Noise Sensitivity of a Principal Component Regression Based RT Interval Variability Estimation Method

Mika P. Tarvainen*, Juha-Pekka Niskanen,
and Pasi A. Karjalainen
Department of Physics
University of Kuopio
P.O.Box 1627, FIN-70211 Kuopio, Finland
*Mika.Tarvainen@uku.fi

Tomi Laitinen and Tiina Lyyra-Laitinen
Department of Clinical Physiology and Nuclear Medicine
Kuopio University Hospital
P.O.Box 1777, FIN-70211 Kuopio, Finland

***Abstract*— Ventricular repolarization duration (VRD) is controlled by neural regulatory system same way as heart rate and, thus, also VRD varies in time. Traditionally, VRD variability is assessed by determining the time differences between successive R and T-waves, i.e. RT intervals. We have recently proposed a method based on principal component regression (PCR) for quantifying RT variability. The main benefit of the method is that it does not necessitate T-wave detection. In this paper, the noise sensitivity of the PCR based method is evaluated by examining the effect of simulated Gaussian noise on the spectral characteristics of the estimated RT variability series.**

I. Introduction

Ventricular repolarization duration (VRD) can be measured from the ECG recording as the time interval between the onset of Q-wave and offset of T-wave, i.e. QT interval. VRD is controlled by neural regulatory system same way as heart rate (HR) and, thus, also QT interval varies in time. It has been argued that abnormal QT variability could be a marker for a group of severe cardiac diseases such as ventricular arrhythmias [1]. In addition, it has been argued that QT variability could yield such additional information which can not be observed from HR variability [2].

Due to the difficulty in fixing automatically the Q-wave onset in VRD determination, RT interval is typically used instead [3], [4]. The RT interval can be defined as the interval from R-wave maximum either to T-wave offset ($\mathrm{RT}_{\mathrm{end}}$) or T-wave apex ($\mathrm{RT}_{\mathrm{apex}}$). The T-wave apex is typically fixed by fitting a parabola around the T-wave maximum [3]. The T-wave offset, on the other hand, can be fixed with a number of methods. In threshold methods, the T-wave offset is fixed as an intercept of the T-wave or its derivative with a threshold level above the isoelectric line [5], [6], [7]. In the slope methods, the T-wave offset is fixed e.g. as an intercept of a line fitted to T-wave downslope with the isoelectric line [6], [8].

We have recently proposed a robust method for quantifying the variation in the RT interval [9]. The method is based on principal component regression (PCR) and it does not necessitate detection of T-wave. In this paper, the noise sensitivity of this method is evaluated by examining the effect of simulated Gaussian noise on the spectral characteristics of the estimated RT variability series. The results are compared with two traditional RT interval estimation methods.

II. Methods

The estimation of RT interval is not always a simple task. T wave is a smooth waveform that can be hard to detect accurately in conditions where the signal-to-noise ratio (SNR) is not high enough. Several artifacts also affect the reliability of the detection remarkably. In this section, we first describe two traditional methods for RT interval measurement which are used as reference. After that, the PCR based method for estimating RT interval variability is described.

A. Simulated noisy ECG signals

The most common approach for evaluating the noise sensitivity of a RT measurement method is to replicate a single noise-free cardiac cycle. This leads to an ECG signal in which the "true" RT interval is constant and the noise sensitivity of the RT measurement method can be evaluated e.g. by determining the standard deviation of RT interval estimates for different noise levels. The proposed PCR based method, however, assumes variability in RT interval and can not, thus, be evaluated this way. In fact, we are interested on the RT variability itself and want to evaluate the effect of noise on the RT variability time series.

To accomplish this we measured ECG from a healthy young male in relaxed conditions (Compumedics Neuroscan, sampling rate $f_s = 1000$ Hz). In order to remove measurement noise and to enable unambiguous detection of R and T-waves, the ECG was bandpass filtered (pass-band 1-30 Hz). The RT interval measures obtained from this noise-free ECG measurement are here considered as the "true" RT intervals. To evaluate the noise sensitivity of different methods, Gaussian zero mean noise of different levels is then added to the noise-free ECG signal. Different RT estimates are calculated again for the noisy ECG and the observed changes in the RT series (compared to the "true" RT series) are evaluated in frequency-domain.

B. Traditional RT measurement methods

Two different RT interval measurement methods are considered. Both methods presume R-wave apex detection which is accomplished by using a QRS detection algorithm similar to the one presented in [10]. The first considered method

measures the time difference between R and T-wave apexes as shown on top of Fig. 1. First, the maximum of a lowpass filtered T-wave is searched from a 0.1-0.4 second window after the R-wave. Then, to reduce the effect of noise, a parabola is fitted around the T-wave maximum and the T-wave apex is fixed as the maximum of the fitted parabola.

The second RT interval measurement method considered measures the time difference between R-wave apex and T-wave offset as shown on bottom of Fig. 1. To fix the T-wave offset, the T-wave is first lowpass filtered by using a 0.02 second moving average filter. The T-wave offset is then fixed as the intercept of the lowpass filtered T-wave downslope with the threshold level above the isoelectric line. The threshold level is set to 10% of the corresponding T-wave maximum.

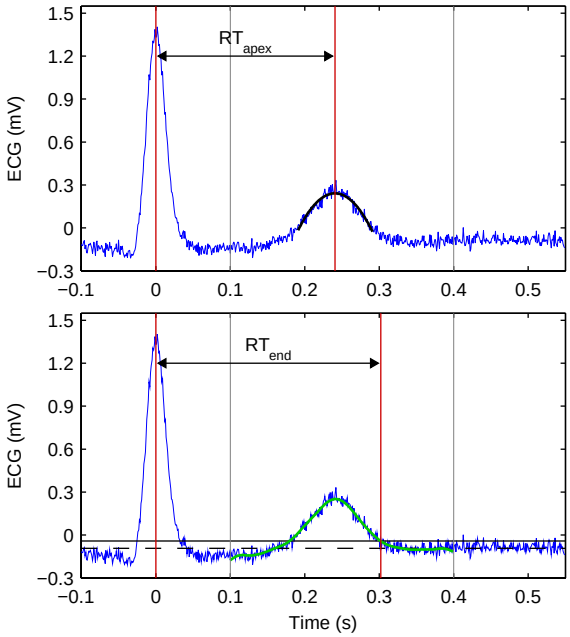

Fig. 1. The two RT interval measurement algorithms considered. $\mathrm{RT}_{\mathrm{apex}}$ (top) where T-wave apex is fixed by fitting a parabola around the T-wave maximum. $\mathrm{RT}_{\mathrm{end}}$ (bottom) where the offset of T-wave is fixed as the intercept of the lowpass filtered T-wave (green line) with the threshold level (black line) above the isoelectric line (black dash line).

C. Principal component regression approach

In the principal component regression, the vector containing the measured signal is presented as a weighted sum of orthogonal basis vectors. The basis vectors are selected to be the eigenvectors of either the data covariance or correlation matrix. The central idea in PCR is to reduce the dimensionality of the data set, while retaining as much as possible of the variance in the original data. [11]

In the method, the ECG measurement is first divided into adequate epochs such that each epoch includes one T-wave. The T-wave epochs are extracted by applying a 0.1-0.4 second window relative to the R-wave fiducial points, see Fig. 2. Let us denote the j'th such epoch with a length N

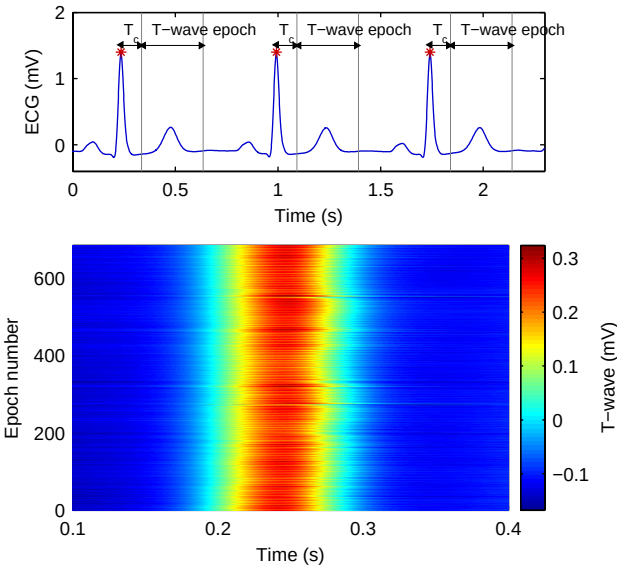

Fig. 2. Extraction of T-wave epochs from the ECG recording.

column vector

$$z_j = \begin{pmatrix} z_j(1) \\ \vdots \\ z_j(N) \end{pmatrix}. \quad (1)$$

In PCR, each of these epochs is presented as a linear combination

$$z_j = H\theta_j + e_j \quad (2)$$

where $H = (v_1, v_2, \ldots, v_K)$ is $N \times K$ matrix consisting of the first K eigenvectors, θ_j is a $K \times 1$ column vector of weights (i.e. principal components) related to j'th epoch, and e_j is error term. If we have M T-waves within the ECG recording, we can define a $N \times M$ measurement matrix $z = (z_1, z_2, \ldots, z_M)$. The observation model (2) can then be written in the form

$$z = H\theta + e \quad (3)$$

where $\theta = (\theta_1, \theta_2, \ldots, \theta_M)$ is a $K \times M$ matrix of PCs and $e = (e_1, e_2, \ldots, e_M)$ is $N \times M$ matrix of error terms.

The columns of H are eigenvectors of either the covariance or correlation matrix of z. Here the correlation matrix, which can be estimated as

$$R = \frac{1}{M} z z^T \quad (4)$$

is utilized. The eigenvectors and the corresponding eigenvalues can be solved from the eigendecomposition. The eigenvectors of the correlation matrix are orthonormal and, therefore, the ordinary least squares solution for the PCs θ becomes

$$\hat{\theta}_{\mathrm{PC}} = H^T z. \quad (5)$$

Quantitatively the first basis vector is the best mean square fit of a single waveform to the entire set of epochs. Thus, the first eigenvector is similar to the mean of the epochs. The second eigenvector, on the other hand, covers

mainly the variation in the T-wave times and is expected to resemble the derivative of the T-wave. The model parameters corresponding to second eigenvector (i.e. the second PCs) are thus expected to reflect the variability of the time difference between the R- and T-waves (RT interval).

III. Results

At first we compare the PCR method with the traditional RT interval measures by using the noise-free ECG signal. The noise-free T-wave epochs used for PCR are shown in Fig. 2. The correlation matrix for the epochs was calculated according to (4) and the first three eigenvectors corresponding to three largest eigenvalues of the correlation matrix are shown in Fig. 3. The first eigenvector clearly represents the mean of the ensemble and the second eigenvector is similar to the first derivative of the T-wave. In fact, it is quite easy to see that in the superposition of the first two eigenvectors the peak is moved according to magnitude and sign of the second PC. For positive values of this component the peak is moved to the right and for negative values to the left.

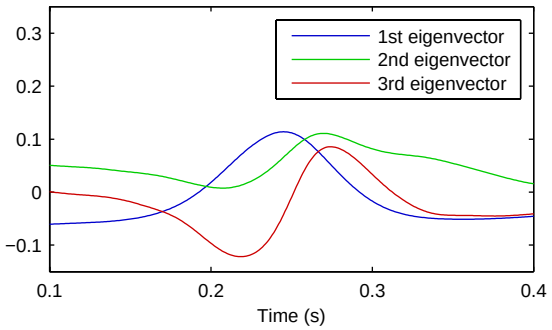

Fig. 3. The first three eigenvectors of the T-wave epochs.

The obtained $\mathrm{RT}_{\mathrm{apex}}$ and $\mathrm{RT}_{\mathrm{end}}$ time series and the second PCs for the noise-free ECG are shown in Fig. 4. It is observed that the variation in the second PC is very similar to the variations in the $\mathrm{RT}_{\mathrm{apex}}$ and $\mathrm{RT}_{\mathrm{end}}$ series. This is further verified in Fig. 5, where the spectrum estimates (calculated using Welch's periodogram method) of the three time series are shown.

The noise sensitivity of the three RT variability estimates was then evaluated by adding Gaussian zero mean noise to the noise-free ECG. The noise levels applied were such that the SNRs of the generated noisy ECG signals were 50, 40, 30, 25, 20, 15, 10, and 5 decibels, see Fig. 6. For each generated ECG, the $\mathrm{RT}_{\mathrm{apex}}$ and $\mathrm{RT}_{\mathrm{end}}$ measures and the second PCs were then recalculated and the corresponding spectrum estimates were obtained. The distortion of the spectrum estimates for decreased SNRs was clearly observed especially for traditional RT measures.

This distortion as a function of SNR was then quantified by calculating spectral band powers in different cases. The considered spectral bands were the low frequency (LF) band (0.04–0.15 Hz) and the high frequency (HF) band (0.15–0.4 Hz). Both the relative LF and HF band powers as well as the ratio between LF and HF band powers, i.e. LF/HF ratio, were calculated. The obtained results as a function of the SNR of the generated ECG signal for the three RT variability estimates ($\mathrm{RT}_{\mathrm{apex}}$, $\mathrm{RT}_{\mathrm{end}}$, and second PC) are shown in Fig. 7. The SNR$=\infty$ corresponds to the noise-free ECG signal.

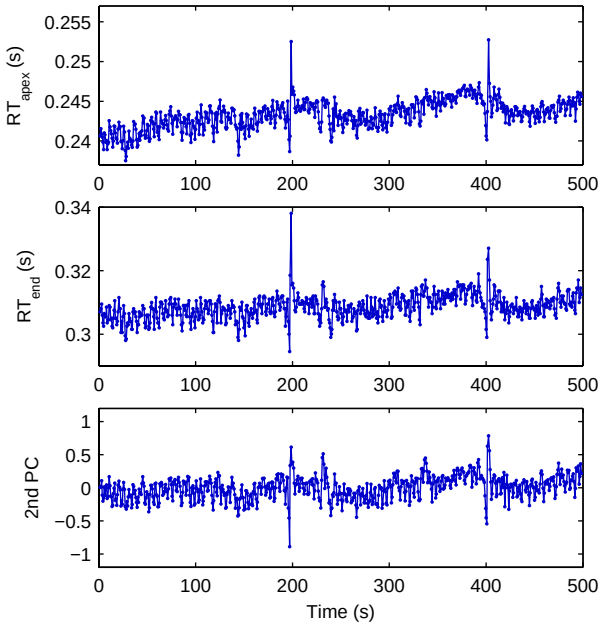

Fig. 4. Comparison of PCR method with traditional RT interval measures. $\mathrm{RT}_{\mathrm{apex}}$ (top), $\mathrm{RT}_{\mathrm{end}}$ (middle), and the second PC (bottom) time series for the noise-free ECG.

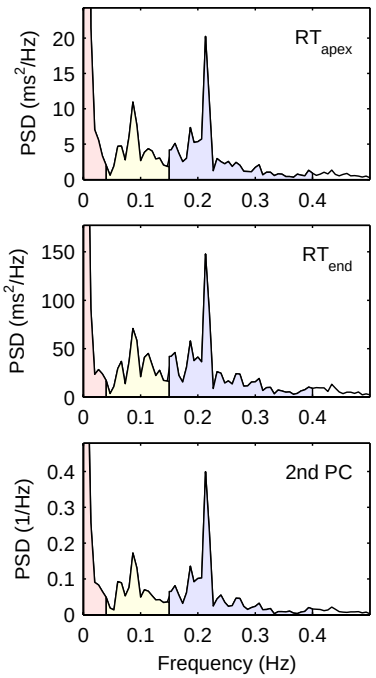

Fig. 5. Comparison of PCR method with traditional RT interval measures. Welch's periodogram spectrum estimates for the $\mathrm{RT}_{\mathrm{apex}}$ (top), $\mathrm{RT}_{\mathrm{end}}$ (middle), and second PC (bottom) time series shown in Fig. 4.

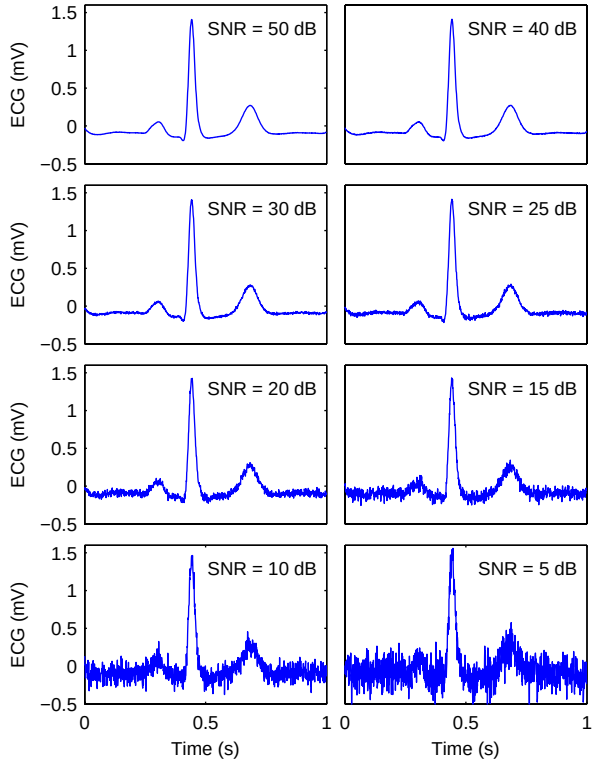

Fig. 6. Samples of the generated ECG signals with different SNRs.

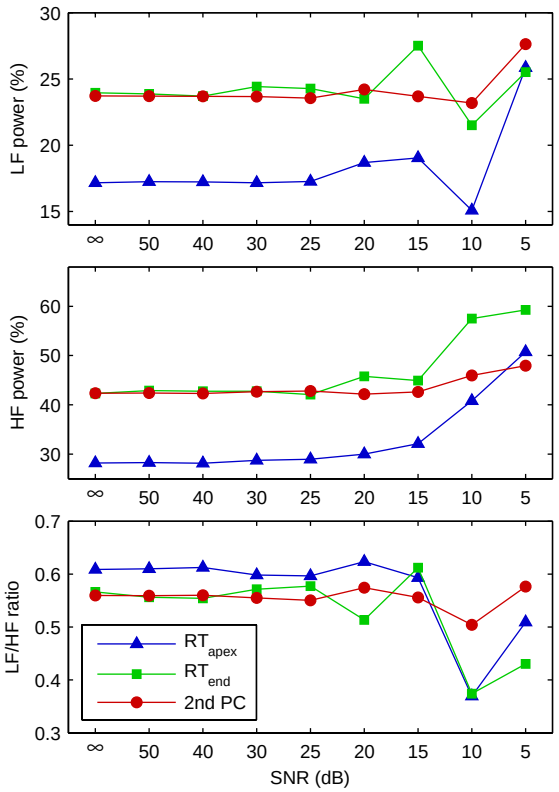

Fig. 7. The noise sensitivity of the PCR method compared to traditional RT interval measures. LF band powers (top), HF band powers (middle), and LF/HF ratios for $\mathrm{RT}_{\mathrm{apex}}$ (▲), $\mathrm{RT}_{\mathrm{end}}$ (■), and second PC (●) time series as a function of the SNR of the generated ECG signal.

IV. Discussion

Ventricular repolarization duration variability, which is typically assessed by examining the variability within the RT interval, is a potential tool in cardiovascular research. The detection of the rather smooth T-wave can be problematic especially in low SNR conditions. We have recently proposed a new PCR based method for estimating the RT interval variability [9]. The main benefit of the proposed method is that it does not necessitate T-wave detection. In this paper, we examined the noise sensitivity of this method and compared it with two traditional RT interval measures, i.e. $\mathrm{RT}_{\mathrm{apex}}$ measure using parabolic fitting and $\mathrm{RT}_{\mathrm{end}}$ measure using a threshold technique.

The noise sensitivity of the method was tested by generating noisy ECG signals having different noise levels. For each noise level, the spectrum estimates of the estimated RT variability time series were calculated and LF and HF band powers evaluated. The proposed PCR based method was clearly less sensitive to noise when compared to the two traditional RT measures as can be seen from Fig. 7. It should be noted that in PCR method the noisy ECG was not preprocessed in any way and, thus, it can be concluded that the method is very robust to noise, at least to Gaussian noise. Baseline oscillations, on the other hand, would most probably cause significant distortion to the method and should, thus, be removed before the PCR analysis. Another issue which can cause significant distortion is if the shape of T-wave changes remarkably within the measurement. These limitations, however, have more or less affect also on the traditional RT measures.

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