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The Effect of Electrocardiographic Lead Choice on RR Time Series

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***Abstract*— Results of heart rate variability analysis depend on the quality of the initial RR time series that is measured only in one lead of the ECG. This work shows that RR time series can subtly change from lead to lead so the choice of the analyzed lead is another source of uncertainty. The standard deviation of the differences of two RR time series obtained from different leads can change from 0.5 ms to more than 20 ms depending on the amount of noise, the morphological changes of the QRS complexes, the strategies of fiducial point determination and the measured subject. This source of uncertainty is in healthy subjects greater than that associated to the sampling frequency of the ECG for sampling frequencies greater than 400 Hz.**

I. Introduction

THE analysis of heart rate variability (HRV) has become a clinical and research tool to study the modulation that the autonomic nervous system exerts on the cardiovascular system. The first step in any analysis of heart rate variability consists on the measurement of the time intervals between consecutive QRS complexes. The obtained time series (RR time series) is further processed applying time domain, frequency domain or non-linear dynamics techniques [1]. In order to perform a reliable analysis, some concern has been raised on the sampling frequency of the ECG that limits the resolution of the RR time series. Some indices are very sensitive to small errors in the determination of the time series especially when the HRV is very small [2],[3].

This sensitivity raises another question: what's the difference in RR time series when obtained from different leads of the ECG? Common sense dictates that using a simple QRS detector or even refining the R wave location, the results from lead to lead can be slightly different due to changes in the morphology of the QRS complex or the presence of noise. The aim of this work is to study these lead-to-lead differences in the obtained RR time series and compare them to the error due to the sampling frequency of the ECG.

Section II describes the employed multilead database, the implemented QRS detector and some refinements of the R wave location as well as the statistics employed to quantify the differences in RR time series. Section III describes the results and compares them with errors due to the sampling frequency of the ECG. Section IV discusses the results and draws conclusions.

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II. Materials and Methods

A. Description of the database

The multilead ECG database used in this work is the PTB (from Physikalisch-Technische Bundesanstalt) Diagnostic ECG database (PTBD) [4,5]. It consists on 549 recording from 290 subjects. Each recording has the twelve conventional leads (the standard limb leads: I, II, III, the augmented leads: aVR, aVL and aVF, and the precordial leads: V_1 to V_6) as well as the three Frank leads (X, Y and Z). Each lead is sampled at 1 kHz.

From this database, 80 recordings correspond to 52 different healthy subjects and 368 recordings correspond to 148 subjects who suffered myocardial infarction. The rest of recordings correspond to patients with conditions as different as heart failure, dysrhythmia, hypertrophy, valvular heart disease or bundle branch block.

In this work and due to the small chance of ectopic beats and other arrhythmias we have primarily focused on healthy subjects and the twelve conventional leads. From the 80 recordings, five were rejected due to the presence of premature beats or other disturbances of rhythm (s0287lre, s0305lre, s0311lre, s0328lre and s0502_re).

The database is freely available at http://www.physionet.org/physiobank/database/ptbdb/

B. QRS Detector Description

The first processing step is to roughly locate every QRS complex in each lead. The next step will be the refinement of the QRS locations (fiducial point) and will be discussed in the next subsection.

The employed QRS detector uses the smoothing properties of the Hodrick-Prescott filter (HP filter) and a nonlinear transformation in order to enhance the QRS complex. The HP filter obtains a smooth version ($\tau(n)$) of the input signal ($x(n)$) by least-squares minimization [6]:

$$\min_{\{\tau(n)\}}\left\{\begin{array}{l}\sum_{n=1}^{N}\left(x(n)-\tau(n)\right)^2+\\ +\lambda\cdot\sum_{n=2}^{N-1}\left[\left(\tau(n-1)-\tau(n)\right)-\left(\tau(n)-\tau(n-1)\right)\right]^2\end{array}\right\} \quad (1)$$

being λ a parameter that controls the smoothness of the output signal.

The algorithm works as follows:

1. Lowpass filtering of the ECG with $\lambda_1 = 10^3$ and $\lambda_2 = 10^4$ being $\tau_1(n)$ and $\tau_2(n)$ the obtained signals
2. Enhancement of the QRS wave by using

$$EQRS(n) = \left|\arctan\left(\frac{\tau_1(n)-\tau_2(n)}{\max\left\{\tau_1(n)-\tau_2(n)\right\}}\right)\right| \quad (2)$$

3. Further smoothing using $\lambda_3 = 10^6$ to obtain $ECGF(n)$
4. Search of local maximum in $ECGF(n)$ by a constant threshold.

The threshold can be changed from lead to lead although in most cases, half of the maximum of $ECGF(n)$ works well. We have adapted automatically the threshold computing the RR time series for thresholds changing from 0.1 to 0.9 times the maximum of $ECGF(n)$ and choosing the threshold that minimizes the standard deviation of the obtained RR time series.

Figure 1 shows an example with the original signal (precordial V2 lead), the enhanced signal and the output signal.

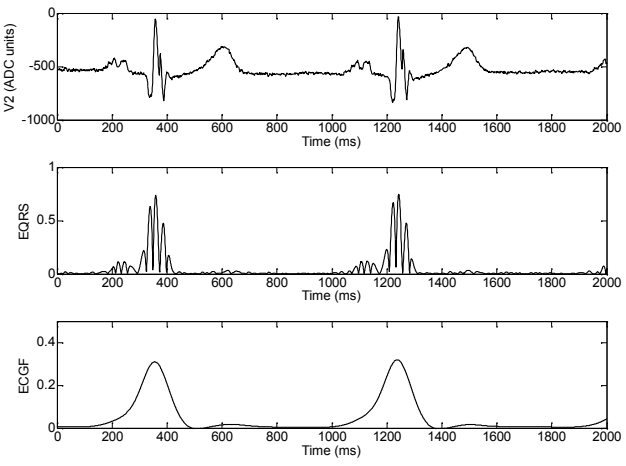

Fig. 1. Example of transformation of the ECG for the proposed QRS detector

The first considered fiducial points (method 1) are directly the output of this detector so they are the local maxima of $ECGF(n)$ that are greater than the threshold.

C. Fiducial Point Refinements

Four more fiducial point definitions have been considered in this work in order to minimize the impact of the QRS detector. All three methods start by bandpass filtering the signal with bidirectional 4th order Butterworth filter. We have chosen a high pass cutoff frequency of 1 Hz and a low pass cutoff frequency of 30 Hz. Moreover, the magnitude of the Hilbert transform of the filtered ECG has been computed and has been smoothed ($\lambda_2 = 10^4$). We have defined observational windows of 100 ms centered at each detected beat both for the filtered ECG (FECG) and the smoothed Hilbert transform (SHECG)

Method 2 redefines the fiducial point as the maximum in the window of FECG. Method 3 assigns the fiducial point to the maximum in the window of SHECG. Method 4 takes the window of FECG corresponding to the first beat as a pattern to match. The fiducial points are obtained by maximizing the correlation of the pattern with the other windows [7]. Method 5 is similar to method 4 but the pattern is obtained by averaging all the observational windows of FECG.

D. Quantification of the effect of lead choice

For each lead of each recording and for the different combinations of cutoff frequencies used to obtain FECG we have defined five RR time series using the previously described methods of fiducial point assignment. So, in each recording for each method there are twelve subtle different RR time series. Figure 2 shows two such RR time series as well as their difference (DRR).

The standard deviation of the differences in RR time series (SDDRR) have been computed for all the combinations of leads. Because the distribution of SDDRR is long tailed we have summarized the results by its mode (D_1), median (D_2), mean (D_3), mean of those values of SDDRR that don't exceed three times the mode (D_4) and maximum (D_5).

Moreover, the standard deviation of the differentiated RR time series (rmsDD) [1] and the approximate entropy (ApEn) [3] using m=2 and r=0.2 have been computed for each lead. The mean and standard deviation of these indices have been computed among leads. The standard deviation normalized by the mean of the indices has been used as a relative error that quantifies the effect of lead choice in each recording.

III. Results

Figure 3 shows an example on how SDDRR can change among leads using method 5. The figure displays the different combinations of standard deviations when computing the differences between one lead (x axis) and other lead (y axis). The colorbar shows the value of these SDDRR in ms. Maximum differences are reached when comparing RR times series from lead 5 (aVL) and from lead 3 (III). For the computation of statistics characterizing this array, the zero values corresponding to the diagonal where rejected.

Figure 4 shows the histogram of SDDRR for the same recording. In this case D1 is 0.74 ms, D2 is 0.71 ms, D3 is 0.73 ms, D4 is 0.73 ms and D5 is 1.27 ms. The values are quite similar owing to the symmetry of the histogram. Nevertheless, if the RR time series from one lead is

substantially different than the rest, the indicators D1 to D5 can be quite different.

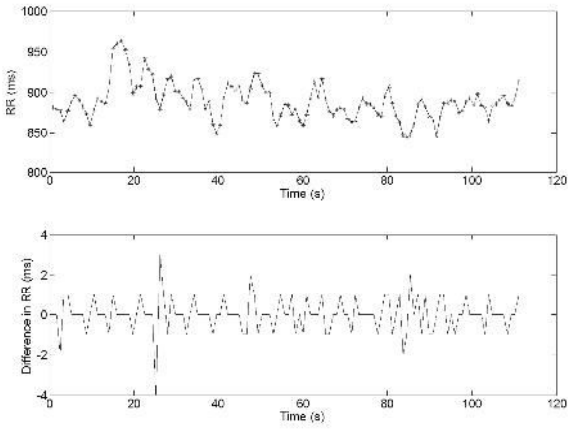

Fig. 2. Example of differences of RR time series. In the upper panel, the standard II and V1 leads of the same recording are shown. The lower panel shows the difference between time series

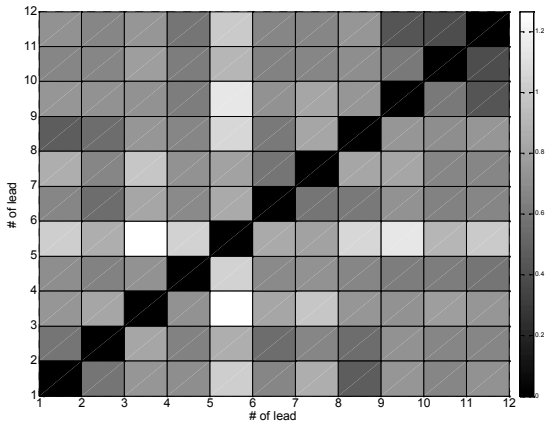

Fig. 3. Example of computation of SDDRR

Table I shows the mean value of the different estimators of the effect of lead choice on the determination of the RR time series. D1 to D5 characterize the SDDRR among leads while the last two columns show the mean errors in indices estimation.

As seen, Method 5 and 4 work very similar and minimize the effect of lead choice. Nevertheless, the mean over the recordings of the maximum SDDRR (the worst differences among leads) is greater than 2 ms. The fiducial point of the proposed QRS detector presents lower differences among RR time series than the correction via maximum search or using the Hilbert transform. The errors in rmsDD and ApEn are, in average, between 2% and 3%. Figure 5 shows how these indices change for method 2 and 5 in a certain recording as well as the differences in RR time series when comparing standard II lead and V4 lead.

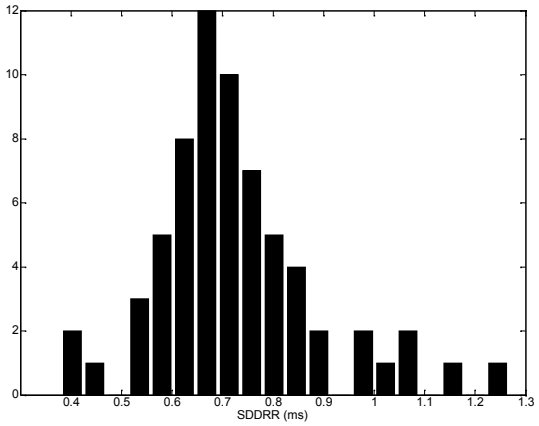

Fig. 4. Histogram of SDDRR for the example of figure 3

TABLE I
ESTIMATORS OF EFFECT OF LEAD CHOICE

Method	D1 (ms)	D2 (ms)	D3 (ms)	D4 (ms)	D5 (ms)	Error rmsDD (%)	Error ApEn (%)
1	0.73	0.97	1.30	0.98	3.44	2.18	3.33
2	0.66	0.80	1.37	0.81	4.27	3.30	2.86
3	0.76	1.12	1.76	1.05	5.35	3.33	3.73
4	0.68	0.81	1.06	0.85	2.63	2.45	2.87
5	0.67	0.81	1.01	0.85	2.36	2.20	2.83

IV. DISCUSSION AND CONCLUSIONS

The RR time series can be subtly different depending on which lead has been chosen. The standard deviation of the difference between two RR time series obtained simultaneously from different leads in the same subject range in healthy subjects from 0.5 ms to as high as 25 ms depending on the fiducial point method, the leads involved and the subject. This effect can be regarded as another source of uncertainty in HRV analysis.

Common practice in HRV analysis show that the greater the sampling frequency of the ECG, the better the estimation of the RR time series is. The digitizing error due to the sampling frequency (f_s) has a typical uncertainty of [8]:

$$u(RR) = \frac{1}{f_s \cdot \sqrt{6}} \tag{3}$$

In this work, the mean SDDRR is around 1 ms that is equal to the error due to the digitizing error if the ECG were sampled at 408 Hz.

The origin of the subtle differences in RR interval determinations can be attributed to several causes but the two most important are the different levels of noise among leads that affect differently to the fiducial point assignment and the morphology changes in the QRS from beat to beat.

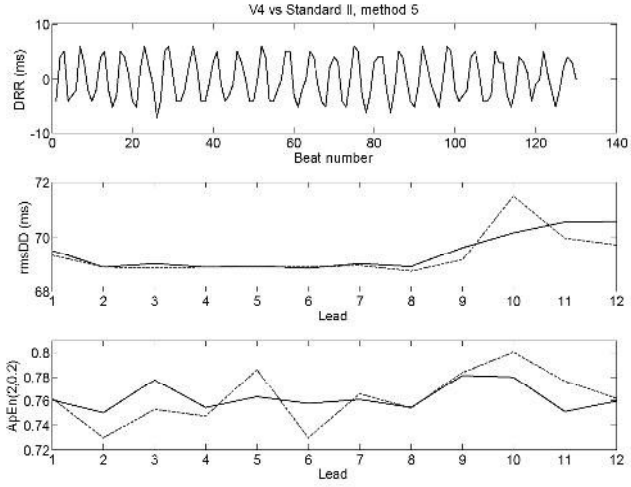

Fig. 5. Example of effect of lead choice in the estimation of HRV indices. Upper panel shows the differences when comparing two leads (II an V4), middle and lower panel shows the estimation of rmsDD and ApEn respectively for each lead. The solid lines are the indices for method 2 while dashed lines are for method 5.

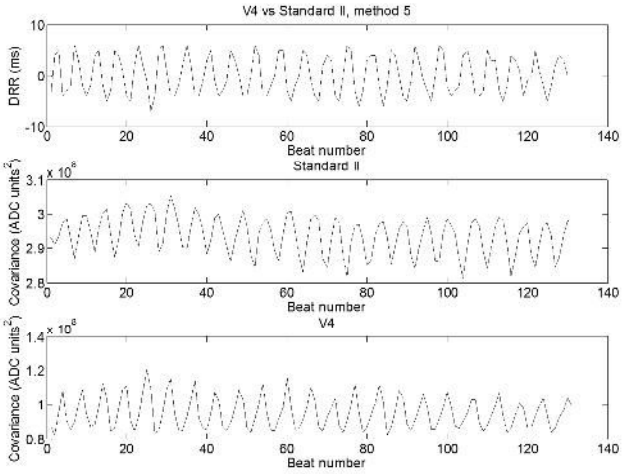

Fig. 6. Relationship between DRR and morphology changes in QRS complexes. The upper panel shows the DRR when comparing V4 and Standard II leads for a certain recording. Middle and lower panels are the covariances of the QRS complexes with the first QRS complex.

As seen in figure 5, the DRR in the upper panel has a pattern quite periodic. Figure 6 shows again this time series and the covariance of the QRS complex with the first QRS complex for the standard II and the V4 leads. As seen, the three time series share the same rhythmicity (presumably the breathing rhythm) but are not in phase.

So, as conclusion, the determination of RR time series is conditioned by the ECG lead choice. Results in HRV analysis may differ due to the analyzed lead, the strategy for fiducial point determination, the amount of noise in the ECG and changes in morphology of the QRS complex throughout the recording.

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