Ectopic Beats Canceler for Improved Atrial Activity Extraction from Holter Recordings of Atrial Fibrillation

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Abstract

In this work, a new method for ectopics removal from ECG recordings is proposed. The method distinguish between normal and ectopic beats through a forward/backward level windowing strategy. Next, by using an adaptive correlation index, the 15 most similar ectopic beats to the one under cancellation are clustered, thus serving to get their eigenvector matrix by singular value decomposition. Finally, the highest variance eigenvector is taken as the template for ectopic beat cancellation. In order to evaluate the proposed method performance, an index called reduction ectopic rate (RER) was defined. The proposed technique has been compared with previously published average QRST cancellation techniques. Twenty 5 hour-length segments extracted from Holter ECG recordings of 20 different AF patients, with a high percentage of ectopic beats, were used in the study. Results provided maximum RER values of 5.76 and minimum of 1.67 *being, in average, of* 3.57 ± 0.25*. In contrast, when ectopic beats were considered as normal beats, maximum RER was* 1.49 *and minimum* 0.88*, being in average* 1.11 ± 0.25*. To sum up, the proposed method is able to improve notably the AA extraction from Holter ECG recordings by reducing notably the residua provoked by the presence of ectopic beats.*

1. Introduction

To date, Holter recording (24-48h) is the most common way to study Atrial Fibrillation (AF) progression across extended periods of time from the Electrocardiogram (ECG). Furthermore, the proper analysis of AF requires the atrial activity extraction which, in most cases, is performed by canceling the ventricular activity (VA). The most efficient techniques for suitable VA cancelation are those that exploit the spatial diversity of the multilead ECG [1], such as the method that solves the blind source separation problem [2] or the spatiotemporal QRST cancelation strategy [3]. However, these techniques yield reduced performance in Holter recordings due to the reduced number of leads available.

On the other hand, the techniques based in Template Matching and Subtraction (TMS) are the most widely used for VA cancelation in Holter recordings. TMS computes the average complex in single-lead mode and use it to cancel out all the beats in the ECG under study, assuming that all of the beats are very similar to each other. However, the beat morphology experience small changes throughout the recording due physiological respiration processes, patient movement or lead sensibility and, therefore, QRST residua and noise are often present in the estimated atrial activity or remainder ECG [4].

On the other hand, ectopic beats (EB), which are a sign of disturbance in the heart's depolarization process, present a morphology quite different to normal beats. Moreover, their occurrence in Holter recordings is very common, overall in those patients whit AF [5]. Therefore the cancellation of VA in long-term recordings by using template-based methods use to reduce drastically their performance in the presence of EB [6]. Thus, an additional preprocessing should have carried out before the application of conventional ventricular cancelation algorithms. Whit this aim, several modifications on TMS techniques have been introduced to improve their cancelation performance on EB [7]. Thereby, morphological criteria has been considered by some authors, to create one or more templates able to perform the VA cancelation [7]. In order to get a correct classification template, the proper detection of EB within the ECG is an important task in the cancelation performance. To this respect, many works have been published and several descriptors have been defined. Thus, descriptors based on QRS morphology and R–R intervals [8], QRS frequency components calculated by Fourier Transform [9] or filter banks [10] have been proposed in the literature.

In this work, a new algorithm for detection, clustering and cancelation of EB is proposed. The method can be used as a preprocessing stage able to improve normal VA cancelation with any of the available methods.

2. Materials

The MIT-BIH AF Database (AFDB) was used in the present work. This database consists of 23 two lead (lead V1, II) ECG recordings of human subjects with atrial fibrillation (mostly paroxysmal). The individual recordings are each approximately 10 h in duration, and contain two ECG signals each sampled at 250 Hz with 12-bit resolution. The number of AF episodes for each subject varies from 2 to 39 with two subjects in persistent AF. This database is publicly available at http://www.physionet.org. Twenty 5 hour-length segments extracted from MIT-BIH AF Database recordings of 20 different AF patients, with a high number of ectopic beats, were used in this work. These segments were preprocessed in order to improve later analysis. Firstly, baseline wander was removed making use of bidirectional high pass filtering with 0.5Hz cutoff frequency. Secondly, high frequency noise was reduced with an eight order bidirectional IIR Chebyshev low pass filtering, whose cut-off frequency was 70Hz. Finally, power-line interference was removed through adaptive notch filtering, which preserves the ECG spectral information.

3. Methods

3.1. Ectopic beat detection

The presented method is able to detect any disturbance in the normal ventricular depolarization, regardless of how it is produced. Thus, premature ventricular contractions (PVC), left and right bundle branch blocks (LBBB, RBBB) and the artifacts provoked by pacemakers (PB) are considered as EB. Since the algorithm relies on the QRS morphology, the first processing stage is to perform reliable detection of the QRS comciplex. This work was carried out using a Phasor Transform-based method (PT) [11]. Although one of the advantages of the PT is that QRS waves are amplified to normalized values regardless of their original amplitude, a windowing strategy was used in order to enhance the QRS detection. Thus, the PT was applied directly to each windowed segment to detect the QRS waves and then R-peaks were detected as the maximum magnitude moduli found in each QRS wave. Once the R-peak ($R[n]$) was detected, two boundary points, γ_{QRS-} and γ_{QRS+}, around the R-peak were primarily established for each beat. They were defined as the closer points in which $x[n]$ was lower than 30% of the $R[n]$ amplitude. Next, a forward 15 ms window relative to this fiducial point was established to search a local minimum ($R'[n]$). Thus, when $R'[n]$ was located, the same aforementioned process was carried out to establish the boundarie points ρ_{QRS-} and ρ_{QRS+}. A number of 5 QRS descriptors were used for the beat classification, which contain representative information about the amplitude, area and specific interval duration, as shown in Fig. 1.(a). The mathematical expression of each descriptor is defined in Table 1.

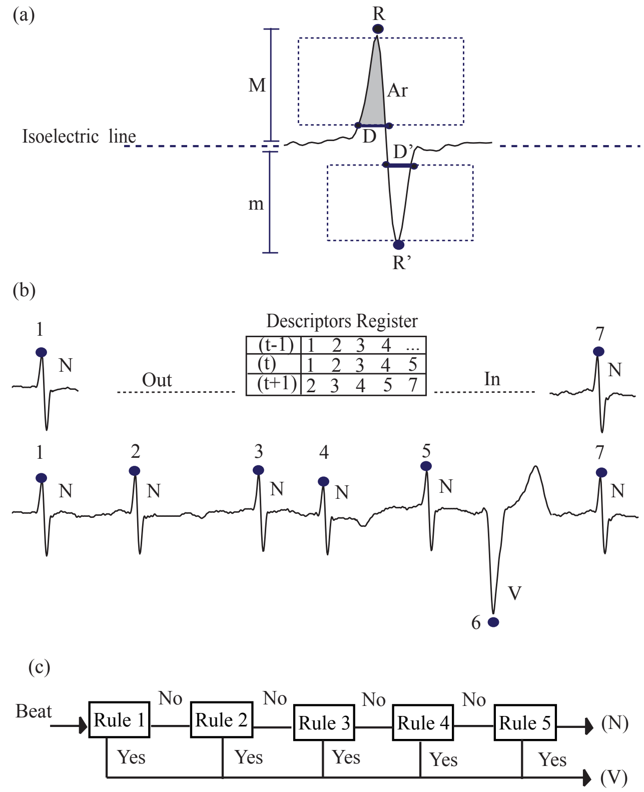

Figure 1. a) Descriptors used in the ectopic detection. b) updating process of comparison matrix. c) Decision rules.

Given that the algorithm was designed to work whit a minimal user intervention, only five normal beats have to be marked within the recording under analysis before the start. Although this number of beats was chosen as a trade-off between performance and execution time, the smaller the number, the lower is the computational cost. Once these beats were chosen, the aforementioned QRS descriptors were calculated over them and the results stored in a register (DR) where each descriptor is represented by one matrix row. Thus, the descriptors were calculated for each located beat and compared consecutively whit the matrix values. When the algorithm labeled a beat as normal, their descriptors were stored within DR, dropping the descriptors' values which was stored in first place, as shown in Fig. 1.(b). Finally, a decision rule structure was used to discriminate between normal and ectopics beats regarding their QRS descriptors, as shown in Fig. 1.(c). Each rule is defined by an inequality regarding each one of the QRS descriptors calculated before as is defined in Table 1.

Table 1. QRS descriptors and decision rules.

QRS Descriptor	Definition
Ar	$\sum_{n=\gamma_{QRS_-}}^{\gamma_{QRS_+}} x[n]$
D	$\gamma_{QRS_+} - \gamma_{QRS_-}$
D'	$\rho_{QRS_+} - \rho_{QRS_-}$ if $R[n] \geq 0$ & $\lvert R'[n] \rvert \geq 0.3 * R[n]$ $\gamma_{QRS_+} - \gamma_{QRS_-}$ if $otherwise$
M	$R[n]$
m	$R'[n]$

# Rule	Inequality
1	$Ar \geq 1.5 * (\frac{\sum_{i=1,j=1}^{j=5} DR_{i,j}}{5})$
2	$D \geq 2 * (\frac{\sum_{i=2,j=1}^{j=5} DR_{i,j}}{5})$
3	$D' \geq 2 * (\frac{\sum_{i=3,j=1}^{j=5} DR_{i,j}}{5})$
4	$M = \geq 2.5 * (\frac{\sum_{i=4,j=1}^{j=5} DR_{i,j}}{5})$
5	$m = \leq 2.5 * (\frac{\sum_{i=5,j=1}^{j=5} DR_{i,j}}{5})$

3.2. Clustering performance

Once the classification was performed, each detected EB was delineated by using the aforementioned PT-based algorithm [11]. The maximum localization error between automatic and manual annotations, achieved with this algorithm, was lower than 6 ms and its standard deviation was in agreement with the accepted tolerances for expert physicians in the onset and offset identification for QRS, P and T waves in the QTDB. To this respect, Q and T waves were found and consequently delineated for each EB.

The duration of ventricular depolarization and repolarization process in the ECG, represented by the QRST segment, varies from each EB. Therefore Q_- and T_+ boundaries were calculated as the mean of Q–R and R–T distances for each EB respectively. Thus, the ectopic matrix (EM) was created by computing the distance normalization using the aforementioned boundaries. Next, an adaptive signal correlation index (ASCI) was used to calculate the morphological similarity between EB. The advantage of using this method, in contrast to others as Pearson's correlation, rely on the fact that ASCI accounts for amplitude differences between signals [12]. Thus, each EB was compared with the remaining and the results were sorted in descending order. Finally, a cancellation matrix (CM) was defined for each EB which contains the fifteen most similar EB found using the ASCI coefficient.

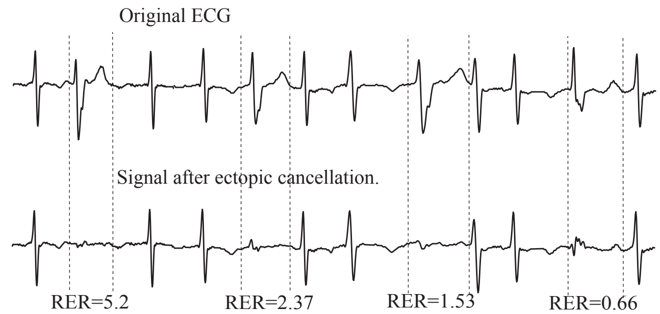

Figure 2. Comparison between original ECG and ECG after of ectopic beat cancelation and their RER coeficient.

3.3. Ectopic cancellation

Once the CM was generated for each EB, the ectopic cancellation was carried out through an adaptive singular value cancellation methodology, described in [6]. This method was developed for normal ventricular activity extraction, so the algorithm was modified to work exclusively whit EB. Thus, the eigenvector matrix of each CM was obtained by singular value decomposition. Finally, the highest variance eigenvector (HVE) was considered as the ventricular template for each ectopic beat cancellation.

3.4. Validation

In order to evaluate the method's performance, an index called reduction ectopic rate (RER) was defined as:

$$RER = \sqrt{\frac{\sum_{n=Q_-}^{T_+} (x[n]_{or})^2}{\sum_{n=Q_-}^{T_+} (x[n]_{ca})^2}} \quad (1)$$

being $x[n]_{or}$ the value of each sample in the original signal and $x[n]_{ca}$ the residue in the ECG signal after ectopic cancellation. A comparison between the original ECG and the signal after cancellation, with different RER index, is depicted in Fig. 2. A coherent relationship between the RER and the visual residue remaining in the QRST segment can be appreciated.

4. Results

The results of the present work are summarized in Table 2. In the first row, the mean (μ), standard deviation (σ), and the maximum and minimum values for RER are shown. These values correspond to the direct application of a previously published QRST cancellation technique, in which ventricular templates were obtained through singular value cancellation [6]. In the second row, the same statistical parameters of RER were computed for the methodology presented in this work.

Table 2. RER comparison between the adaptive average template cancellation and the present work, making use of the AFDB segments.

RER				
$Method$	μ	σ	maximum	minimum
Alcaraz et al. [6]	1.11	0.25	1.49	0.88
This work	3.57	0.25	5.76	1.67

5. Discussion and conclusions

The occurrence of EB in ECG recordings is a problem for the estimation of some characteristic descriptors. Thus, heart rate variability (HRV) analysis programs require user intervention, or automatic detection algorithms, for ectopic beat identification, especially in the case of supraventricular ectopic beats [13]. To ensure a proper measurement of HRV, the RR-series should be cleared of any coupling intervals and compensatory pauses of ectopic beats. These are observed as spikes or valleys in the final discrete HRV signal, which need to be corrected somehow. Thereby, existing HRV analysis systems require an automatic correction of the morphological distinction between normal beats and EB events. Several works have been published whit this aim [13, 14]. However, the adopted techniques present a remarkable computational cost, which turns real-time implementation a difficult task. In contrast, the method presented in this work could be a low-cost alternative to facilitate improved EB-free HRV measurements.

Results show that the mean RER, considering all the ectopics presented in the signals under study, is almost tree times higher that results obtained through the application of [6]. Regarding EB detection, the proposed method presents a high simplicity and the decision rules are based on simple inequalities, taking as a reference past events. Therefore, its real-time implementation is feasible. Moreover, given that the number of EB to cancel out is notably lower than the number of normal beats, the clustering and cancelation method is carried out with high speed and effectiveness.

Acknowledgments

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