Detection and Estimation of T Wave Alternans with Matched Filter and Nonparametric Bootstrap Test

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Abstract

Though alternans phenomena in the cardiac repolarization phase has been shown to be related to arrhythmgenesis, a definitive estimation method from the T wave of ECG recordings is not yet available. We propose a statistical signal processing scheme which compares the T-wave morphology of even and odd beats by using a running matched filter, in order to increase the signal to noise ratio of the estimation. Given that previously proposed hypothesis tests for alternans detection rely on the knowledge of noise statistical distribution, we also analyzed the usefulness of a nonparametric bootstrap test. Data set composed of 100 ECG recordings included in the Challenge Database were used. Principal Component Analysis was previously made for multilead recordings. Subsequent preprocessing for each available lead consisted of conventional baseline removing, filtering, R-wave detection, exclusion of too noisy segments, T-wave segmentation, and template generation for even and odd beats. The difference between the template and a given beat was obtained by minimizing the absolute error of their comparison with a windowed circular shift. A paired bootstrap resampling test was made for deciding whether the averaged differences between the template and the T-waves were significant compared to the noise level.

1. Introduction

T wave alternans (TWA) that can be observed in the Electrocardiogram (ECG) under adequate conditions have been defined as a beat-to-beat consistent fluctuation in the repolarization morphology [1]. TWA have been shown to be related to cardiac instability and increased arrhythmogenicity, and more, clinical studies suggest that there is a patent relationship between large amplitude microscopic (microvolt level) TWA and the risk of sudden cardiac arrest [2]. Therefore, TWA represents a strong marker of cardiac electrical instability and have the potential for arrhythmic risk stratification [3].

Though a number of methods have been proposed to detect and estimate the TWA, there is no definite method available to date, mostly due to the difficulties in the definition a gold standard that allows the comparison and validation of the proposed algorithms [1].

Many of the detection and estimation schemes in the literature present two characteristics which can be analyzed for improving the available algorithms. First, several procedures look for the most patent difference in amplitude between even and odd beats at a given time instant in the T wave, but TWA can be present in any part of the T-wave morphology, so that comparisons should be better made in terms of all the T-wave duration. Second, hypothesis tests have been proposed to detect the actual presence of TWA, which rely on a pre-assumed statistical shape of the noise, but to our knowledge, no nonparametric statistical test has been proposed, which can be robust in situations when the statistical characteristics of noise distribution are not the pre-assumed ones.

We propose here a statistical signal processing scheme which aims to exploit both issues. Comparisons between T wave and (even and odd) templates are made using an amplitude matched filter scheme with circular shift, which yields the minimum error attainable in the comparison with independence of their relative time shifting. Also, a nonparametric paired bootstrap test is used to obtain the relative magnitude of the TWA and its significance difference with respect to the noise level.

The paper is structured as follows. In the next section, the processing blocks of the TWA detection and estimation scheme are described, with emphasis in the proposed matched filter and in the nonparametric paired bootstrap test, and simple application examples are used to illustrate each block. Next, results on the Challenge Data Base are presented. Finally, conclusions are drawn.

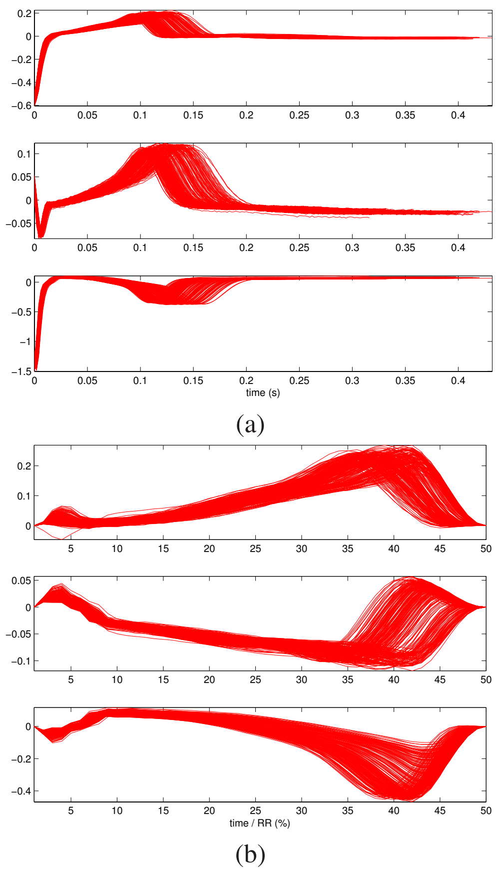


Figure 1. Example of T wave segmentation. (a) Segmented T waves for three leads in case 9 in the data base. (b) Segmented T waves after windowing (Tukey), time normalization with respect to preceding RR.

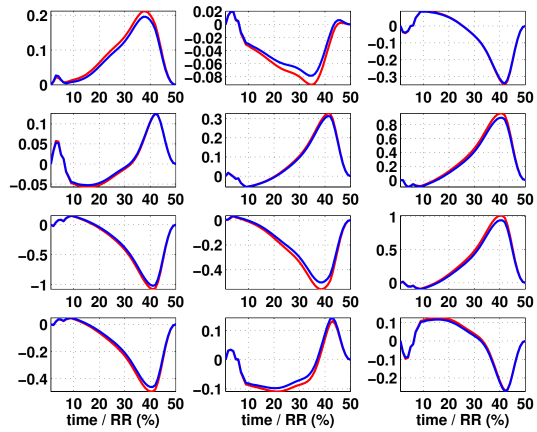


Figure 2. Example of T wave templates for even and odd beats (case 9 in the data base). Note that the differences between even and odd prototypes are not the same magnitude in all (orthogonalized leads).

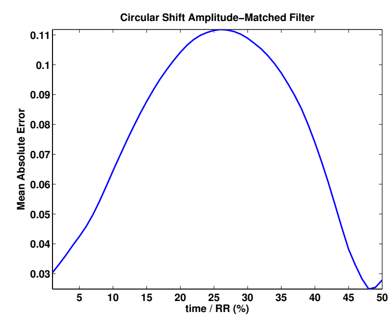


Figure 3. Example of mean absolute error between the template and the segmented T wave in terms of the circular shift (relative temporal position) between both.

2. TWA detection and estimation scheme

Preprocessing. The first processing block consisted on a preprocessing stage, in which ECG from a single lead are separately analyzed. Baseline noise was removed from each ECG by using a median filter together with spline interpolation (sliding window of 700 ms), and high frequency noise could be filtered out with a 32^{th} order low-pass filter. R-wave detection was performed by using an adaptive threshold on a lead which had been previously checked to be not distorted by too high level of noise, and these R-wave time instants were subsequently used for all the leads in each recording. In order to make orthogonal the available leads, a Principal Component Analysis was made on the available leads of each recording.

T Wave Segmentation. Each T wave was segmented by taking the signal between the R wave from the preceding stage and to 70% of the preceding cycle length, to ensure that all the T wave was included in the segment to be analyzed. Each segment was windowed using a Tukey window (ratio of taper to constant section 0.35), in order to minimize the possible distortion due to lasting R wave and to the end of the T wave. Also, each segment was normalized in time to the previous RR interval, and reinterpolated to 50 samples up to 50% of the time to RR horizontal axis. Figure 1 shows an example of T wave segmentation, windowing, and signal reinterpolation, in three orthogonalized leads from recording 9 in the data base.

Templates and Amplitude-Matched Filter. T wave templates were separately generated for even and odd beats for each lead (see Fig. 2), and the difference between the template and a given beat was obtained by minimizing the absolute error of their windowed circular shift comparison. Figure 3 shows an example of the mean absolute error obtained in terms of the relative time shift between the template and the tested beat. We will denote by $\Delta e_n^{e,o}$ the mean absolute error obtained by circular shift comparison between T wave at beat n and for the even,odd templates.

Accordingly, two separate error sequences were ob-

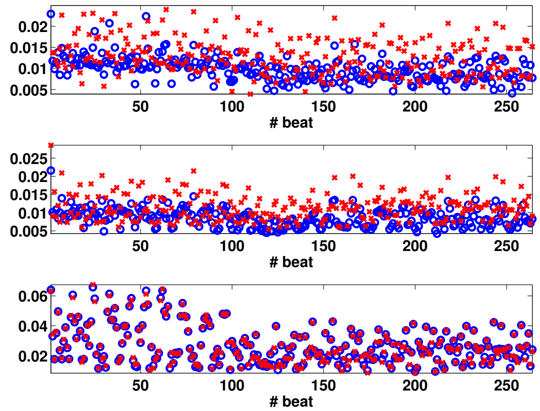


Figure 4. Examples of error sequences for correct and crossed alignment. In the upper and middle panels, there is a clear presence of TWA, which can be observed in the dissociation between both sequences. In the lower panel, the presence of TWA is not clear.

tained for each T wave series, corresponding to: (1) the errors of each T wave with respect to the correct template in terms of its relative position in the series (i.e., even beats with respect to even template and odd beats with respect to odd template); and (2) the errors of each T wave with respect to the incorrect template (i.e, even beats with respect to odd template and viceversa). These two series (for beat n) will be denoted as

$$E_n^{correct} = \begin{cases} \Delta e_n^e & \text{for } n \text{ even} \\ \Delta e_n^o & \text{for } n \text{ odd} \end{cases} \quad (1)$$

$$E_n^{cross} = \begin{cases} \Delta e_n^e & \text{for } n \text{ odd} \\ \Delta e_n^o & \text{for } n \text{ even} \end{cases} \quad (2)$$

Figure 4 shows examples for three leads on recording 9. In the upper and middle panels, there is a clear dissociation of both sequences, hence indicating that there is a marked difference between using the appropriate template for even/odd beats and not doing so. In the lower panel, there is no visible difference between both error series, and hence the presence of TWA in this lead is less clear.

Bootstrap Resampling Paired Test. A possible nonparametric test for checking for statistically significant differences between both error series could be to check if the confidence interval of the error difference series,

$$\Delta e_n = E_n^{correct} - E_n^{cross} \quad (3)$$

overlaps the zero level. Note that we are implicitly making a paired comparison between both error series, and hence, any statistical test that we build on Δe_n series will be a paired test. This approach, shown in Fig. 5, yields no clear statistical cut-off test, as far as all the histograms are wide and all of them overlap zero. This effect is mostly due to the high variance of series Δe_n, which precludes the use of the observed samples as simple criterion.

In order to overcome this limitation, and to have a nonparametric hypothesis test for comparison, bootstrap resampling can be made for estimating the averaged value of Δe_n series, denoted by $\bar{\Delta e}_n$, by sampling with replacement of the series samples and then estimating the averaged value for the replicated series [4]. In this case, the histograms of the resampled average will be narrower, given that they are referred now to the standard error of the estimation of the averaged, and hence, deciding whether the estimated averaged TWA is significantly different from the noise level can be achieved in each lead by using a statistical test on the confidence interval of the resampled averaged value. Figure 5 shows that, for the previous example, histograms are much narrower, and significant differences can be detected by checking that the confidence interval does not overlap zero. This can be checked for different magnitudes of the alternan phenomena in the different leads. Also note the difference in the histogram widths, which points to a different noise level being present in different leads.

Full Recording Estimation and Detection of TWA. The estimation of TWA can be done in each lead by taking the averaged value of error series in that particular lead, which will be denoted as $\bar{\Delta e}_n^i$ for i^{th} available lead in the recording. Given that Principal Component Analysis has been previously made, the estimated TWA magnitude can be readily obtained by using the Euclidean estimate of the averaged in all leads, this is,

$$A = \sqrt{\sum_{i=1}^{I} (\bar{\Delta e}_n^i)^2} \quad (4)$$

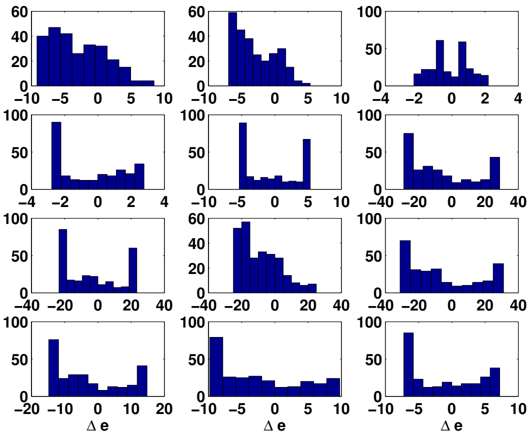
The relative contribution of each orthogonalized lead to the original lead set in the recording can be taken into account by using the corresponding eigenvalues λ_i, and hence, the eigenvalue corrected TWA estimate is

$$A_\lambda = \sqrt{\sum_{i=1}^{I} \lambda_i (\bar{\Delta e}_n^i)^2} \quad (5)$$

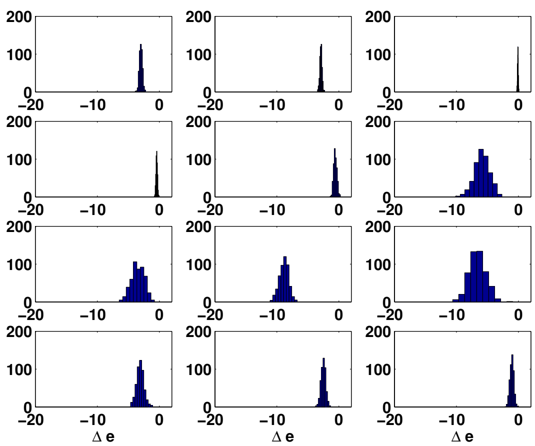
Finally, the overall detection probability P_d for each recording can be expressed as the sum of detected presence of alternans in the available leads normalized by the number of leads. In the example in Fig. 5, the 95% confidence interval does not overlap zero in 10 of 12 leads, and hence, $P_d = 5/6$.

3. Results

We tested the proposed estimation and detection algorithm on the 100 ECG recordings included in the 2008



(a)



(b)

Figure 5. Histograms of Δe_n. (a) Using the observed series, the high noise level makes the histograms wide. (b) Using $\Delta\bar{e}_n$ (from nonparametric bootstraping) makes possible the use of confidence interval.

Challenge data base, in which the presence of alternans was not known. Figure 6 shows the outputs obtained from the algorithm, sorted by the magnitude of A estimated TWA magnitude. It can be seen that the outputs are similar among them, which can be confirmed by scatter plots in Fig. 7. Specifically, there is a highly linear relationship between the (log-transformed) estimated and the eigenvalue corrected output, as well as a slightly lower linear relationship between the (log-transformed) estimated and the P_d in each recording.

4. Conclusions

An amplitude-matched filter and nonparametric bootstrap resampling have been proposed for developing schemes for TWA estimation and detection. Further work will be devoted to clinically validating the approach.

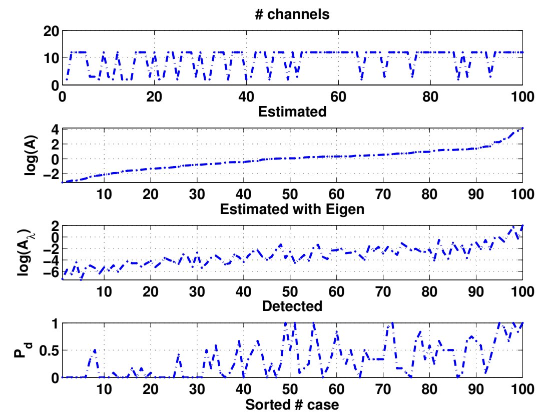
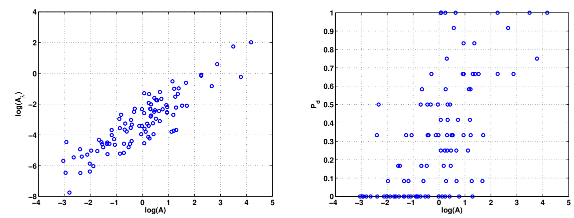


Figure 6. TWA estimation and detection output for the data base. Values are sorted with respect to TWA magnitude as estimated by A statistic.



(a) (b)

Figure 7. Scatter plots for (log) estimated TWA magnitude, (log) magnitude corrected by eigenvalues, and P_d.

Acknowledgements

This work has been partly supported by Research Grant TEC2007-68096-C02-TCM from Spanish Government.

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