A Novel Preprocessing Tool to Enhance ECG R-wave Extraction

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Abstract

Various approaches have been proposed to detect the R-waves in the ECG. From the derivative-based to more complicated wavelet transform methods, the main goal of these approaches is to extract the R-waves from the perturbations present in the ECG. Our study aims at proposing a simple preprocessing tool that suppresses perturbations and enhances the R-waves in the ECG. Using sliding windows, short- and long-term signal energies are calculated for each sample in the ECG. A coefficient signal is then created as the ratio between the corresponding short- and long-term energies. The enhanced ECG is then calculated by multiplying the coefficient signal and the original ECG. The MIT-BIH database was used for evaluation and the proposed method was tested against synthetic white and EMG noises. Using the proposed method as a preprocessing tool to the classic Pan-Tompkins approach lead to a significant decrease over the number of false positive and false negative QRS complexes, when synthetic noise is added to ECG.

1. Introduction

Electrical activity within the heart generated in the atria and propagated throughout the heart can be captured at body surface. A time-series representation of these activity, i.e. the electrocardiogram (ECG), comprises different waveforms representing depolarization and repolarization of different sections of the heart. Detection of heartbeats brings useful information that enables studies such as heart rate variability (HRV), cardiac disease diagnostics and the detection of ectopic beats such as premature ventricular contractions (PVC). The QRS complex is the most distinct waveform in the ECG. It corresponds to the contraction of ventricles, and has been mainly used for automatic heartbeat detection. However, the detection of R-waves is not an easy task as perturbations such as power-line interference and base-line wandering can be present in the ECG.

Over the years many R-wave detection algorithms have been proposed. A review of traditional approaches can be found in [1][2]. From basic derivative to complex approaches such as time-frequency analysis, generally the ECG at hand is first filtered by either low-pass filtering in order to remove high frequency activities and remove the effect of power-line interference, or by band-pass filtering to remove the effect of baseline wandering as well as the aforementioned unwanted activities. Then, the filtered ECG is further analyzed in order to extract the R-waves using heuristically chosen features. Pan and Tompkins proposed a detection approach based on the analysis of slope, amplitude and width of the QRS-complexes [3]. Mathematical morphology methods benefit from the shape and location of fiducial points in the QRS-complex and used them to extract R-waves [4][5]. Filter bank and Wavelet methods detect QRS-complexes by investigating modulus maxima in respectively different sub-bands and wavelet scales [6][7].

All QRS complex detection methods aim at finding a suitable mathematical description which can identify the R-wave in the ECG while suppressing perturbations and other ECG waveforms, i.e. P-,T- and U-waves. While complex methods have proven to be powerful R-wave detectors, they are not suitable for low cost and energy consumption scenarios such as body area networks (BAN). In BANs computation cost and power consumption set the limits and therefore fast, energy efficient and yet robust methods are only considered as suitable candidates. In this paper, we aim at proposing a novel, fast and efficient algorithm that can be used as an R-wave detection method or as a preprocessing tool to other R-wave detection methods. The proposed method works based on the relative short- and long-term energies in the ECG and aims at suppressing perturbation while enhancing ECG R-waves.

2. Methods

2.1. Evaluation Data

In order to evaluate the proposed method, the publicly available database of MIT/BIH-arrhythmia database was used [8]. Over the years, this database has become a standard database on which several algorithms have reported their results. The MIT/BIH arrhythmia database has a set of 48 two-lead ECG recordings with a length of 30 minutes with a sampling frequency of 360 Hz and 11-bit resolution within the range of 10 mv. The evaluation on this database

Computing in Cardiology 2016; VOL 43 ISSN: 2325-887X DOI:10.22489/CinC.2016.185-142

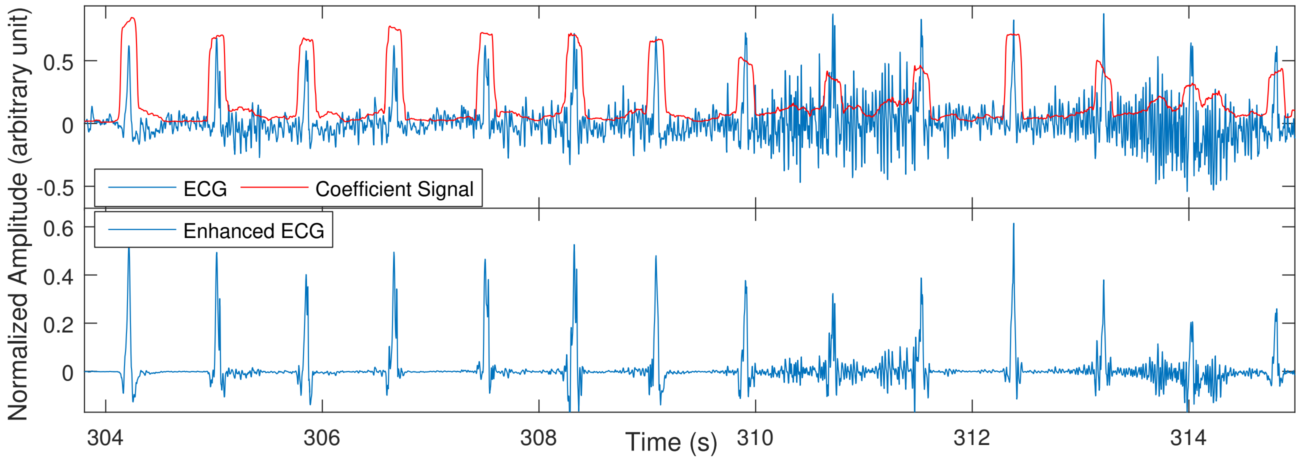

Figure 1. Performance of the relative short-long term energy on Tape 104 of the MIT/BHT arrhythmia database.

was performed on the first lead, which is either a modified lead II or lead V5, and results were checked with the reference annotation file provided for this database.

2.2. Method Outline

By analyzing the QRS complex in noisy ECG recordings, we came to the understanding that even in cases where severe levels of noise are presents in the ECG, QRS complexes are discernible due to the impulsiveness of R-waves. In other words there is a meaningful difference between the baseline power and that of a QRS complex. The proposed method in this paper, referred to as the relative energy algorithm, works on this basis.

Using two sliding windows, short- and long-term signal energy powers are calculated for each sample in the ECG. For each sample a coefficient signal is created using Eq. 1.

$$Coeff(n) = \frac{\sum_{i=n-s_{win}}^{n+s_{win}} (Sig(i))^2}{\sum_{j=n-l_{win}}^{n+l_{win}} (Sig(j))^2} \tag{1}$$

Where n represents the n^{th} sample of Sig. Parameters s_{win} and l_{win} are respectively half of the length of short and long sliding windows.

In our study, the short sliding window has a duration of $150ms$ while the longer sliding window has a one second duration. Afterwards, the non-negative coefficient signal is divided by its maximum value in order for it to have a range of $[0, 1]$. Finally, the enhanced ECG is calculated by multiplying the coefficient signal and the original ECG. As QRS complexes have relatively higher energy in comparison with P-, T-waves and the noise in the signal, the coefficient signal values are close to one where QRS complexes take place in the ECG while smaller elsewhere. Fig.1 illustrates an example of ECG enhancement based on the short-long term relative energy on a noisy part of tape 104 of the MIT/BIH arrhythmia database.

3. Results and discussion

In order to evaluate the proposed algorithm on the MIT/BIH arrhythmia database, first ECGs were high-pass filtered with a $4Hz$ cutoff frequency followed by applying the relative energy algorithm. Then, the R-waves were extracted from the output by finding peaks with normalized amplitude greater than 0.02 and a minimum distance of $250ms$. Tape-by-tape results are reported in table 1. In this table, the detection error rate (DER) as well as sensitivity (Se) and positive prediction value (PPV), calculated through Eq. 2-4, were used for evaluation.

$$Se = \frac{TP}{TP + FN} \tag{2}$$

$$PPV = \frac{TP}{TP + FP} \tag{3}$$

$$DER = \frac{FP + FN}{Total\ No.\ of\ Beats} \tag{4}$$

where TP, FN and FP respectively represent true positive, false negative, and false positive beats calculated based on the reference annotation file.

Table 2 compares the performance obtained by our algorithm with that of well-known QRS detection methods. As shown in this table, the relative energy algorithm leads to robust ECG R-wave extraction with results comparable to that of the state-of-the art.

Results reported in tables 1 and 2, suggest that the proposed method can efficiently extract R-waves from the ECG. In order to find out how the proposed method performs when perturbations are present the ECG, we evaluated it against white and synthetic electromyographic

Table 1. Performance of the proposed method on QRS complex detection on MIT/BIH arrhythmia database.

Tape No.	No. of Beats	FP	FN	DER %	Sensitivity	PPV
100	2272	0	0	0	1	1
101	1869	2	2	0.11	0.9989	0.9989
102	2186	0	0	0	1	1
103	2083	0	0	0	1	1
104	2228	28	0	0	1	0.9874
105	2602	23	14	0.54	0.9946	0.9911
106	2027	1	0	0	1	0.9995
107	2137	0	0	0	1	1
108	1771	20	1	0.056	0.9994	0.9887
109	2531	0	0	0	1	1
111	2124	2	1	0.047	0.9995	0.9991
112	2538	0	0	0	1	1
113	1794	0	0	0	1	1
114	1880	1	0	0	1	0.9995
115	1958	0	1	0.051	0.9995	1
116	2411	1	17	0.71	0.9929	0.9996
117	1534	1	0	0	1	0.9993
118	2278	1	0	0	1	0.9996
119	1987	0	0	0	1	1
121	1862	0	0	0	1	1
122	2477	0	2	0.081	0.9992	1
123	1518	0	0	0	1	1
124	1618	1	0	0	1	0.9994
200	2600	8	2	0.077	0.9992	0.9969
201	1963	0	6	0.31	0.9969	1
202	2137	2	3	0.14	0.9986	0.9991
203	3006	7	38	1.3	0.9873	0.9976
205	2656	0	5	0.19	0.9981	1
207	2334	7	1	0.043	0.9996	0.997
208	2962	1	20	0.68	0.9932	0.9997
209	3011	2	0	0	1	0.9993
210	2650	6	10	0.38	0.9962	0.9977
212	2748	1	0	0	1	0.9996
213	3250	0	1	0.031	0.9997	1
214	2266	2	4	0.18	0.9982	0.9991
215	3362	0	1	0.03	0.9997	1
217	2209	0	1	0.045	0.9995	1
219	2154	0	0	0	1	1
220	2047	0	0	0	1	1
221	2427	0	3	0.12	0.9988	1
222	2482	2	0	0	1	0.9992
223	2604	0	0	0	1	1
228	2077	24	6	0.29	0.9971	0.9884
230	2257	0	0	0	1	1
231	1570	0	0	0	1	1
232	1780	16	0	0	1	0.991
233	3080	0	4	0.13	0.9987	1
234	2753	0	1	0.036	0.9996	1
Total	110070	159	144	0.28	0.9987	0.9986

Table 2. Comparison of performance with previously proposed methods on MIT/BIH arrhythmia database.

Fiducial point	No. of Beats	FP	FN	Failed detection %	Ref. No.
REL_EN	110070	159	144	0.28	—
Pan and Tompkins	116137	507	277	0.675	[3]
Li et al.	104184	65	112	0.170	[7]
Yazdani and Vesin	109494	108	137	0.224	[4]
Zhang and Lian	109510	204	213	0.38	[9]
Ravanshad et al.	109428	651	1216	1.71	[10]
Martinez et al.	109428	153	220	0.34	[11]
Bahoura et al.	109809	135	184	0.29	[12]
Moody and Mark	109428	94	1861	1.79	[13]
Lee et al.	109481	137	135	0.43	[14]

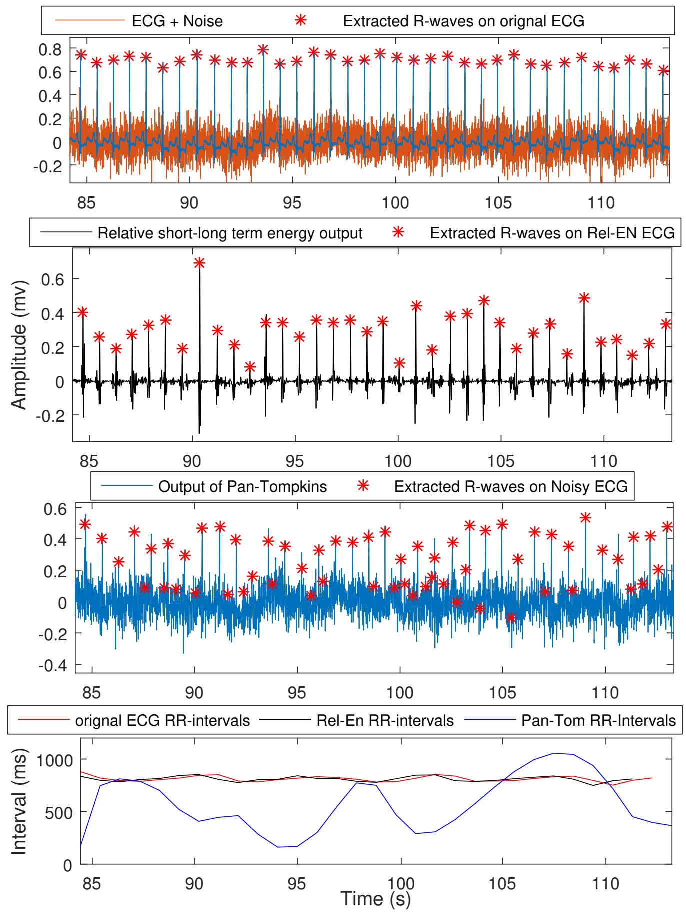

Figure 2. Performance of the relative short-long term energy against added synthesized EMG noise. RR-intervals are uniformly sampled in time, for demonstration. Tape 100 of the MIT/BHT arrhythmia database.

(EMG)noise, created by fitting an autoregressive model on EMG recordings from the Physionet/CinC2014 challenge database [15]. Using clean segments of ECGs in the MIT/BIH arrhythmia database, different levels of noise, from an input signal-to-noise ratio (SNR) of 100 to -20, were incrementally added to the ECG. Then, R-wave extraction performance was tested against Pan-Tompkins algorithm and the hybrid Pan-Tompkins/relative short-longterm energy algorithm, in which the output of the proposed method was used as the input to the Pan-Tompkins QRS detection algorithm. Results show robust extraction of R-waves up to an input SNR of 0 or below, both against white and synthetic EMG noises. Figure 2 illustrates the performance of the hybrid algorithm and compares it with Pan-Tompkins. In this example, an EMG noise was added to tape 100 from the MIT/BIH arrhythmia database making an input SNR of -0.12. Since the number of extracted R-waves are different in the top three sub-figures, the calculated RR-intervals were uniformly sampled in time in order to have a more sensible comparison. As seen in this figure, the RR-interval extraction is significantly improved when the hybrid approach is applied to the ECG, with similar results on white noise. This simply defined algorithm can be used to make R-wave extraction more robust.

4. Conclusion

In this paper, we propose a simple preprocessing tool that uses the ratio between short- and long-term ECG energies in order to suppress perturbations and make QRS complexes more prominent in the ECG. The proposed method is simply defined and can be easily computed, making it a suitable preprocessing tool for QRS complex detection algorithms. Using two simple thresholds on the output of the proposed method, an efficient R-wave extractor was created and evaluated on the MIT/BIH arrhythmia database. With sensitivity of 99.87% and a detection error rate of 0.28%, the proposed method obtained results comparable to more complex state-of-the-art algorithms.

Acknowledgements

This study was performed in the framework of the Nano-Tera initiative supported by the Swiss National Science Foundation (SNSF).

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