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Effects of ECG sampling rate on QT interval variability measurement

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1. Introduction

The QT interval of ECG is a measure of ventricular depolarization and repolarization duration. Corrected for heart rate, it is clinically used to diagnose congenital or acquired QT syndromes [1,2]. The QT interval fluctuates from beat to beat and quantification of this so-called QT interval variability (QTV) has received increasing interest as evidence of the association between increased QTV and elevated risk of cardiac and overall mortality is mounting [3–5]. Aside from its potential use for cardiac risk stratification QTV may be used as a noninvasive marker of sympathetic outflow to the heart, because studies in humans have repeatedly demonstrated increased QTV during periods of acute cardiac sympathetic activation, elicited by pharmacological beta receptor activation or by orthostatic challenge, in particular in healthy subjects [6–8] or subjects with structurally normal hearts [9,10]. The level of QTV measured during rest was shown to be directly correlated with cardiac noradrenaline spillover in hypertensive subjects [11], but not in normal subjects or patients with major depressive disorder or panic disorder [12]. A canine model of tachycardia induced heart failure showed a direct correlation between the QTV and integrated left stellate-ganglion nervous activity [13].

Although QTV has been widely studied in various clinical research settings, some basic technical considerations regarding the QT measurement have been insufficiently addressed. Technical aspects are of particular significance since beat-to-beat fluctuations in the QT interval are typically small, with a standard deviation of less than 5 ms when measured at stable heart rates during rest [14]. Addressing the issue of high precision QT interval delineation of body surface ECG, we have previously shown that template matching algorithms specifically dedicated to the analysis of QTV are better suited to measure subtle beat-to-beat changes in QT interval than conventional delineation techniques [15]. At a more fundamental level, however, ECG data acquisition requirements for measuring meaningful QTV have not been thoroughly investigated yet. Previous studies performing QTV analysis used ECG that was sampled at rates as low as 128 Hz [16]. The aim of this study was to systematically explore the effects of sampling rate on QTV metrics, using simulated ECG with predefined QTV as well as real ECG recordings from healthy subjects to offer guidance for ECG recording requirements. Experimental conditions characterized by a low and high sympathetic drive were considered (i.e. resting in the supine position and standing, respectively).

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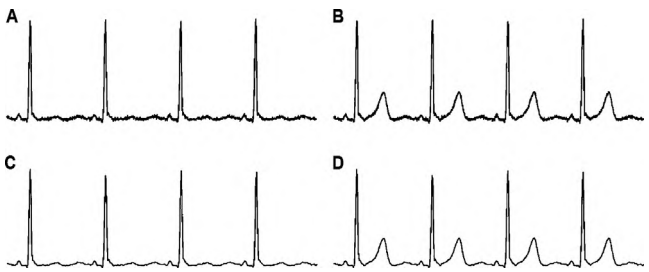

Fig. 1. Examples of simulated noisy ECG with artificially imposed QT variability in the high and low frequency range. (A) T wave acquisition range: 0.6%, sampled at 1000 Hz; (B) T wave acquisition range: 6.4%, sampled at 1000 Hz; (C) T wave acquisition range: 0.6%, sampled at 125 Hz; (D) T wave acquisition range: 6.4%, sampled at 125 Hz.

2. Methods

2.1. Data

2.1.1. Simulated ECG

Simulated ECG signals were generated as described previously [15,17]. Briefly, we obtained a noise-free cardiac cycle (starting from a QRS peak and ending at the subsequent QRS peak) of an ECG (lead II) that was recorded in a healthy 26 years old volunteer. The ECG was digitized with an A/D board of 12-bit resolution at a sampling rate of 1000 Hz. Considering the overall input range (4096 quanta), the two R-peaks spanned a range from 1983 to 2940 quanta (i.e. the R-peak amplitude covered 957 quanta), while the T-wave spanned the range from 1984 to 2246 quanta (i.e. the T wave amplitude covered 262 quanta). Hence, the R-peak and T-wave occupied 23.4% and 6.4%, respectively of the A/D board's range. The T-wave amplitude was scaled by factor k, where $k \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0\}$, resulting in 10 cardiac beats with decreasing T-wave amplitudes. The 10 cardiac cycles were then repeated 500 times, resulting in ten synthetic signals with 500 cardiac cycles each, characterized by null variability in heart rate and ventricular repolarization duration, but different T wave amplitudes (Fig. 1). White Gaussian noise was superimposed to each of the ten synthetic ECG to provide a realistic signal. The mean value of the noise was zero and the standard deviation was 3% of the T-wave amplitude of the original cardiac cycle.

Artificial QT variability was introduced by modulating the ST interval of the simulated ECG with oscillatory components at frequencies of 0.1 and 0.25 Hz, respectively, mimicking the effects of the low frequency oscillations (LF) that have been associated with the Traube–Hering–Mayer waves that can be observed in the cardiovascular system and the high frequency oscillations (HF) associated with respiration. The power of LF oscillations was 2.2 ms^2 and the HF power was 12.8 ms^2.

2.1.2. Real ECG

The study conformed to the principles outlined in the Declaration of Helsinki. We enrolled 10 healthy athletes (5 males, age: 26.6 years [26.5–28.8]; 5 females, age: 24.8 years [24.7–26.4]. Participants took part in a two-week training camp and measurements were repeated after the first week of training as well as 3–4 days after completing the camp. All participants provided written informed consent. Details have been published previously [18,19]. As part of a study on the effects of overtraining on autonomic cardiovascular control, 3-lead ECG (modified Frank lead system) was recorded at 1600 Hz during rest in the supine position for 30 min and subsequently during standing for another 20 minutes. QTV analysis was performed on the lead with the tallest T-wave, which spanned 4683 quanta on average and represents 27% of the R-amplitude, on average. For the purpose of this study we collated the ECG from all athletes obtained during the three recording sessions, distinguishing only between resting and standing, respectively, thus enabling the assessment of QTV with respect to sampling rate during conditions of low and high sympathetic activity.

2.1.3. Down-sampling

To investigate the effect of sampling rate on QTV measurement, we generated versions of the data down sampled at 500 Hz, 250 Hz and 125 Hz for simulated ECG, and 800 Hz, 400 Hz, 200 Hz and 100 Hz for real ECG, respectively, using a poly phase finite impulse response filter, where the number of taps was $N = 2 \times 20 \times$ (original sampling rate/down-sampling rate) + 1, employing Kaiser windowing. Examples of original and down sampled simulated ECG are shown in Fig. 1.

2.1.4. Beat-to-beat QT interval measurement

For this study, we employed a template matching technique that relies on the recently developed two-dimensional warping (2DSW) algorithm [20]. The method is able to account for complex morphological changes in the ECG waveform and was shown to track QT changes with high precision while being robust toward signal artifacts at the same time. Briefly, the algorithm first identifies QRS complexes automatically and uses these fiducial points to generate an averaged template beat, by employing an improved version of Woody's time delay estimation method [21]. Subsequently, points of interest, such as Q-onset and T-wave end, are marked on the template beat by the operator in a semi-automated manner. Using a two-dimensional grid of so-called warping points, the Euclidean distance between template and each beat in the signal is minimized by warping the ECG waveform piece-wise along the warping points. Relative variations in the QT interval, as annotated by the operator on the warped template, are utilized to measure beat-to-beat changes in QT intervals. Time series of RR and QT intervals were visually checked for missing beats and affected beat-to-beat intervals were removed. We then calculated a set of QTV metrics (see below) for each recording, using the last 256 valid consecutive beats of the ECG.

2.1.5. QTV metrics

To quantify QTV we adopted a set of metrics originally proposed for HRV analysis that have been subsequently used for QTV assessment. Time domain assessment comprised:

- SDQT—standard deviation of QT intervals; in ms,
- RMSSD—root-mean-square of successive differences in QT interval; in ms.

For spectral analysis the series were modeled as an autoregressive process describing the dynamics as a linear combination of past samples weighted by constant coefficients plus a zero mean white noise [22]. The Levinson–Durbin recursive algorithm was utilized to estimate the coefficients of the AR model and the variance of the white noise. The number of coefficients was chosen according to the Akaike's figure of merit in the range from 14 to 18 [23]. Power spectral density was computed from the coefficients of the model and from the variance of the white noise according to the maximum entropy spectral estimation approach [22]. The power spectral density was factorized into spectral components each associate to a real pole or pair of complex and conjugated poles, the sum of which provides the entire power spectral density [24]. Power spectral factorization provided the central frequency of the components expressed in cycles $\times$ $beat^{-1}$, converted into Hz by dividing it by the heart period mean, and decomposition of the overall variance. In the frequency domain we quantified:

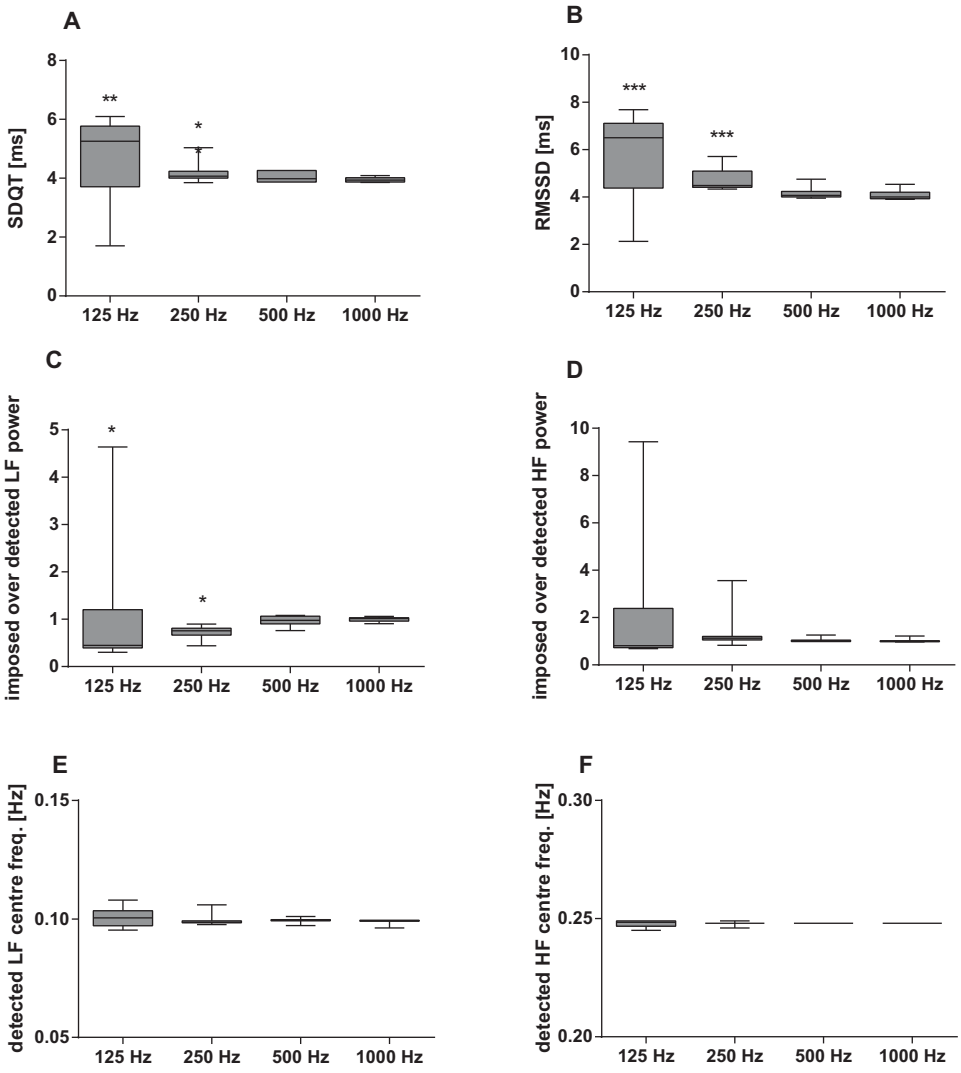

Fig. 2. Sampling rate effect on QT variability in simulated ECG quantified in the time and frequency domains, presented as median and interquartile ranges. For definitions of variables see text. * $p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

- LF—power in the low frequency band (0.04–0.15 Hz); in ms^2,
- HF—power in the high frequency band (0.15–0.4 Hz); in ms^2.

For simulated ECG we also calculated the center frequencies of LF and HF powers.

To quantify the complexity of QTV we computed measures of symbolic dynamics as proposed previously [25]. Briefly, beat-to-beat QT interval time series were transformed into sequences of six symbols [0, 1, 2, 3, 4, 5], where the rule of transformation was based on the data distribution, divided into six equal spaced bins. From the resulting symbol sequences, patterns of length $m = 3$ were constructed. Each pattern was grouped into one of 4 categories:

- 0V—zero variation (all 3 symbols were equal); in %,
- 1V—one variation (two consecutive symbols were equal and the remaining symbol was different; in %,
- 2LV—two likewise variations (three symbols formed an ascending or descending ramp); in %,
- 2UV—two unlike variations (the second symbol was larger or smaller than the other two symbols, forming either a peak or a valley); in %.

2.1.6. Statistics

For statistical analysis of simulated ECG we computed non parametric statistics due to the small number of simulations (i.e. ten ECG with varying T wave amplitude). Descriptive statistics included group medians and interquartile ranges. Repeated measurement non-parametric statistics was used (Friedman test) to compare QTV metrics of down-sampled simulated ECG. For post-hoc comparison of QTV metrics with regard to highest available sampling rate (i.e. 1000 Hz), we used the Dunn's multiple comparison test.

For statistical analysis of real ECG we computed group means and standard deviation. Two-way ANOVA was performed to test for intervention effect (supine vs. standing) and sampling rate effect. Post-hoc comparison was carried out for pooled sampling effect with respect to the highest sampling rate (1600 Hz) using Dunnett's multiple comparison test.

3. Results

3.1. Effect of sampling rate on QTV using simulated ECG

Standard deviation of QT intervals (SDQT; Fig. 2A) increased artificially at sampling rates lower than 500 Hz ($p = 0.01$). Similarly, average magnitude of beat-to-beat change in QT interval

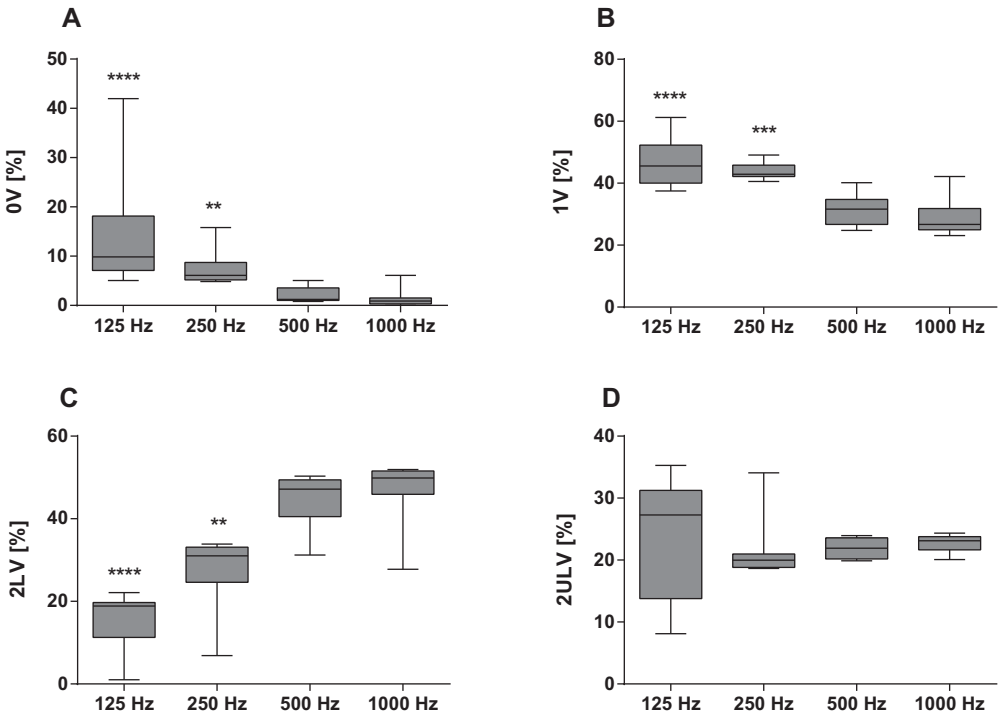

Fig. 3. Sampling rate effect on QT variability in simulated ECG quantified in symbolic dynamics, presented as median and interquartile ranges. For definitions of variables see text. ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$.

(RMSSD; Fig. 2B) increased below 500 Hz ($p = 0.0004$). Frequency domain analysis showed significant departure in detected power from induced LF power (Fig. 2C) at 250 Hz and below ($p = 0.003$). Although not statistically significant, HF power tended to be underestimated at 125 Hz (Fig. 2D). Center frequencies of simulated LF (Fig. 2E) and HF (Fig. 2F) power were detected with high accuracy at all sampling rates although the LF frequency was statistically dependent on sampling rate ($p = 0.03$)

Complexity assessment of QTV using symbolic dynamics showed high sensitivity to the sampling rate in three out of four measures ($p < 0.0001$). At sampling rates of 250 Hz and below, the percentage of zero and one variability word types (0V and 1V, Fig. 3A and B) was artificially increased while the percentage of word types with monotonously increasing or decreasing QT interval (2LV, Fig. 3C) was significantly underestimated. The percentage of word types with unlike wise variations (2ULV, Fig. 3D) tended to increase at low sampling rates ($p = 0.07$).

3.2. *Effect of sampling rate on QTV using real ECG*

Sampling rate significantly affected overall QT variability (SDQT; $p = 0.02$, Fig. 4A) and the magnitude of beat-to-beat changes (RMSSD; $p < 0.0001$, Fig. 4B). Post-hoc comparison showed significantly elevated values with respect to the baseline sampling rate of 1600 Hz at a sampling rate of 100 Hz, while values obtained at 200 Hz appear to be intermediate. Although postural change showed the expected significant overall increase in QTV during standing (SDNN: $p < 0.0001$); RMSSD: $p < 0.001$), down-sampling to 100 Hz resulted in artificially increased QTV values during rest, which were similar to those observed during sympathetic activation upon standing. Frequency domain analysis showed a similar pattern in the high frequency power (HF; $p < 0.02$, Fig. 4D), but statistically non-significant changes in the low frequency power (LF; $p > 0.05$, Fig. 4C), with post hoc tests demonstrating significantly artificially increased power in the former at sampling rates of 100 Hz versus 1600 Hz. Compared to the supine position, standing increased QTV in both frequency bands (LF: $p < 0.0001$; HF: $p < 0.01$). Similar to the time domain assessment, QTV spectral power values sampled at 100 Hz during rest were artificially increased to values similar to those observed during standing.

Symbolic analysis of QTV (Fig. 5) showed significant sampling rate effects on three of the four assessed metrics (0V: $p < 0.05$; 1V: $p < 0.05$; 2ULV: $p < 0.0001$). Post-hoc analysis revealed significantly reduced 0V values for sampling rates of 100 Hz and 200 Hz, while 2ULV values were statistically increased at those sampling rates. The percentage of 1V word types was artificially increased at a sampling rate of 100 Hz. Comparing symbolic metrics recorded in the supine position versus the standing posture, only 2ULV showed significant changes, i.e. a reduction upon standing.

4. Discussion

The main finding of this study is the introduction of artificial beat-to-beat variability in QT interval when ECG is sampled at low rates, which may significantly blunt diagnostic attributes of QTV. Our analysis suggests that QTV can be confidently measured from (relatively noise-free) ECG when the sampling rate is 500 Hz or above. This observation is of importance as several previous investigations of QTV were based on ECG data sampled at notably lower rates [16,26–28].

This is the first study to systematically investigate the effects of sampling rate on QTV. A previous study that only compared QTV measured in ECG recorded at 500 Hz versus 1 kHz observed similar values of QTV for both sampling rates [29], which is in line with the results of our analysis. A study into ECG sample rate requirements found that 500 Hz are sufficient for heart rate variability analysis [30], which appears to be valid for QTV, too, given that the ECG frequency content of the T wave is typically lower than that of the QRS complex, which is the primary concern in heart rate variability analysis.

Comparing sampling rate effects on QTV in simulated versus real ECG, time domain metrics consistently show an overestimation of

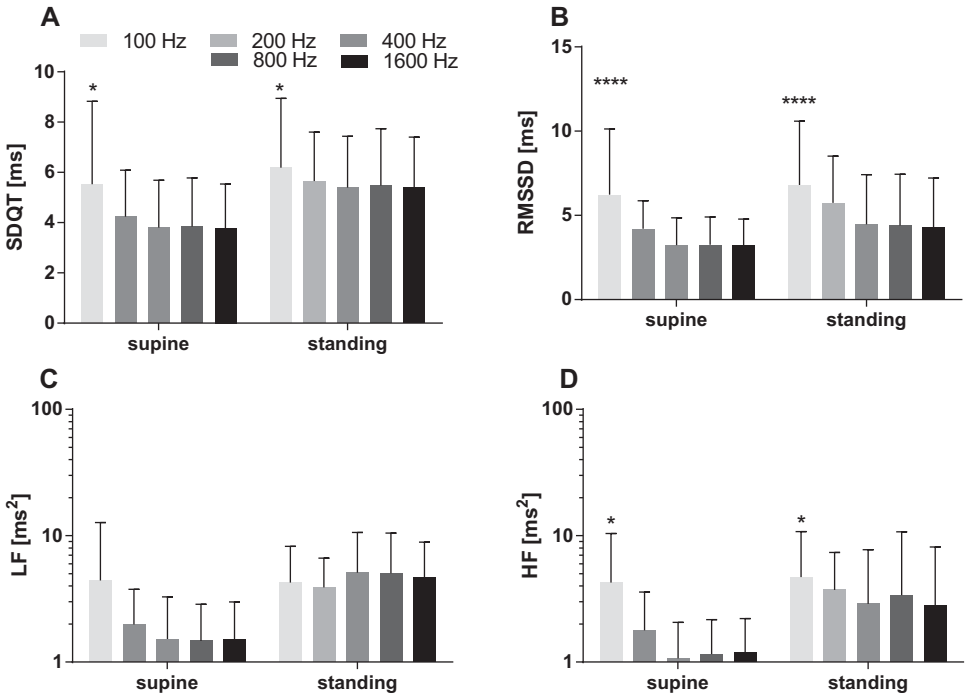

Fig. 4. Sampling rate effect on QT variability in real ECG recorded in the supine position and during standing quantified by time and frequency-domain indexes, presented as group means and standard deviations. For definitions of variables see text. * $p < 0.05$; **** $p < 0.0001$.

variability at low sampling rates. This overestimation of variability can also be observed in the frequency domain analysis of QTV in real ECG recordings. Simulated ECGs suggest that estimation of the LF and HF powers cannot be accurate when the sampling rate is low. It leads to an underestimation of frequency specific power in the group median with a wide spread across simulations. Combined, both these observations not only indicate a constant bias, but also an increased variance in the estimate that limits the statistical power of spectral indexes derived from QTV.

Symbolic analysis of QTV in simulated ECG suggests an overestimation of features characterized by low variability of the QT interval (0V and 1V word types) at low sampling rates. The opposite finding was found in real ECG recorded during standing. This inconsistency might be the consequence of the simplicity of the simulations: QTV was modeled as a deterministic and sinusoidal-based process, thus disregarding stochastic and nonlinear QTV dynamics. Nonetheless, this result illustrates that the effect of the low sampling rate on the same QTV metric depends on the

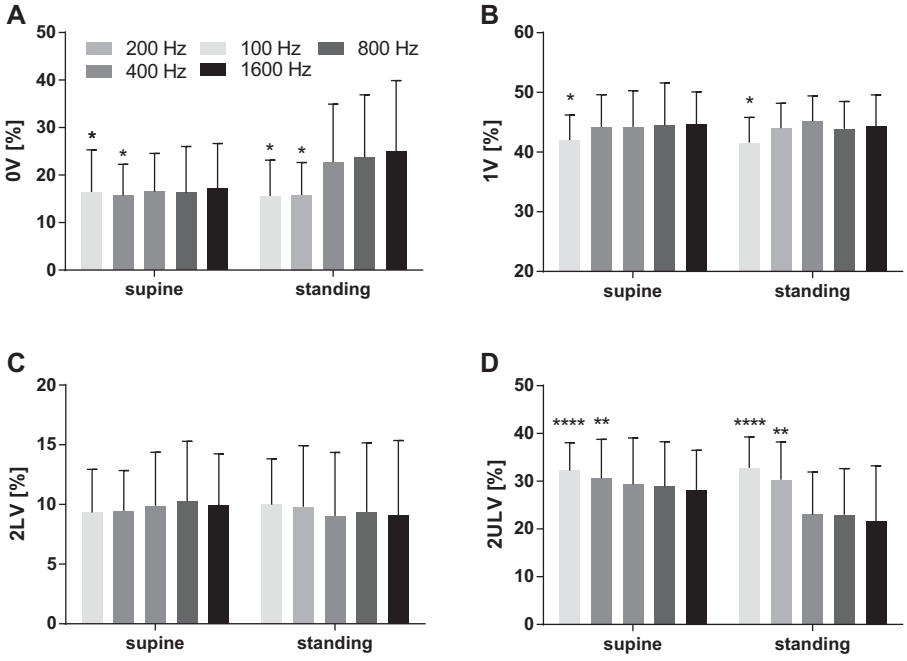

Fig. 5. Sampling rate effect on QT variability in real ECG recorded in the supine position and during standing quantified by symbolic domain indexes presented, as group means and standard deviations. For definitions of variables see text. * $p < 0.05$; ** $p < 0.001$; **** $p < 0.0001$.

experimental condition. It is thus prohibitive to compensate for the bias based on the result of simple simulations and the need to standardize the ECG sampling rate for the QTV analysis is emphasized. The relative frequency of other word types seems to be affected by low sampling rates too, but again results of simulated and real ECG are inconsistent, thus confirming the impossibility to correct results from real data based on simulations.

To provide an indication of the extent to which QTV measurement inaccuracies caused by low sampling rates may have practical implications, we compared QTV measured in the supine position and during active standing. Standing results in a well-documented increase in QTV [7,9,31], which, at least in part, can be attributed to sympathetic activation of the heart, thus providing a gold-standard, real-world experimental condition. Our data show the expected increase in QTV during standing assessed by time and frequency domain metrics, while symbolic measures appear to show little response to the change in posture. Importantly, our data demonstrate that low sampling rates entirely mask the QTV response to postural change from the supine position to standing, resulting in statistically non-significant effects when the sampling is as low as 100 Hz. Even though we did not study the sampling rate effect on QTV in a clinical population, e.g. for mortality risk prediction, it is conceivable that low sampling rates will equally reduce prognostic power of the QTV.

Although the results of our study may have been influenced by the choice of the low pass filter, no fundamental change in our observation is expected. Likewise, other QT interval measurement algorithms may respond differently to slowly sampled ECG. The algorithm used in this study was specifically designed for QTV measurement and has demonstrated state-of-the-art performance [20,32].

In conclusion, QTV can be reliably estimated when ECG is sampled at 500 Hz. Sampling rates of 200 Hz and below result in artificial QTV.

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References

[1] J. Nemec, W.K. Shen, Congenital long QT syndromes and Brugada syndrome: the arrhythmogenic ion channel disorders, Expert Opin. Pharmacother. 2 (2001) 773–797.
[2] U.B. Diamant, A. Winbo, E.L. Stattin, A. Rydberg, M. Kesek, S.M. Jensen, Two automatic QT algorithms compared with manual measurement in identification of long QT syndrome, J. Electrocardiol. 43 (2010) 25–30.
[3] M.C. Haigney, W. Zareba, P.J. Gentlesk, R.E. Goldstein, M. Illovsky, S. McNitt, M.L. Andrews, A.J. Moss, Multicenter Automatic Defibrillator Implantation Trial II investigators, QT interval variability and spontaneous ventricular tachycardia or fibrillation in the Multicenter Automatic Defibrillator Implantation Trial (MADIT) II patients, J. Am. Coll. Cardiol. 44 (2004) 1481–1487.
[4] G. Piccirillo, D. Magri, S. Matera, M. Magnanti, A. Torrini, E. Pasquazzi, E. Schifano, S. Velitti, V. Marigliano, R. Quaglione, F. Barilla, QT variability strongly predicts sudden cardiac death in asymptomatic subjects with mild or moderate left ventricular systolic dysfunction: a prospective study, Eur. Heart J. 28 (2007) 1344–1350.
[5] L.G. Tereshchenko, B.J. Fetics, P.P. Domitrovich, B.D. Lindsay, R.D. Berger, Prediction of ventricular tachyarrhythmias by intracardiac repolarization variability analysis, Circ. Arrhythm. Electrophysiol. 2 (2009) 276–284.
[6] A. Porta, E. Tobaldini, T. Gnecchi-Ruscone, N. Montano, RT variability unrelated to heart period and respiration progressively increases during graded head-up tilt, Am. J. Physiol. Heart Circ. Physiol. 298 (2010) H1406–H1414.
[7] V.K. Yeragani, R. Pohl, V.C. Jampala, R. Balon, J. Kay, G. Igel, Effect of posture and isoproterenol on beat-to-beat heart rate and QT variability, Neuropsychobiology 41 (2000) 113–123.
[8] F. El-Hamad, E. Lambert, D. Abbott, M. Baumert, Relation between QT interval variability and muscle sympathetic nerve activity in normal subjects, Am. J. Physiol. Heart Circ. Physiol. 309 (2015) H1218–H1224.
[9] J.W. Sacre, B. Franjic, J.S. Coombes, T.H. Marwick, M. Baumert, QT interval variability in type 2 diabetic patients with cardiac sympathetic dysinnervation assessed by 123I-metaiodobenzylguanidine scintigraphy, J. Cardiovasc. Electrophysiol. 24 (2013) 305–313.
[10] S. Nayyar, K.C. Roberts-Thomson, M.A. Hasan, T. Sullivan, J. Harrington, P. Sanders, M. Baumert, Autonomic modulation of repolarization instability in patients with heart failure prone to ventricular tachycardia, Am. J. Physiol. Heart Circ. Physiol. 305 (2013) H1181–H1188.
[11] M. Baumert, M.P. Schlaich, E. Nalivaiko, E. Lambert, C.I. Sari, D.M. Kaye, M.D. Elser, P. Sanders, G. Lambert, Relation between QT interval variability and cardiac sympathetic activity in hypertension, Am. J. Physiol. Heart Circ. Physiol. 300 (2011) H1412–H1417.
[12] M. Baumert, G.W. Lambert, T. Dawood, E.A. Lambert, M.D. Esler, M. McGrane, D. Barton, E. Nalivaiko, QT interval variability and cardiac norepinephrine spillover in patients with depression and panic disorder, Am. J. Physiol. Heart Circ. Physiol. 295 (2008) H962–H968.
[13] G. Piccirillo, D. Magri, M. Ogawa, J. Song, V.J. Chong, S. Han, B. Joung, E.K. Choi, S. Hwang, L.S. Chen, S.F. Lin, P.S. Chen, Autonomic nervous system activity measured directly and QT interval variability in normal and pacing-induced tachycardia heart failure dogs, J. Am. Coll. Cardiol. 54 (2009) 840–850.
[14] V. Avbelj, R. Trobec, B. Gersak, Beat-to-beat repolarisation variability in body surface electrocardiograms, Med. Biol. Eng. Comput. 41 (2003) 556–560.
[15] M. Baumert, V. Starc, A. Porta, Conventional QT variability measurement vs. template matching techniques: comparison of performance using simulated and real ECG, PLoS ONE 7 (2012) e41920.
[16] W.J. Kostis, J.C. Belina, Differences in beat-to-beat variability of the QT interval between day and night, Angiology 51 (2000) 905–911.
[17] A. Porta, G. Baselli, F. Lombardi, S. Cerutti, R. Antolini, M. Del Greco, F. Ravelli, G. Nollo, Performance assessment of standard algorithms for dynamic R–T interval measurement: comparison between R-Tapex and R–T(end) approach, Med. Biol. Eng. Comput. 36 (1998) 35–42.
[18] M. Baumert, L. Brechtel, J. Lock, M. Hermsdorf, R. Wolff, V. Baier, A. Voss, Heart rate variability, blood pressure variability, and baroreflex sensitivity in overtrained athletes, Clin. J. Sport Med. 16 (2006) 412–417.
[19] M. Baumert, M. Javorka, M.M. Kabir, Joint symbolic analyses of heart rate, blood pressure, and respiratory dynamics, J. Electrocardiol. 46 (2013) 569–573.
[20] M. Schmidt, M. Baumert, A. Porta, H. Malberg, S. Zaunseder, Two-dimensional warping for one-dimensional signals—conceptual framework and application to ECG processing, IEEE Trans. Signal Process. 62 (2014) 5577–5588.
[21] A. Cabasson, O. Meste, Time delay estimation: a new insight into the Woody's method, IEEE Signal Process Lett. 15 (2008) 573–576.
[22] S.M. Kay, S.L. Marple Jr., Spectrum analysis—a modern perspective, Proc. IEEE 69 (1981) 1380–1419.
[23] H. Akaike, A new look at the statistical model identification, IEEE Trans. Autom. Control 19 (1974) 716–723.
[24] G. Baselli, A. Porta, O. Rimoldi, M. Pagani, S. Cerutti, Spectral decomposition in multichannel recordings based on multivariate parametric identification, IEEE Trans. Biomed. Eng. 44 (1997) 1092–1101.
[25] A. Porta, S. Guzzetti, N. Montano, R. Furlan, M. Pagani, A. Malliani, S. Cerutti, Entropy, entropy rate, and pattern classification as tools to typify complexity in short heart period variability series, IEEE Trans. Biomed. Eng. 48 (2001) 1282–1291.
[26] B.T. Jensen, C.E. Larroude, L.P. Rasmussen, N.H. Holstein-Rathlou, M.V. Hojgaard, E. Agner, J.K. Kanters, Beat-to-beat QT dynamics in healthy subjects, Ann. Noninvasive Electrocardiol. 9 (2004) 3–11.
[27] M. Sachdev, B.J. Fetics, S. Lai, D. Dalal, J. Insel, R.D. Berger, Failure in short-term prediction of ventricular tachycardia and ventricular fibrillation from continuous electrocardiogram in intensive care unit patients, J. Electrocardiol. 43 (2010) 400–407.
[28] B.T. Jensen, S.Z. Abildstrom, C.E. Larroude, E. Agner, C. Torp-Pedersen, O. Nyvad, M. Ottesen, K. Wachtell, J.K. Kanters, QT dynamics in risk stratification after myocardial infarction, Heart Rhythm 2 (2005) 357–364.
[29] V.K. Yeragani, R. Pohl, V.C. Jampala, R. Balon, C. Ramesh, K. Srinivasan, Increased QT variability in patients with panic disorder and depression, Psychiatry Res. 93 (2000) 225–235.
[30] M. Merri, D.C. Farden, J.G. Mottley, E.L. Titlebaum, Sampling frequency of the electrocardiogram for spectral analysis of the heart rate variability, IEEE Trans. Biomed. Eng. 37 (1990) 99–106.
[31] G. Piccirillo, M. Magnanti, S. Matera, S. Di Carlo, T. De Laurentis, A. Torrini, N. Marchitto, R. Ricci, D. Magri, Age and QT variability index during free breathing, controlled breathing and tilt in patients with chronic heart failure and healthy control subjects, Transl. Res. 148 (2006) 72–78.
[32] S. Zaunseder, M. Schmidt, H. Malberg, M. Baumert, Measurement of QT variability by two-dimensional warping, in: Cardiovascular Oscillations (ESGCO), in: 2014 Eighth Conference of the European Study Group on, IEEE, 2014, pp. 163–164.