Improved QT Variability Quantification by Multilead Automatic Delineation

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Abstract

In this work we evaluate the joint robustness of a multilead delineation and a parametric approach to study the relations between HRV and QTV. The performance of the automatic system is studied over simulated 3-lead ECG signals in order to quantify the improvement allowed by the multilead delineation. Respiratory effect and contamination with realistic noise extracted from a real ECG, rescaled to obtain SNR levels from 30 to 5 dB, were also considered. Compared with same parametric methods over RR and QT series measured from a single lead based approach, the multilead delineator allows to reduce the error in QTV quantification, in particular the error bias in signals at SNR $= 20$ *dB. It improves the joint performance facing realistic 3 lead noise at SNR* ≥ 20 *dB, remarkably around 20 dB, making it usable for ECG signals with QTV levels corresponding to a QT standard deviation* ≥ 13 *ms.*

1. Introduction

Ventricular repolarization (VR) duration variability is currently measured as the beat to beat QT interval variability (QTV). It is known that QTV is, to some extent, driven by the autonomic nervous system (ANS) through the RR interval. Even so, several authors refer direct influences of the ANS over the VR and evidences that the QTV fraction not driven by the beat to beat RR variations (Heart Rate Variability - HRV) can itself have clinical meaning.

In a previous work [1] we explored QTV versus HRV interactions using a linear low order model proposed by Porta el al [2], which allows quantifying the QTV Fraction ($R_{\mathrm{QT|RR}}$ %) driven by HRV. The RR and QT intervals were computed from automatic delineation provided by a wavelet transform (WT) based single lead system [3]. These methods were evaluated over simulated ECG signals, with known QTV and QT versus RR dependencies and noise contamination, in order to evaluate the accuracy lost in the QTV estimation. We achieved a satisfactory joint performance at SNR $\geq$ 20 dB. For noisier ECG signals the system was unusable due to delineation errors.

One of the main problems in studying these relations are the low amplitude T waves, with flat boundaries and consequent uncertainty in T end location. Noise contamination increases delineation difficulty and can result in spurious QTV. To cope the need of a more robust boundaries delineation we proposed a multilead VCG extension of the delineation system, developed to reduce the noise effect over the measured series. From 3 orthogonal leads and the adequate WT scale, we obtain the WT loop (essentially the differentiated signal) that describes the *electrical heart vector* (EHV) evolution during the interval of interest with respect to a particular boundary. A projected WT signal corresponding to the direction parallel to the loop trajectory at the wave boundary is used for its detection. In a standard manual annotated database, multilead delineation provides more robust and accurate T wave end locations than any of the 3 leads by itself and outperforms strategies based in post-processing selection rules over the 3 sets of annotations [4]. Same results are found for QRS onset.

In this work we study the QTV versus HRV relations using the multilead delineation approach proposed for computing the RR and QT intervals. The improvement allowed by the multilead delineation is quantified by evaluating the joint robustness over simulated 3-lead ECG signals facing respiration and realistic noise contamination.

2. Multilead delineation

The multilead delineation system proposed is an extension of the WT based single lead system [3], by considering simultaneously the orthogonal Frank leads $X(k)$, $Y(k)$, $Z(k)$ to locate the waves boundaries. The theoretical basis for using a 3-lead system is the dipole hypothesis, stating that the electrical activity of the heart can be approximated by a time-variant electrical dipole (the EHV). According to this hypothesis, any hypothetical lead can be synthesized by an adequate projection of the EHV. Using the WT of the orthogonal leads at a scale $a = 2^m|_{m\in\{1,2,3,4,5\}}$ we define the loop $\mathbf{L^m(k)} = [W^X_{2^m}(k), W^Y_{2^m}(k), W^Z_{2^m}(k)]^T$. $\mathbf{L^m(k)}$, $k \in I$

is proportional to the ECG derivative and describes the EHV evolution in a time window I, as a consequence of the WT prototype used [3]. Moreover, $\mathbf{U}$, the director of the best line fit (in Total Least Squares sense) to the points in $\mathbf{L^m(k)}$, is the main direction of EHV in I. A derived wavelet signal $D(k)$, corresponding to the ECG lead $ECG(k)$ along the axis defined by $\mathbf{U}$ can be constructed by projecting the loop points over the direction of $\mathbf{U}$. The strategy proposed for multilead delineation consists in a multi-step iterative search for a better spatial lead for delineation improvement, using WT VCG loops (Fig. 1). This new derived lead $Dg_n(k)$ is constructed for each step g using a direction $\mathbf{Ug_n}$ determined separately for each beat n and boundary, by using the adequate time interval Ig_n and wavelet scale. The window Ig_n is updated at each step, according to the new wave boundary limits, to increase SNR and insure very steep slopes in $Dg_n(k)$, and thus well suited for boundaries detection using the single lead delineator criteria. Basing the lead direction choice in the W_{2^m} loop, instead of the VCG directly, allowed to avoid the higher frequency noise contamination, allowing a more accurate direction choice.

3. Parametric approach

The methodology used to explore QTV and HRV interactions assumes an open loop linear model [2] over the series corrected for the mean $x_{\text{RR}}(n)$ and $x_{\text{QT}}(n)$. The $x_{\text{RR}}(n)$ series is modelled as an order p autoregressive (AR_p) stationary random process and QT trend, $x_{\text{QT}}(n)$, is assumed to result from two uncorrelated sources, one driven by RR and other resulting from an exogenous input ($ARARX_q$ model, [5]). A flexible model-orders version, previously described in [1], is considered. For simplicity, the same order q was assumed for all ARARX polynomials, while a possible different order p is allowed for the AR model. The assumption of uncorrelated sources allows to compute the power spectral density of QT, $S_{\text{QT}}(F)$, as the sum of the partial spectra, $S_{\text{QT|RR}}(F)$ and $S_{\text{QT|QT}}(F)$, that express the contributions related and unrelated to RR interval. Each spectrum $S_{\text{QT|E}}(F)$, $E \in \{RR, QT\}$ can be decomposed in l_E components, each one referred to one of its poles z_k, $k = 1, \ldots, l_E$ [6] and [7]. Due to the symmetry of $S_{\text{QT|E}}(F)$ with respect to $F = 0$, frequencies associated to complex conjugate poles correspond to complex conjugate components that can be combined in a real $S^{(g)}_{\text{QT|E}}(F)$, related to a power component $\gamma_g + \gamma_g^* = 2\Re(\gamma_g)$ [6]. Therefore, each $S_{\text{QT|E}}(F)$ can be decomposed into components $S^{(g)}_{\text{QT|E}}(F)$, contributing mainly at frequencies $0 \leq F_g \leq Max[F]/2$. The power within a given frequency band $\mathcal{B}$, denoted by $P^{\mathcal{B}}_{\text{QT|E}}$, can be obtained by summing the contributions of the poles located in the band $\mathcal{B}$,

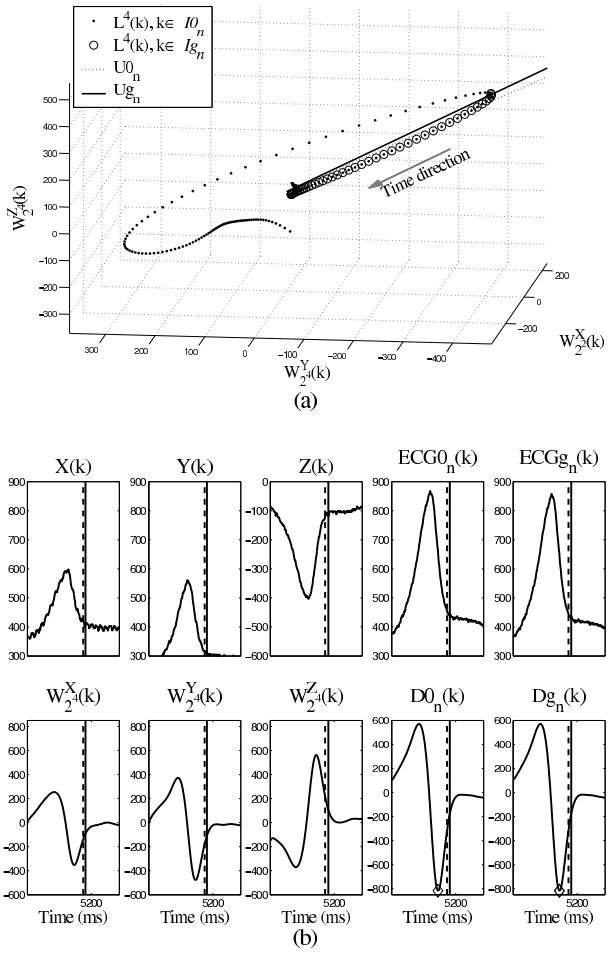

Figure 1. Multilead delineation strategy applied to T wave end: (a) loop $\mathbf{L^4(k)}$ in the initial ($I0_n$) and final (Ig_n, $g = 2$) windows and the respective best fit directions ($\mathbf{U0_n}$, $\mathbf{Ug_n}$); (b) orthogonal leads, respective WT for $a = 2^4$ and $k \in I1_n$ chosen in the first step, derived WT ($D0_n(k)$, $Dg_n(k)$) and ECG signals ($ECG0_n(k)$, $ECGg_n(k)$) corresponding to the directions $\mathbf{U1_n}$ and $\mathbf{Ug_n}$. Vertical dashed (solid) line stands for found (reference) T end mark.

$$P^{\mathcal{B}}_{\text{QT|E}} = \sum_{\substack{g \\ F_g \in \mathcal{B}}} c_g \, \Re(\gamma_g) \tag{1}$$

where $c_g = 1$ for real poles and $c_g = 2$ for complex conjugate poles. The relative fraction of the QTV driven by RR in the frequency band $\mathcal{B}$ is given by

$$R^{\mathcal{B}}_{\text{QT|RR}} = \frac{P^{\mathcal{B}}_{\text{QT|RR}}}{P^{\mathcal{B}}_{\text{QT|RR}} + P^{\mathcal{B}}_{\text{QT|QT}}} \times 100. \tag{2}$$

Orders p, q between 2 and 18 were considered. The adequacy of the models are tested using residual analysis

and ensuring admissible power measures. Optimal p and q were automatically selected from the adequate orders by minimizing the *Akaike Information Criteria* (AIC) [5].

4. Simulation set-up

We simulated 50 trials of $RR(n)$ series realizations using the Integral Pulse Frequency Modulation model following a AR modulating signal that match the typic spectra at supine rest records [1]. Assuming that the linear model holds, the $QT(n)$ series were simulated using a priori chosen coefficients corresponding to distinct QTV levels, in way to know the QTV fraction correlated with RR. In this study were modelled six different QTV levels, corresponding to QT standard deviations of $\sigma_{\text{QT}} = 17$, 13, 10, 8, 3 and 5 ms. A segment of 350 beats from every realization of the simulated series from each QTV level were considered in the data set C_c (*clean* test data).

A clean and well defined template beat was chosen from a 3-lead baseline corrected real file. Artificial ECG signals corresponding to the simulated series were constructed by concatenation of the template beat, following the $RR(n)$ beat intervals, properly scaled from QRS end to T wave end to reflect the variability inherent to $x_{\text{QT}}(n)$ series. By applying the same scaling to template beats from the orthogonal leads X, Y and Z, 3-lead artificial ECG signals with same QTV and HRV in all leads $\left(y^L(k), L \in \{X, Y, Z\}\right)$ can be obtained. Automatic delineation over these signals provided the series *signal derived* ("*s*"). Segments of consecutive 350 valid beats measures (without RR outlier or missing QT values) were considered as the data set C_s.

The *respiratory effect* ("*r*") was simulated assuming that the angular variation around a lead axis is a function of the amount of air in the lungs at each time, which was modelled as a sinusoid. The respiratory frequency was set to $F_r = 0.24$ Hz and the data set C_r was constructed from the series of delineated intervals over the ECG signal affected by respiratory noise. To consider other contamination types, a realistic 3-lead noise was extracted from a real file by subtracting a running averaged and amplitude fitted beat. The 3-lead noise file was multiplied by a constant factor to get a predefined global SNR when added to the artificial ECG, considering levels from 30 to 5 dB. The data set C_v was defined from the delineation over these *noisy* ("*v*") ECGs and comprehends the $x_{\text{RR}}(n)$ and $x_{\text{QT}}(n)$ series obtained from the contaminated ECGs considering all noise types and SNR levels. Again, only segments of consecutive 350 valid beats measures were considered.

5. Results

The data sets C_s, C_r and C_v were constructed considering single lead delineation (over lead Y) and multilead delineation. Valid segments of 350 consecutive beats were found in data sets C_s and C_r for all 50 series relative to each QTV level, for both delineation strategies. To help the comparison between SNR levels, for data set C_v were only included the qualified segments across SNR levels, for each QTV level. The number of consecutive valid beats lessen with SNR, reducing the number of valid segments. At SNR$<$ 20 dB the number of common segments was quite reduced, even for high QTV levels. Thus only segments with SNR $\geq$ 20 dB were considered. Common segments were found for a minimum of 49 (out of 50) series from single lead approach and for a minimum of 32 series from multilead delineation. Adequate model identification was achieved for a minimum of 98% of the valid segments in each data set and QTV level using multilead delineation (96% of the valid segments using single lead delineation).

The actual spectra of the simulated series was obtained directly from the reference parameters in each QT reference model used to generate the simulated series. The spectral decomposition was performed as described and the reference variability measures $P^{\mathcal{B}}_{\text{QT|RR}}$ calculated by (1). The percentage errors $\varepsilon^{\mathcal{B}}$ in the quantification of the QTV fraction correlated with HRV are defined as the difference between the ratios calculated from (2) for estimated, $\hat{R}^{\mathcal{B}}_{\text{QT|RR}}$, and reference measures, $R^{\mathcal{B}}_{\text{QT|RR}}$. Total power was taken as the band from 0.04 Hz to the highest frequency present in each spectrum ($\mathcal{B} = \mathcal{TP}$).The distributions of $\varepsilon^{\mathcal{TP}}$ by data set and for QTV level $\sigma_{\text{QT}} \geq 10$ ms are presented in the Fig.2. No performance differences were noticed between data sets C_c and C_s for both delineation strategies. A relevant reduction on the error bias is achieved in data set C_v, especially important for QTV level $\sigma_{\text{QT}} = 13$ ms. The improvement is particularly remarkable at SNR = 20 or 25 dB. For more reduced QTV levels ($\sigma_{\text{QT}} < 10$ ms) the errors are high even at high SNR, using any of the delineation approaches, making the method unusable. Results for data set C_r point out to a slightly performance decrease using the multilead delineation. This decay is no longer true if comparing with delineation over lead X, case in which the single lead delineation performs quite badly. Thus the single lead delineation errors facing respiratory noise are very dependent of the particular lead used.

The percentage of segments with $\varepsilon^{\mathcal{TP}} \leq 15\%$ out of the valid segments for each adequante model is presented in the Fig.3, for each data set and QTV level $\sigma_{\text{QT}} \geq 10$ ms. The multiled delineation increases the percentage from 78% to 95% for QTV level $\sigma_{\text{QT}} = 17$ ms and from 72% to 95% for QTV level $\sigma_{\text{QT}} = 13$ ms, at SNR $\geq$ 20 dB.

6. Concluding remarks

Using multilead based delineation of simulated 3-lead records allows to reduce the error in QTV quantification. In particular, the bias of the error in signals with QTV le-

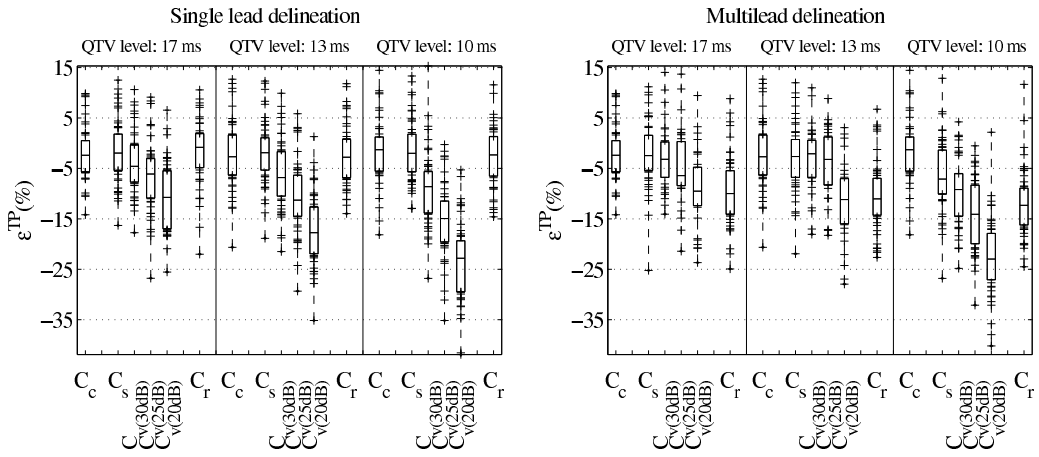

Figure 2. Distributions of $\varepsilon^{\mathcal{TP}}$ using single lead or multilead delineation: box-and-whisker plots.

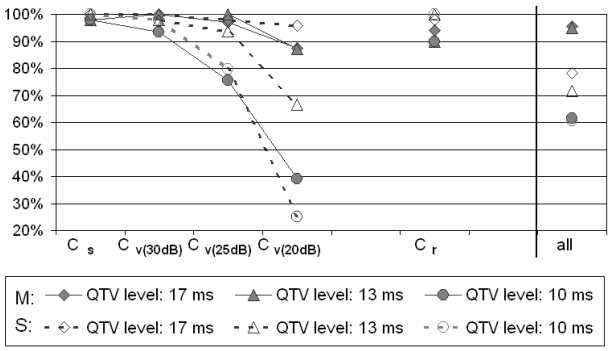

Figure 3. % of segments with $\varepsilon^{\mathcal{TP}} \leq 15\%$ using multilead delineation (M) single lead delineation (S).

vels corresponding to a QT standard deviation $\geq$ 13 ms at SNR $\geq$ 20 dB. The joint system of multilead automatic delineation plus QTV parametric quantification allows to analyse and quantify the QTV fraction driven by HRV in ECG signals with a QTV level $\geq$ 13 ms, facing respiratory and other noise at SNR $\geq$ 20 dB. For a lower QTV level ($\geq$ 10 ms), the joint system can deal adequately at SNR $\geq$ 25 dB. The application of these methodologies to real data should attend to the range of applicability established in this study. The necessary studies on the clinical interpretation of the QTV fractions, particularly in the importance of the variability uncorrelated to HRV, can now be conducted in the framework of this modelling.

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