero mean. The EMD technical performs decomposition into sub-bands very close to what would be obtained with wavelet analysis (multiresolution). Indeed, it explores the signal from the higher frequencies to the lower frequencies. However, this technique suffers from the problem of fusion or mixing mode that is a bank of self-adaptive filters which does not decompose any signal. This problem was resolved by new proposal version of EMD which is the ensemble empirical mode decomposition EEMD.
Given a signal x(t), its principle is the following [15]:

1. We generate Ne Gaussian white noise realizations with the same variance σ_i^2, 1< i <Ne
2. We calculate the noisy signal for each realization,

$$S_i(t) = x(t) + b_i(t) \qquad 1 \le i \le Ne \tag{1}$$

3. We extract the N IMFs of this noisy signal using the original EMD method. The Ne realizations give access to Ne noisy signals which allow the extraction of Ne sets of N IMFs: $IMF_{ki}(t)$, $1 \le k \le N$ and $1 \le i \le Ne$. The IMFs of EEMD method are then the average of these Ne sets of N IMFs.

$$IMF_{EEMD_K} = \frac{1}{Ne}\sum_{i=1}^{Ne} IMF_{ki}(t) \qquad 1 \le K \le N \tag{2}$$

3. Approach Description and Implementation

The adopted approach is based on ensemble Empirical Mode Decomposition for ECG feature extraction. This choice relies on the fact that the IMFs resulting from the decomposition have a similar structure to QRS complex in time scale domain. In order to ensure the presence of low frequency components signal, decomposition is done in ten levels. In fact the reconstructed wave is formed by an appropriate set selection of IMFs. Fig. 1 illustrates the different procedures followed during detection. First, the original signal is decomposed by EEMD technique into IMFs as shown in Fig. 2. Then a suitable choice of the coefficients is made for R peak detection. Once the R point is determined, four IMFs are identified for Q and S peak detection. Finally the relevant coefficients are selected for P and T peak detection.

3.1. R Peak Detection

The robust detection of QRS complex constitutes the prerequisite for any ECG signal analysis. A good detection of this complex requires a better selection of IMFs.

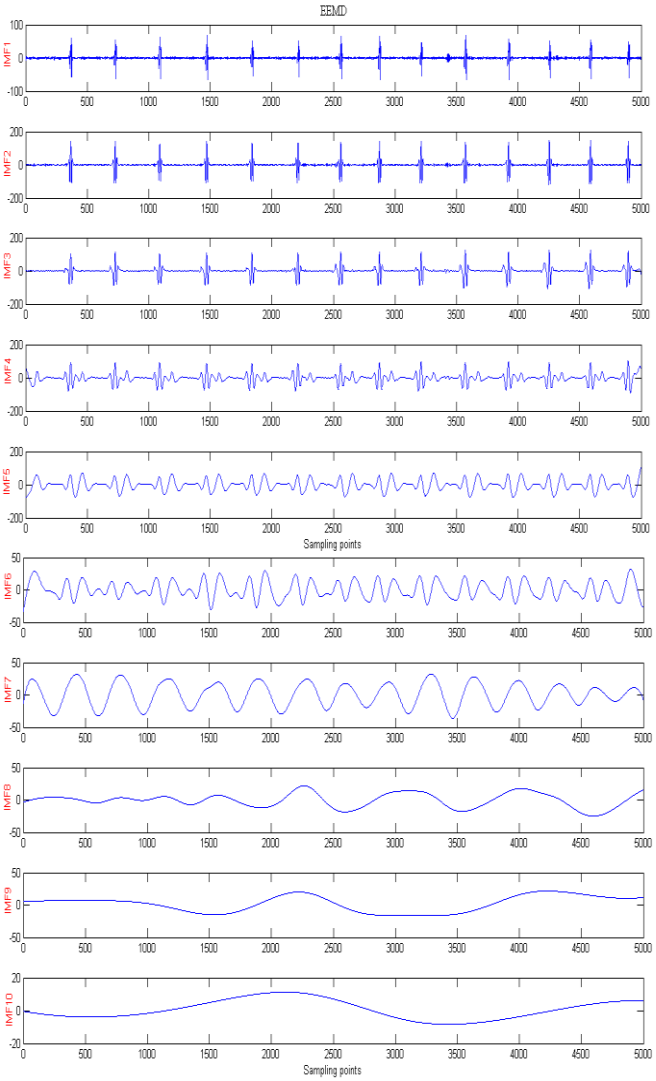

Fig. 2. IMFs obtained by EEMD for levels 1-10

The first point to be determined is the R peak which is manifested by its amplitude. Indeed, once the R peaks are identified, the heart rate can be calculated and various anomalies are detected. The obtained IMFs as shown in Fig. 2, have

arranged from low to high level. As we can see, the oscillations in the first IMFs are primarily designed for the QRS complex which is propagated in the high frequency bands. In fact the IMFs 1, 2 and 3 are used to delineate the QRS complex specifically the R-peak.
A function $f1$ is determined as follows:

$$f1 = IMF1 + IMF2 + IMF3 \quad (3)$$

The representation of this reconstructed wave illustrated in Fig. 3 shows that the QRS region is captured. However, it is difficult to correctly locate the R peak view the presence of oscillations characterized by peaks with varying amplitudes. In order to eliminate these fluctuations another function $f2$ is calculated as follows:

$$f2 = IMF1 \times (IMF2 + IMF3) \quad (4)$$

As shown in Fig. 4, the modulus of f1×f2 is taken. It is clear that the oscillations are suppressed and the QRS complex appears more closely spaced in time.

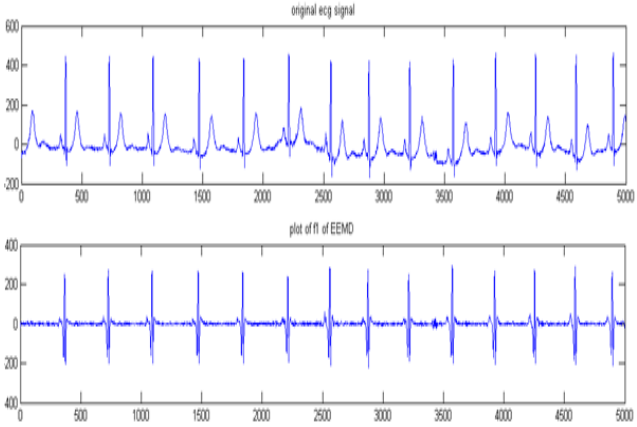

Fig. 3. Original signal and plot of $f1$=IMF1+IMF2+IMF3

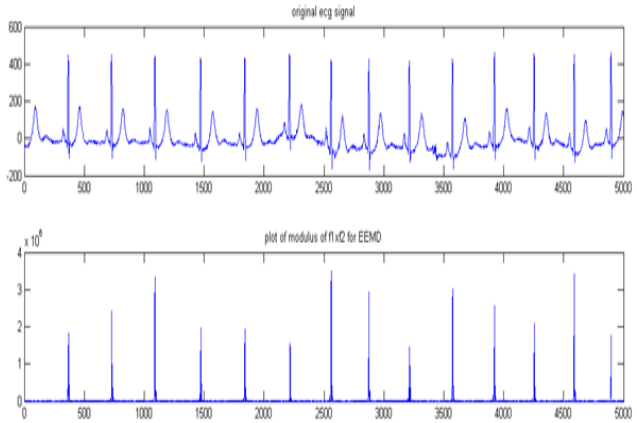

Fig. 4. Original signal and plot of modulus of $f1 \times f2$

Hence the R waves are correctly identified as maximum amplitudes points knowing that no pretreatment is applied to the original ECG signal. The detection results for a healthy subject and with pathology are illustrated in Fig. 5.

3.2. Q and S Peaks Detection

After locating the R peak, it comes to detect Q and S points in order to identify the complete QRS complex. Commonly these two waves have low amplitude and are propagated in the mid-high-frequency bands. Oscillatory models in the first coefficients indicate a link between these models and the complex.

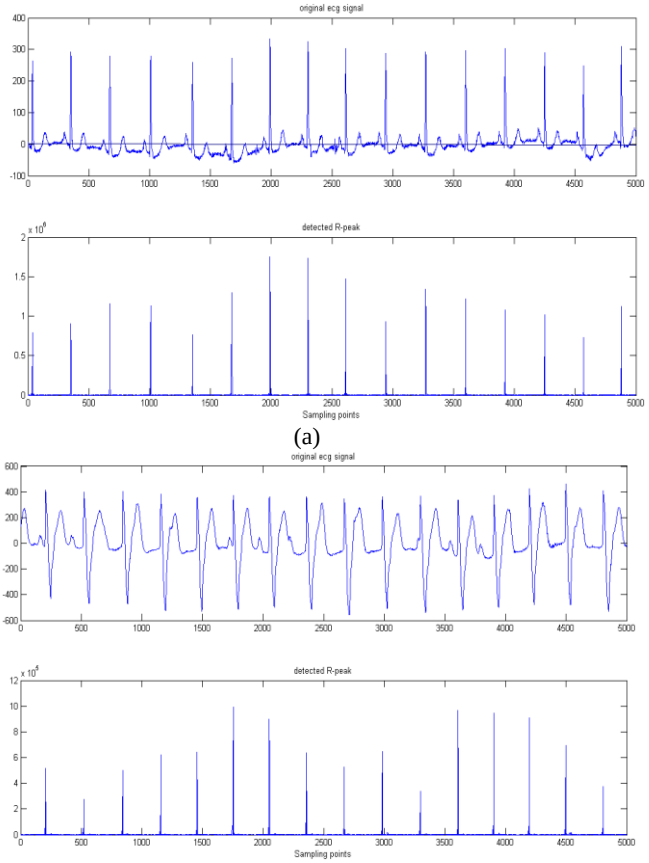

Fig. 5. Detection of R peaks using MIT-BIH Arrhythmia Database: (a) Tape 101, (b) Tape 107: paced beats

For this the IMFs 1 to 4 are preserved such as a function $f3$ is calculated as follows:

$$f3 = IMF1 + IMF2 + IMF3 + IMF4 \quad (5)$$

Fig. 6 illustrates the representation of the reconstruction wave. As shown in this figure, the S point is identified as the local minimum just to the right of the R peak while the Q point is identified as the minimum just to the left of the peak R.

3.3. P and T Peaks Detection

P and T waves delineation is important for medical interpretation of ECG signal. In fact, the energies of these two waves are essentially at the level of IMFs 5, 6 and 7 according

to ECG power spectrum. But, the baseline drift is serious at IMF7, so IMFs 5 and 6 are selected to detect P and T points. The reconstructed wave is determined by the following expression:

$$f4 = IMF5 + IMF6 \quad (6)$$

In Fig. 7, a plot of function $f4$ is shown. Thus, the T wave is identified as the local maximum following the QRS complex while the T wave is identified as the maximum preceding the complex.

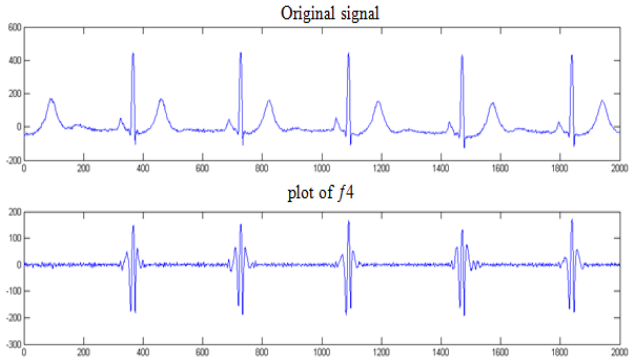

Fig. 6. Original signal and plot of $f3$=IMF1+IMF2+IMF3+IMF4

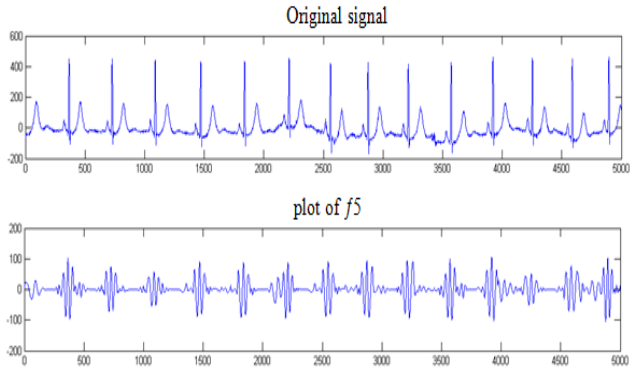

Fig.7. Original signal and plot of $f4$=IMF5+IMF6

4. Results and Analysis

As there is no predefined rule to extract the peak of ECG waves, the evaluation of the delineator is done by manually annotated databases. For these purposes, the signals exploited in this study are taken from some easily available databases such as QT and MIT-BIH Arrhythmia Databases.

The MIT-BIH arrhythmia database contains 48 records obtained from 47 subjects studied by the BIH arrhythmia laboratory. The recordings are sampled at 360 Hz per channel with a resolution of 11 bits over a range of 10 mV. Two cardiologists have independently annotated each electrocardiogram. The QT database includes recordings which have been selected to represent a wide variety of QRS and of morphologies. It actually contains 105 records of fifteen minutes sampled at 250 Hz. MITDB and QTDB are used for evaluating the QRS detection and the QTDB for evaluating the waveform boundary. The manually determined values are compared with the measured values and the measurement accuracy is calculated.

The reliability of the proposed method is evaluated by the sensitivity (Se), which represents the ability to correctly detect beats, and the detection error rate (DER), which expresses the accuracy of the system, and the positive predictivity (P+) which is the discriminability between true and false beats. These parameters are defined as follows:

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

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

$$DER = \frac{FP + FN}{Total \;\; Beat} \quad (9)$$

Where TP means the number of true positive detections, FN is the number of false negative detections and FP is the number of false positive misdetections.

The detection performance on the QT database and MIT-BIH arrhythmia database obtained by our QRS detector and others published detectors are presented in Table I and II. It should be noticed that our method has a higher sensitivity and positive predictivity in comparison to other delineator. It attains Se=99.95% and P+=99.92% (0.13% of DER) for the first database. The performance in the second database is Se=99.95%, P+=99.88% and DER=0.16% over 109521 beats. In fact, the proposed delineator performs well for all signals from the two databases. Its performance in QRS complex detection is high as it provides 100% efficiency in most cases.

Table 3 shows the validation of the proposed EEMD-based approach on the QT database. In this table, the results of P-wave, QRS edges and T-wave detection are presented. The delineation performance proves that our algorithm can detect with excellent sensitivity the P and T waves in the ECG signals: Se=99.92% for P waves and 99.89% for T waves, and can delineate them with low errors: DER=0.16% for P waves and 0.24% for T waves.

The comparison of our results with those of known prior works in Table 4 allows to observe that our method outperforms the others clearly in all waves delineation. It provides a reliable and accurate detection of ECG characteristic. In fact, the sensitivity and the positive predictivity values for the P points: Se=99.92%, P+=99.90% are higher than in [5,8,10,18]; the same applies to the results of T points: Se=99.89% and P+=99.86% .

Finally, the proposed system could suitably delineate the various morphologies of QRS, P and T waves presented in the MIT-BIH and QT databases. Moreover the algorithm presents mathematical simplicity and low computational cost.

5. Conclusion

The proposed method provided a new delineation algorithm of ECG events. It investigated the EEMD techniques for ECG peaks detection using some conventional databases including MITDB, QTDB. This approach is based on the appropriate choice of IMFs for accurate detection.

Table 1. Performance comparison of previously QRS detection algorithms on MIT/BIH arrhythmia database

QRS detector	# annotations	TP	FP	FN	DER(%)	Se(%)	P+(%)
This method	109521	109463	136	58	0.16	99.95	99.88
Pan et al. [3]	109809	109532	507	277	0.71	99.75	99.54
Hamilton et al. [4]	109267	108927	248	340	0.54	99.69	99.77
Martinez et al. [8]	109428	109208	153	220	0.34	99.80	99.86
Li et al. [9]	104182	104070	65	112	0.17	99.89	99.94
Chaffari et al. [10]	109428	109327	129	101	0.21	99.91	99.88
Chaffari et al. [16]	109428	109215	160	213	0.34	99.80	99.85
Moody et al. [17]	109428	107567	94	1861	1.79	98.30	99.91

Table 2. Performance comparison of previously QRS detection algorithms on QT database

QRS detector	# annotations	TP	FP	FN	DER(%)	Se(%)	P+(%)
This method	86892	86851	68	41	0.13	99.95	99.92
Martinez et al. [8]	86892	86824	107	68	0.20	99.92	99.88
Ghaffari et al. [10]	86892	86845	79	47	0.15	99.94	99.91
Ghaffari et al. [16]	86892	86819	94	73	0.19	99.92	99.89
Moody et al. [17]	86892	84458	459	2434	3.33	97.2	99.46

Table 3. Fiducial points detection results on QT database

Fiducial points	Se(%)	P+(%)	DER(%)
R-wave	99.95	99.92	0.13
Q-point	99.82	99.77	0.39
S-point	99.75	99.68	0.56
P-wave	99.92	99.90	0.16
T-wave	99.89	99.86	0.24

Table 4. Performance comparison of delineation algorithms on QT database

Method	Accuracy parameters	P_{peak}	T_{peak}
Our work	Se(%) P+(%)	99.92 99.90	99.89 99.86
Laguna et al. [5]	Se(%) P+(%)	97.7 91.17	99.0 97.74
Martinez et al. [8]	Se(%) P+(%)	98.87 91.03	99.77 99.79
Ghaffari et al. [10]	Se(%) P+(%)	99.46 98.83	99.87 99.80
Plesnik et al. [18]	Se(%) P+(%)	99.06 94.87	99.66 99.66

The results prove that the EEMD algorithm is very promising, in fact verifying our system with the QT Database gave the following results: 99.95% of Se for the QRS complexes, 99.92% for the P waves and 99.89 for the T waves and 99.92% of P+ for the QRS complexes, 99.90% for the P waves and 99.86 for the T waves. The performance of our ECG delineator proves to be more effective as compared to others detectors published. In our future work, we intend to explore the detected fiducial points for studies of beat classification and also for arrhythmia detection.

6. References

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