

QRST Cancellation Based on the Empirical Mode Decomposition

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Abstract

Baseline drift and QRST residues are frequently present after QRST cancellation. This study deals with the improvement of atrial signal quality after QRST cancellation using an empirical mode decomposition (EMD) based post-processing. The EMD decomposes non-stationary signals into narrow-band components, known as intrinsic mode functions (IMFs). Simulated and clinical 30-second segments of estimated atrial activity (after QRST cancellation) on lead VI were decomposed into IMFs using an EMD algorithm. The DF and the energy ratio between TQ and QRS segments for each enhanced IMF component were used to select the IMFs that correspond to atrial activity. The atrial activity signal was taken as the sum of the selected IMFs. The performance of the method is compared with that of a standard post-processing approach using an infinite impulse response bandpass filter.

1. Introduction

Atrial fibrillation (AF) is the most common type of human cardiac arrhythmia. On the ECG, AF signals are characterized by continuous, apparently disorganized, fibrillatory waves (F-waves). Due to the much higher electrical amplitude of the electrical ventricular activity (VA) on the surface ECG, isolation of the atrial activity (AA) component is crucial for the study of AF. Some methods used for solving this problem are based on the average beat subtraction (ABS). An average of the ventricular complexes (QRST complexes) is used to cancel these ventricular components. In general, results from ABS based methods are accurate but visible baseline drift and QRS residues are frequently present after VA cancellation. Standard filters are usually applied in order to remove these artefacts.

Fourier methods, wavelet analysis and principal component analysis (PCA) are some of the major approaches used for decomposing time series into components. All of these satisfy two criteria: (1) completeness of the basis and (2) orthogonality of the basis. The limitation of stationarity, of time resolution (wavelet) or the lack of characteristic time of frequency components (PCA) are some of the motivations for new analysis techniques. The EMD was first

introduced by Huang et al. in 1998 [1]. This technique was proposed to analyze non-stationary and nonlinear time series and to determine characteristic time/frequency scales. These components are called Intrinsic Mode Functions (IMF). Recently, Andrade et al. have proposed to use of a filtering method based on EMD to denoise electromyographic signals [2].

In this paper, we study the effectiveness of an EMD-based method for post-processing the ECG signals after QRST cancellation. The method selects the IMFs that represents AA using their DFs and the energy ratios between their TQ and QRS segments. An infinite impulse response (IIR) highpass filter is applied to remove the baseline drift in the last stage. The performance of this method is studied in its application to ECG signals generated by a biophysical model of the atria, as well as to clinical recordings. The performance of the method is compared to that of an IIR bandpass filter.

2. Methods

2.1. Empirical mode decomposition

The EMD technique decomposes time series into complete, almost orthogonal, local and adaptive basis functions, named intrinsic mode functions (IMFs). These IMFs should have a well-behaved Hilbert transform (and thus a well-defined instantaneous frequency). To get the well-behaved Hilbert transform, one must locally eliminate riding waves and asymmetries. In order to possess the properties mentioned above, the IMFs are required to satisfy two criteria: (1) the number of extrema and the number of zero crossings must differ by one at most and (2) the mean value of the envelopes, one defined by the local maxima (upper envelope) and the other by the local minima (lower envelope), is 0. Any signal that satisfies these two criteria is considered to be an IMF.

This definition of IMFs is empirical and there is no explicit equation for estimating them. Rilling et al. have proposed an effective implementation of EMD [3, 4]. Given a signal $x(t)$ to be decomposed, the initial step is defining with $x_{i,j}(t)$ to be equal to $x(t)$, where the first index i refers to the i^{th} IMF and the second index j refers to the

j^{th} iteration to find the i^{th} IMF. The subsequent steps are:

1. identification of all extrema of $x_{i,j}(t)$;
2. extrapolation of the lower envelope $e_{i,j}^{lo}(t)$ (respectively upper envelope $e_{i,j}^{up}(t)$) by an interpolation between minima (respectively maxima);
3. computation of the mean of both envelopes $e_{i,j}^{me}(t) = (e_{i,j}^{lo}(t) + e_{i,j}^{up}(t))/2$;
4. extraction of the i^{th} IMF candidate $c_{i,j}(t) = x_{i,j}(t) - e_{i,j}^{me}(t)$;
5. if candidate $c_{i,j}(t)$ fulfills the criteria defining an IMF, it is assigned as the i^{th} IMF, the new $x_{i+1,1}(t) = x(t) - \sum_{k=1}^i IMF_k$ and steps (1) to (5) are repeated;
6. if candidate $c_{i,j}(t)$ does not fulfill the criteria defining an IMF, it is assigned to the variable $x_{i,j+1}(t)$ and the steps (1) to (5) are repeated.

When $x_{i,j}(t)$ is equal to $e_{i,j}^{me}(t)$, the whole procedure stops and $x_{i,j}(t)$ is assigned as the last i^{th} IMF. The criteria defining an IMF were the ones proposed by Rilling et al., [3]. A candidate $c_{i,j}(t)$ is considered as an IMF if its evaluation function $\sigma_{i,j}(t)$ is lower than θ_2 for all values and lower than θ_1 for $(1 - \alpha)\%$ of the values. The evaluation function is defined as $\sigma_{i,j}(t) = |e_{i,j}^{me}(t)/m_{i,j}(t)|$, where $m_{i,j}(t) = (e_{i,j}^{up}(t) - e_{i,j}^{lo}(t))/2$. Fig. 1 shows the first iteration on an ECG signal during AF after QRST cancellation. It demonstrates that EMD technique has the tendency to isolate the residue in the first IMFs.

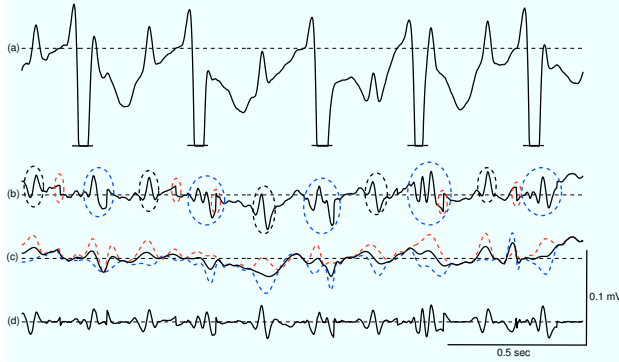


Figure 1. (a) Clinical 2-second ECG signal on V1 (R-waves saturated). (b) Signal (a) after QRST cancellation. Blue (respectively black) dashed ellipses represent possible QRS residues (respectively T-wave residues). Red dashed ellipses represent steplike residuals after template subtraction. (c) Mean envelope $e_{1,1}^{me}(t)$ of (b) with its upper ($e_{1,1}^{up}(t)$) and lower ($e_{1,1}^{lo}(t)$) envelopes. (d) The first candidate $c_{1,1}(t)$.

2.2. ECG post-processing

Let $x(t)$ be an ECG signal after application of QRST cancellation, see [5]. In some cases, baseline drift and

QRST residues remain.

The procedure used in this study is the following:

1. decomposition of $x(t)$ into IMFs;
2. identification of the DFs for each IMF by using a power spectral density (PSD) estimate;
3. computation of the energy ratio between TQ and QRS segments for each IMF;
4. selection of the IMFs that represent AA using their DFs and energy ratios;
5. reconstruction of the estimated AA with the summation of the selected IMFs;
6. application of a final highpass filter to the estimated AA signal.

Welch's method was used to obtain the PSD estimate. Due to the properties of IMFs, the DFs slowly decrease from the first to the last IMF. We define all the values of the i^{th} IMF in the TQ segments (respectively QRS segments) by an N -by-1 vector \mathbf{a}_i (respectively M -by-1 vector \mathbf{b}_i). The energy ratio r_i of the i^{th} IMF was computed as follows: $r_i = (\sum \mathbf{a}_i^2/N)/(\sum \mathbf{b}_i^2/M)$. The IMFs taken to represent AA were those with DF below 10 Hz and r_i above 0.5. The highpass IIR filter used to remove the baseline drift was a zero-phase (bidirectional) fifth-order Butterworth filter with a cutoff frequency of 2 Hz.

2.3. Synthetic signals

A three-dimensional model of the human atria was constructed from magnetic resonance (MR) images, including the openings at the sites of the entries and exits of the vessels as well as at the locations of the valves connecting the atria to the ventricles [6]. In order to create substrates for AF, patchy heterogeneities in action potential duration were introduced by modifying the local membrane properties. Simulated AFs induced by rapid pacing in the left atrium appendage were observed as multiple reentrant wave fronts that propagate and interact in a random fashion over the atrial surface. Nine different simulated AF types, ranging from 11.3 to 23.9 seconds, were created by modifying the pacing protocol and the heterogeneities.

Body surface potentials associated with the AA were computed by using a compartmental torso model including the atria, the ventricles, blood cavities and the lungs, constructed from MR images [7]. The nine ECG episodes of simulated AF were duplicated to cover thirty seconds. These nine 30-second ECGs of simulated AA were combined with four different clinical 30-second standard 12-lead ECGs of patients in sinus rhythm, from which the P waves were removed. In this manner, 36 realistic simulated 30-second AF signals sampled at 500 Hz were created in the standard 12-lead system.

2.4. Clinical signals

A clinical database, composed of 72 30-second standard ECGs of patients in sustained AF was used. The signals were recorded and stored using a commercial recording system (CardioLaptop[®] AT-110, SCHILLER). The system used electrocardiographic filtering (0.05 to 150 Hz), a dynamic range of $\pm 10\text{mV}$ AC (resolution of $5\mu\text{V}$) and a sampling rate of 500 Hz.

2.5. Evaluation procedure

The energy ratio between the TQ and QRS segments, the kurtosis value and the DF were used to evaluate the simulated and clinical performance of the proposed method on lead V1. The RMS based relative difference (RD) was also used to evaluate the performance on the simulated ECG signals. The relative difference between the estimated AA signals and the original simulated AA signals was computed for each post-processing method. The energy ratio (respectively the kurtosis value) is generally close to 1 (respectively lower than 0) for AA signal. The results were compared to those of a bidirectional IIR bandpass filter (zero-phase fifth-order Butterworth). The cutoff frequencies for the bandpass filter were 2 and 15 Hz.

3. Results

	Energy ratio	Kurtosis	RD (%)	DF (Hz)
Real VA	0.0 ± 0.0	18.1 ± 2.3	-	2.0 ± 1.0
AA simulated	1.0 ± 0.1	-0.5 ± 0.5	-	6.2 ± 1.2
after cancellation	1.3 ± 0.2	0.4 ± 0.4	1.2 ± 0.1	1.5 ± 2.6
EMD	1.1 ± 0.2	0.0 ± 0.4	0.6 ± 0.1	5.9 ± 1.3
IIR bandpass	1.2 ± 0.2	-0.1 ± 0.4	0.5 ± 0.1	6.2 ± 1.2

Table 1. The performance of the EMD-based method compared to that of applying a IIR bandpass filter. Documented are: the energy ratio between the TQ and the QRS segments, the kurtosis and the RD values (mean \pm standard deviation) on the 36 simulated signals.

Table 1 summarizes the performance of both methods applied to the 36 simulated ECGs. Table 2 summarizes the performance of both methods applied to the 72 clinical ECGs. Fig. 2 shows the results (in detail) obtained by the proposed method and with the other filter applied to a clinical 2-second segment. For all results, the three parameters θ_1 , θ_2 and α of the EMD algorithm were fixed at 0.5, 0.05 and 0.05, and the maximum number of iterations was fixed at 300, default values in [3].

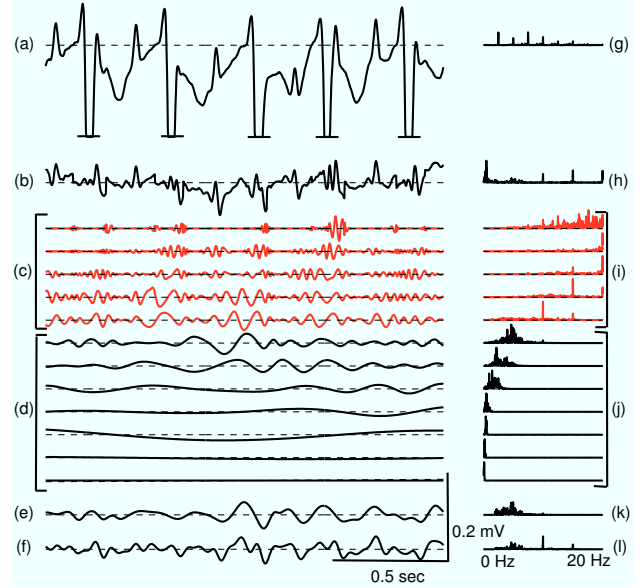


Figure 2. (a) Clinical 2-second ECG signal on V1 (R-waves saturated) and its PSD estimate (g) with a DF of 7.48 Hz. (b) Signal (a) after QRST cancellation and its PSD estimate (f) with a DF of 0.50 Hz. (c) and (d) are the IMFs obtained from (b) and their corresponding PSD estimates ((i) and (j)). The black IMFs (group (d)) were the ones that represent AA. (e) Post-processed estimated AA (sum of black IMFs, group (d)) with the EMD-based method and its PSD estimate (k) with a DF of 4.97 Hz. (f) Post-processed estimated AA with a bandpass IIR filter (cutoff frequency of 2 and 15 Hz) and its PSD estimate (l) with a DF of 9.98 Hz.)

4. Discussion and conclusions

In regard to the simulated ECG signals, Table 1 shows that no significant statistical difference exists between the performances of the EMD-based method and of the IIR bandpass filtering over the 32 simulated signals in terms of energy ratio and kurtosis value. In terms of relative difference, the IIR bandpass filtering ($0.5 \pm 0.1\%$) outperformed the EMD-based method ($0.6 \pm 0.1\%$). In terms of the DF accuracy, the IIR bandpass filter also outperformed the EMD-based method; the average of DFs of the simulated AAs is 6.2 ± 1.2 Hz in comparison to the IIR bandpass filter (6.2 ± 1.2 Hz) and the EMD-based method (5.9 ± 1.3 Hz).

In regard to the clinical signal, Table 2 shows that no significant statistical difference was present between the performances of the EMD-based method and the IIR bandpass filtering over the 72 clinical signals in terms of energy ratio, kurtosis value and DF. The average of DFs estimated from these signals with the EMD-based method

	Energy ratio	Kurtosis	DF (Hz)
ECG (V1)	0.03 ± 0.04	10.00 ± 4.85	3.08 ± 1.95
after cancellation	1.16 ± 0.32	1.30 ± 2.24	0.87 ± 1.47
EMD	1.02 ± 0.24	0.62 ± 0.99	5.83 ± 1.36
IIR bandpass	1.05 ± 0.28	0.64 ± 1.05	5.70 ± 1.41

Table 2. The performance of the EMD-based method is compared to that of applying a IIR bandpass filter. Documented are: the energy ratio between the TQ and the QRS segments, the kurtosis and the RD values (mean \pm standard deviation) on the 36 simulated signals.

(5.83 ± 1.36 Hz) and the average of the DFs estimated with the IIR bandpass filter (5.70 ± 1.41 Hz) also show that no significant statistical difference was present between the performances of both methods.

Interestingly, in some of the clinical cases, the performance of the EMD-based method was better than the performance of the IIR bandpass filter in terms of the DF accuracy. These few case results are masked in Table 2 by the high total number of signals. The clinical example shown in Fig. 2 is one of these cases. In Fig. 2, the frequency components of the QRST residues (around 10 and 15 Hz) are still present after applying the IIR bandpass filter which is not the case with the EMD method.

The relative difference and the estimated DF in the simulated and in most of the clinical cases demonstrate that the IIR bandpass filtering performs well when the QRST residues do not dominate. Filtering may obviously be inefficient in cases where the artifacts have significant power inside the band of interest (in Fig. 2). In these specific cases, the EMD-based method performs well in terms of the DF accuracy. This may be explained by the properties of the IMFs. The IMFs are forced to be symmetric and without riding waves. When the artifacts due to QRST residues, pacemaker pulses, etc. are dominant, they are mainly contained in the first IMFs. The QRST residues present in the other IMFs are less concentrated and their impact on the estimate DF is attenuated, see Fig. 2 (c).

Acknowledgements

This study was made possible by grants from the Swiss National Science Foundation (SNSF, $n^{\circ}205321$ –

100624/1) and the Theo-Rossi-Di-Montelera Foundation. The authors would like to thank Andrei Forclaz who heads the project that made this study possible. The authors would also like to thank Veronique Prudent for the clinical database. The authors would also like to thanks Prof. Adriaan van Oosterom for helpful discussions and suggestions.

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