

# Quantification of Short Term QT Variability versus Heart Rate Variability

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## Abstract

In this work we propose to assess the relation between HRV and QTV measured by an automated QT delineator. ECG records of young normal subjects from POLI/MEDLAV database were processed to obtain the RR and QT series. A low order linear autoregressive model on RR versus QT interactions was used to explore short term relations and quantify the fractions of the QTV correlated and not correlated with HRV. Power Spectral density measures were estimated from the total QTV and from the two separated fractions considering Total Power and Very Low Frequency (0-0.04 Hz), Low Frequency (0.04-0.15 Hz) and High Frequency (0.15-0.4 Hz) bands. The high percent value of the RR non correlated fraction on the global variability indicates that an important part of QTV could be driven by other factors rather than by RR.

## 1. Introduction

The duration of ventricular repolarization expressed on the QT interval is known to be affected by the RR interval and its variations. However it is not clearly quantified which fraction of QT variability (QTV) is effectively correlated with heart rate variability (HRV). The uncertainty in defining the QT interval due to the delineation method variability (both on manual and automatic measures) allied to the smaller amplitude of the QTV compared to HRV, represent main difficulties in exploring this relationship.

Assuming that dependence of ventricular repolarization on cardiac cycle of ventricular repolarization is concentrated mainly in the early portion of the QT interval, some authors [1] studied the changes in the interval between the R peak and the apex of the T wave (RT interval). This approach ignores fluctuations in repolarization that mainly affect the last part of the T wave, likely to be of increasing significance in specific pathological conditions. As a counterpart,

the QT interval comprehends all the ventricular repolarization and its larger amplitude benefits variability measurement.

A wavelet transform based ECG delineation system previously developed by the group [2]-[3] and evaluated on several manually annotated databases, has proven to be quite robust, both against noise and morphological variations. This fact together with the automatic nature of the detector that will avoid the inter/intra-expert variability in the measures, leads us to use the measured intervals to explore the relation between the HRV and the QTV.

A linear, dynamic parametric model of the RT-RR variability interactions was proposed by Porta et al [1], taking into account the possible dependency of the RT period on its past samples and on past values of the RR interval. This open loop model allows to separate the fraction of the RT variability driven by RR changes from that independent of the RR variations and to quantify the gain and phase of the relationship between the RR and RT intervals.

The main goal of this work is to explore the short term HRV and QTV relationship using a linear low order model approach similar to the proposed in [1] to quantify the fraction of the QTV not driven by RR. This method allows to separate and study the QTV fraction not correlated with the HRV, aiming to understand its truly significance and origin.

## 2. Methods

### 2.1 Parametric Model Formulation

A linear, dynamic parametric model of the HRV and QTV interactions, based on the one proposed by Porta et al [1] for RT-RR variability interactions was considered. The RR and QT (measured from QRS onset to T wave end) sequences [2]-[3] were mean corrected.

For  $A_{11}$ ,  $A_{12}$ ,  $A_{22}$  and  $D$  polynomials in  $z^{-1}$  the open loop model considered is schematized in Figure 1.

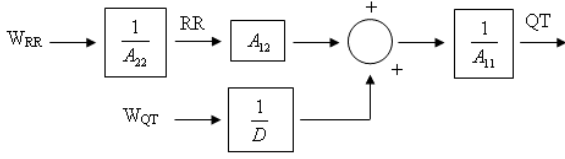


Figure 1: Schematic representation of the QTV versus HRV interactions model.

An autoregressive model was used to describe HRV

$$RR(z) = \frac{1}{A_{22}(z)} W_{RR}(z), \quad (1)$$

where  $W_{RR}$  is white noise with zero mean and variance  $\lambda_{RR}^2$ . The QT interval is considered to possibly depend of its own past and on past values of the RR interval. The model is defined by

$$QT(z) = \frac{A_{12}(z)}{A_{11}(z)} RR(z) + \frac{1}{A_{11}(z)D(z)} W_{QT}(z), \quad (2)$$

where  $W_{QT}$  is white noise with zero mean and variance  $\lambda_{QT}^2$ , uncorrelated with  $W_{RR}$ . Therefore, QTV is assumed to result from two non correlated sources: one driven by HRV and other non dependent of RR. This allows computing the Power Spectral Density (PSD) of QTV ( $S_{QT}$ ) as the sum of the two partial spectra that express the contribution of each source in the total variability

$$S_{QT}(\omega) = S_{QT/WRR}(\omega) + S_{QT/WQT}(\omega) \quad (3)$$

with

$$S_{QT/WRR}(\omega) = \overline{RR} \lambda_{RR}^2 \left| \frac{A_{12}(z)}{A_{11}(z)A_{22}(z)} \right|_{z=\exp(j\omega\overline{RR})}^2 \quad (4)$$

$$S_{QT/WQT}(\omega) = \overline{RR} \lambda_{QT}^2 \left| \frac{1}{A_{11}(z)D(z)} \right|_{z=\exp(j\omega\overline{RR})}^2 \quad (5)$$

where  $\overline{RR}$  stands for the RR mean value.

## 2.2 Model Identification

The coefficients of polynomial  $A_{22}$  can be estimated from equation (1) and least squares. A generalized least squares (GLS) methodology [4] applied to the problem of equation (2) allows a recursive estimation of the coefficients in  $A_{11}$ ,  $A_{12}$  and  $D$ , until white noise residual  $W_{QT}$  is obtained. For adequate model orders the GLS convergence is expected to occur in a reasonable small number

of iterations. Therefore in this implementation was considered that convergence must be achieved within a maximum of 100 iterations.

For simplicity the same order is assumed for all polynomial in the model. An order is considered adequate for modelling a segment of data if  $W_{RR}$  and  $W_{QT}$  satisfy a 10% confidence bilateral test for normalized autocorrelation and crosscorrelation. The test is performed both in lags lower than 40 [1] and taking all the lags.

## 3. Results

In this study were used ECG records of young normal subjects from POLI/MEDLAV database [5], which consists on 24-minute recordings of 3 leads and 500 Hz sampling rate. The first lead was processed by a wavelet transform based delineation system previously developed and evaluated by the group [2]-[3]. The automated delineation allows to avoid intra/inter-observer variability. Possible outliers were detected and only segments with minimum length of 315 consecutive beats with valid RR and QT intervals were considered in the subsequent analysis. For each segment were considered models with order from  $\{6, 8, 10, 12\}$ . The coefficients were estimated and the non correlation tests of residues were performed (Table 1).

ID segment	File	Segment		Orders that satisfied autocorrelation test	
		begin (sec)	length (beats)	$W_{QT}$	$W_{RR}$
1	ra2	252.99	360	10,12	8,10,12
2	ra2	902.46	598	-	12
3	rb2	44.03	808	10,12	all
4	rb2	462.22	932	all	10,12
5	rc1	706.32	344	all	12
6	rc2	852.96	361	all	8,10,12
7	re2	76.26	541	all	10
8	re2	414.28	757	all	all
9	rf1	306.80	463	10,12	all
10	rf1	661.47	343	-	all
11	rf1	922.45	584	all	10,12
12	rf2	46.74	424	all	8,10,12
13	rg1	314.40	318	8,10,12	12
14	rh1	104.11	399	-	all

Table 1: Lead 1 segments of POLI/MEDLAV database that were qualified for the analysis and correspondent orders for which the estimated model converged with autocorrelations not significantly different from zero.

In 3 of the segments we do not obtain convergence of the GLS algorithm to a white noise residue in the maximum allowed number of interactions for any of the tested orders. The crosscorrelation between  $W_{RR}$  and  $W_{QT}$  was not significantly different from zero in all cases.

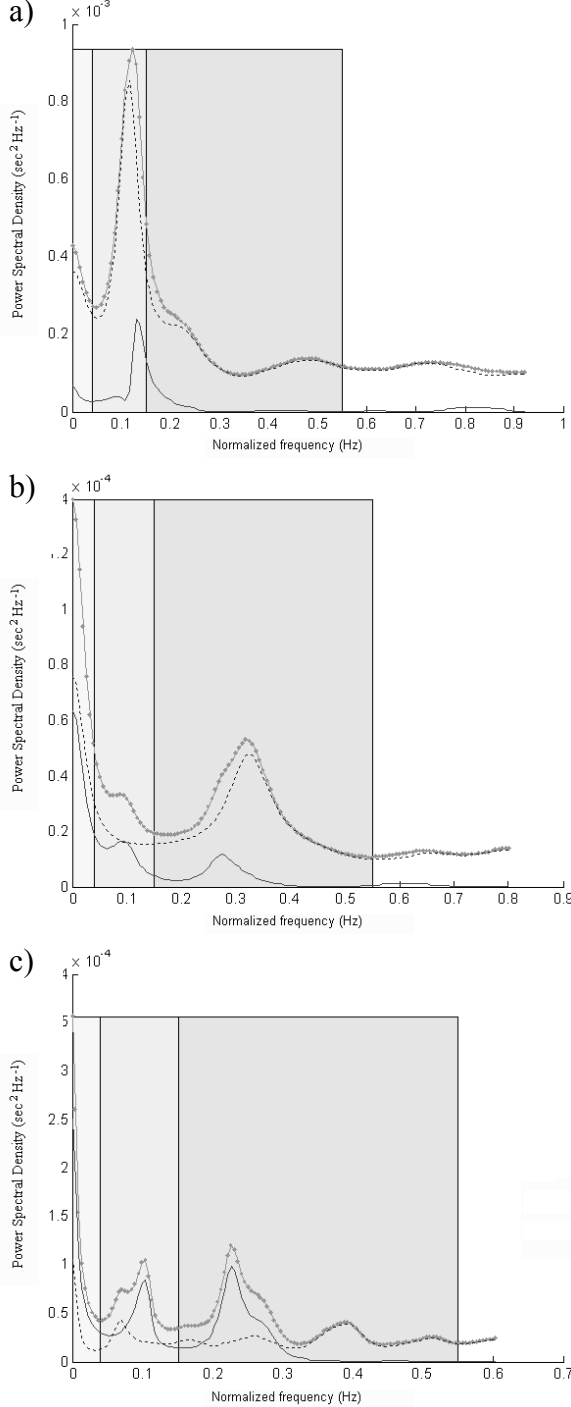


Figure 2: Power Spectral Density of QTV: Total Power  $S_{QT}$  (—•—) and separated fractions  $S_{QT/WRR}$  (—) and  $S_{QT/WQT}$  (-----); a) ID segment 4, model order 10; b) ID segment 7, model order 10; c) ID segment 13, model order 12. The shadowed areas correspond to the frequency bands considered for VLF, LF and HF.

The two partial PSD  $S_{QT/WRR}$  and  $S_{QT/WQT}$  are calculated using equations (4) and (5) and the total spectra of QTV ( $S_{QT}$ ) taken as the sum. As illustrated in Figure 2 for three of the segments,  $S_{QT/WQT}$  is frequently found to be higher than  $S_{QT/WRR}$ . The dissimilarity found in the  $S_{QT/WRR}$  and  $S_{QT/WQT}$  shapes suggests that the two fractions reflect different influences over QT.

PSD measures were estimated to quantify the fractions of the QTV correlated and not correlated with HRV. Total Power and Very Low Frequency (0-0.04 Hz), Low Frequency (0.04-0.15 Hz) and High Frequency (0.15-0.4 Hz) bands were considered. The ratios between the measures of  $S_{QT/WQT}$  and  $S_{QT}$  allow to evaluate the relative importance of the QTV not driven by RR. The obtained values in each frequency band are presented in Table 2.

ID segment	Model order	TP (%)	VLF (%)	LF (%)	HF (%)
1	10	37.50	60.00	18.67	75.00
	12	36.94	54.55	18.06	70.59
3	10	88.20	90.53	73.93	97.97
	12	88.74	90.53	72.76	97.39
4	10	90.86	90.91	85.86	90.21
	12	89.53	86.96	82.30	90.21
5	12	23.00	32.35	7.35	55.56
6	8	59.65	30.00	55.56	78.95
	10	58.62	25.00	55.56	78.95
6	12	55.93	23.81	55.56	75.00
	7	10	78.46	58.33	54.55
8	6	58.57	31.03	36.36	93.75
	8	57.97	33.33	33.33	87.50
	10	54.79	25.81	33.33	87.50
	12	51.35	21.88	33.33	87.50
9	10	57.53	44.44	60.00	46.43
	12	56.76	44.44	60.00	42.86
11	10	63.08	41.18	75.00	57.14
	12	61.19	38.89	75.00	50.00
12	8	50.00	14.29	77.78	71.05
	10	46.46	10.17	77.78	67.50
	12	44.70	7.94	70.00	68.29
13	12	49.44	26.67	38.10	47.37

Table 2: Ratios between  $S_{QT/WQT}$  and  $S_{QT}$  measures considering Total Power (TP) and bands of Very Low Frequency (VLF), Low Frequency (LF) and High Frequency (HF).

The ratio for TP in 9 from the 11 segments analysed was found to be higher than 40%, what also stands for all segments in HF band. This

suggests that an important part of QTV could be driven by other factors rather than RR.

#### 4. Concluding Remarks

This work discusses the application of a linear low order model approach to study the short term HRV and QTV relation, in analogy to the proposed by Porta et al [1] for the RT interval variability.

The results point out an important part of QTV not being driven by RR and challenge further exploration and interpretation.

As matter of fact, the use of the same order for all the polynomials in the model and the predefined set of orders are a restriction to the results obtained. There is no reason to constrain the QT and RR sequences to the same memory of its on past and in the future a strategy for order selection in each part of the model should be included. A goodness-of-fit measure, like Akaike's Final Prediction Error or the Information Theoretic Criteria could be used over *a priori* information based set of orders.

Since no additional information about the non RR correlated sources is available, an extension of this model must be considered to improve its characterization and interpretation. Trying to identify and understand the phenomena behind these influences is the driving force of future studies.

#### Acknowledgments

The first author acknowledges the grant SFRH / BD / 5484 / 2001 supported by FCT and ESF (III CSF). This work was also supported by the integrated action HP2001-0031 / CRUP-E26/02.

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