Articles in PresS. J Appl Physiol (September 21, 2017). doi:10.1152/japplphysiol.00927.2016

The impact of artifact correction methods of RR series on heart rate variability parameters.

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ABSTRACT

Heart rate variability (HRV) analysis is widely used to investigate the autonomic regulation of the cardiovascular system. HRV is often analyzed using RR time series, which can be affected by different types of artifacts. Although there are several artifact correction methods, there is no study that compares their performances in actual experimental contexts. This work aimed to evaluate the impact of different artifact correction methods on several HRV parameters. Initially, 36 ECG recordings of control rats or rats with heart failure or hypertension were analyzed to characterize artifacts occurrence rates and distributions, in order to be mimicked in simulations. After a rigorous analysis, only sixteen recordings (N=16) with artifact-free segments of at least 10.000 beats were selected. Then, RR interval losses were simulated in the artifact-free (reference) time series according to real observations. Correction methods applied to simulated series were deletion (DEL), linear interpolation (LI), cubic spline interpolation (CI), modified moving average window (mMAW) and nonlinear predictive interpolation (NPI). Linear (time- and frequency-domain) and nonlinear HRV parameters were calculated from corrupted-corrected time series, as well as for reference series to evaluate the accuracy of each correction method. Results show that NPI provides the overall best performance. However, several correction approaches, for example, the simple deletion procedure, can provide good performance in some situations, depending on the HRV parameters under consideration.

Keywords: Heart rate variability, artifact correction, time domain, frequency domain, nonlinear analysis.

NEW & NOTEWORTHY

This work analyzes the performance of some correction techniques commonly applied to the missing beats problem in RR time series. From artifacts-free RR series, spurious values were inserted based on actual data of experimental settings. Our work has the intention to be a guide to show how artifacts should be corrected to preserve as much as possible the original HRV properties.

INTRODUCTION

Time series of successive RR intervals are widely studied and used as a source to investigate various physiological phenomena related to heart rate variability (HRV). Changes in HRV have been associated with several cardiac and systemic diseases, such as hypertension, heart failure, obesity, epilepsy, diabetes, and sudden death (16, 21, 28). Although RR time series can be easily obtained noninvasively, arrhythmias, HR transients, recording artifacts and beat misdetections influence these time series, leading to misinterpretations in HRV analysis.

Spurious values in RR series are mostly consequences of arrhythmias, premature ectopic beats, atrial fibrillation, among others (1, 17). However, in experimental settings, it is very common to find outliers in RR series due, for example, to animal movements, poorly fastened electrodes, power source noise, and so forth.

In order to deal with this kind of problems, different correcting methods have been proposed. Some of them are based on simple deletions or interpolation replacements of the problematic segments (1, 4, 14, 17). Additionally, methods that are more sophisticated have been proposed claiming to be more efficient. Some of these methods are: comparison and merging (5), predictive autocorrelation (5, 14), nonlinear predictive interpolation (14), exclusion of RR interval segments with divergent duration (17), impulse rejection (18), integral pulse frequency model (18), sliding window average filter (13) and threshold filtering using Wavelet transform (13, 29).

Despite the high number of correction methods, it has already not been established a systematic study showing the most suitable methods to deal with artifacts in RR series, and its impact on the different HRV parameters. Therefore, the purpose of this study is to compare some of the most important correction methods, assessing the accuracy of those approaches in preserving the original features of RR series.

MATERIALS AND METHODS

Database: Original ECG recordings, obtained from previous studies, were selected (20, 27). These data were collected from 36 recordings of conscious rats with or without pathophysiological conditions such as hypertension or heart failure. The different physiological situations provide a more realistic scenario for evaluating the accuracy of each correction methods on RR interval time series. From the whole dataset, we selected only the animals which ECG recordings have at least 10.000 consecutive beats free of artifacts. All experiments used in the present study were approved by the Committee of Ethics in Animal Research of the Medical School of Ribeirão Preto, University of São Paulo.

Heart Failure: Heart failure (HF) was induced by myocardial infarction (coronary artery ligation) in male Wistar rats (240-320 g, N=9), according to the procedure described by Pfeffer et al. (23). Additionally, sham-operated rats submitted to a similar surgical procedure without coronary artery ligation (N=18) were used as control animals. Five weeks after coronary artery ligation or sham, rats were implanted with subcutaneous electrodes for ECG recording. Two days after electrodes implantation, conscious animals were connected to an ECG amplifier (8811A, Bioelectric Amplifier, Hewlett-Packard) attached to an analog/digital interface (DI-220, Dataq Instruments), and basal ECG was sampled at 2 kHz for 2 h with the animals freely moving inside their cages (20).

Hypertension: Male spontaneously hypertensive rats (SHR, N=5) and Wistar-Kyoto (WKY, N=4) normotensive counterparts (210-290 g, N=4), were implanted with telemetry-based biopotential amplifier and transmitter (TR50B, Telemetry Research Auckland, New Zealand) for ECG recording. Three days after the implantation of the telemeter, basal ECG was continuously sampled (2 kHz) with a dedicated receiver (TR180 SmartPad, Telemetry Research) attached to a data acquisition system (PowerLab, ADInstruments, Castle Hill, NSW, Australia). Recordings were carried out during 90 minutes with animals freely moving inside their cages (27).

Study design: Initially, the entire database was carefully inspected to identify the number of spurious values, due to any reason, in each series. Following, series with at least 10,000 consecutive values completely free of losses or artifacts were selected. Spurious values were then artificially inserted in the artifact-free series based on actual typical rates of loss or misdetections in experimental data. Finally, series with artificial losses were corrected using different approaches, and HRV parameters were calculated for each corrected time series.

Rate of losses: Table 1 shows the percentage of values and segments of values (lengthening from 1 to 10) found as corrupted (spurious values). We observed an average of 2.5% and a maximum of 5% of the entire HRV series length corrupted.

Simulation of Spurious Values: From the total amount of 36 time series, 16 fulfilled the criterion of having 10,000 consecutive points without any outlier or spurious value, being 6 from sham-operated control rats, 3 from rats with HF, 4 from WKY and 3 from SHR. We named these as the reference series for HRV analysis. Missing RR intervals were simulated in the reference series based on the criteria described previously and with the purpose of mimicking the findings from the recorded data. Corrupted series of RR intervals where artificiality generated by removing single beats, segments with 3 or 10 consecutive values from the reference series at the proportion of 79%, 11%, and 10%, respectively. We chose these proportions as representative of the distribution shown in Table 1, keeping it consistent with the experimental findings. The overall percentages of removal were selected to be 2.5% or 5% of the total amount of beats. Figure 1 illustrates the loss simulation process in RR interval time series. Then we applied the different correction methods to the corrupted series and calculated all HRV parameters for both, reference (lossless) and corrected series.

Correction techniques: Different methods are used in the literature to recover information due to signal corruption. In this study, we applied five of the commonly found methods to correct simulated HRV time series that follow the procedures previously described. Simple deletion (DEL) of spurious beats eliminates all inconsistent values on RR series, leading to a reduction in the number of points of corrected series. Linear (LI) or cubic spline interpolation (CI) were used to replace missing beats in RR time series by interpolated ones, maintaining the length of original series (11, 19). Nonlinear predictive interpolation (NPI) is a method that scans all available segments with similar neighbourhood characteristics to the spurious values and uses the most similar segment to replace the affected part of the signal (14). Modified moving average windowing (mMAW), which is a modified version of moving average that replaces each point on a time series by the average formed by the six successive points before and after the missing segment. Usually, these methods have been applied to solve problems of ectopic beats, noise and non-uniform sampling of the RR time series. In a few cases, they were used to correct missing beats (6, 11, 14).

Analysis of ECG and HRV: The peaks of all R waves were detected from ECG recordings using a computer software (ECG Module from LabChart Software, ADInstruments, Castle Hill, NSW, Australia) and RR time series were created as the intervals between each consecutive R waves.

Linear and nonlinear approaches were used to evaluate HRV from original (reference) and corrected RR time series, and estimate the impact of each correction method. Linear techniques involve the quantification of time- and frequency-domain parameters, whereas nonlinear techniques give information about predictability, long-range correlations and patterns of the HRV.

In the time domain, we calculated the average, the standard deviation of all RR intervals (AVRR and SDNN) and the root mean squared value of successive differences between RR intervals (RMSSD). The frequency domain parameters correspond to the estimation of the of RR spectra at the standard frequency bands of rats identified as very low (VLF: <0.2 Hz), low (LF: 0.2 to 0.75 Hz) and high-frequency bands (HF: 0.75 to 3.0 Hz) (2, 3). The procedure implies the calculation of the power spectral density (PSD) and the estimation of total power (energy) at each particular frequency band. In this study, the PSD was estimated by the Lomb's periodogram algorithm, introduced by N. Lomb in 1976 (15) as a technique to deal with signals containing unevenly acquired samples. Estimation of PSD based on Fourier transform (FT) requires evenly sampled time series as inputs. Therefore, it requires interpolation of RR series prior to the PSD estimation, as the RR time series are unevenly sampled. We adopted the Lomb algorithm to avoid changing the RR series, as it may introduce some bias to the performance of the correction techniques. Previous studies showed that Lomb's approach results in parameters that are very similar to interpolated FT method (6, 9, 19).

Detrended fluctuation analysis (DFA), multiscale entropy (MSE) and symbolic dynamics methods, were selected because they represent three of the most commonly used approaches in the nonlinear analysis (31). DFA allows quantification of long-range correlations on non-stationary time series (22). Scaling properties and fractal structures contained in the signal are evidence of these correlations. Short-term (α1) and long-term (α2) scaling exponents, to characterize the RR time series fractal properties, were calculated in this study. The crossover point (n) between α1 and α2 was adaptively chosen for each group. From n=9 to n=30, we selected the crossover that gives the lowest cumulative error of the two regression lines regarding α1 and α2 range. As a result, it was set n=10 for all group of animals (control, HF and for SHR).

MSE measures the predictability of time series over multiple time scales (7, 8). MSE analysis is based on the sample entropy (SampEn) calculated for different scales in the signals. SampEn is a refinement of the approximate entropy method introduced by Pincus (24) and widely used in the physiological signal analysis (12, 26). MSE was calculated from scales 1 to 10 and the entropy at scale 1 (MSE1), as well as the sum of the entropy of all scales (MSET), were used as a single number to represent MSE.

Symbolic dynamics is a method to characterize the variation patterns of time series in a simple and coarser symbolic notation, capable of retaining the essential dynamic characteristics of the original time series. The conversion of a time series into a set of symbols begins dividing the original signal into six equally distant levels (uniform quantization). Next, patterns of length three are constructed, followed by grouping these patterns into four families, according to the symbol variation: 0V (zero variation), 1V (one variation), 2LV (two like variation) and 2UV (two unlike variation). Finally, the rates of occurrence of these families are evaluated (10, 25). Here, only 0V and 2UV variations were used as they have been demonstrated, in previous studies, to be highly correlated with sympathetic and vagal cardiac modulation, respectively (26, 30).

Statistical analysis: Friedman's statistical test was used to verify differences in HRV parameters between the reference and corrected RR time series. Besides, the error for each HRV parameters was calculated as the average of the absolute differences between parameters obtained for each reference and corrected time series. Errors are presented as a median value with their respective 1st and 3rd quartiles (Median [1st; 3rd]). On the other hand, ANOVA on ranks method was applied to find statistical differences between error values from different correction techniques to evaluate the performance of each technique for each HRV parameter.

RESULTS

Tables 2, 3 and 4 show median and quartile values for HRV parameters calculated from original (reference) and corrupted-corrected series in time and frequency domain, as well as by nonlinear approaches, respectively. The median AVRR interval calculated from series corrected by any of the approaches used in this study was identical to median AVRR derived from reference series. Correction with DEL did not affect time domain parameters of HRV, i.e. SDNN and RMSSD of RR series with 2.5% of losses, while for series with 5% of losses, DEL affected only RMSSD. All other correction methods affected both SDNN and RMSSD.

For frequency-domain indices, the RR time series PSD at VLF band in original series was found different from corrected series with DEL (2.5 and 5% of losses) or mMAW (only 5% of losses). Only the series corrected by NPI showed the PSD unmodified at LF band. On the other hand, none of the methods of correction used in the study were able to preserve the RR time series power spectra at HF band. The LF/HF ratio is different from reference series only for those series corrected by interpolation, i.e. either LI or CI.

For nonlinear parameters, differences are more exacerbated for corrected series after 5% of losses. While MSE1, i.e. sample entropy itself, presented the lowest number of differences considering all correction methods, the symbolic dynamics 0V showed the greatest number of differences from reference series. NPI gave the lowest number of significant differences from reference series, whereas interpolation-based methods (LI and CI) presented the greatest number of significant differences when considering both 2.5% and 5% of missing points.

Figures 2, 3 and 4 show the median error value of HRV parameters calculated between original and corrected series for time-domain, frequency-domain and nonlinear techniques, respectively. For time-domain, one can observe that median error values of corrections with DEL in RMSSD are much lower as compared to the other correction approaches. For AVRR, although the correction with DEL presents the highest median error, the difference between the reference and corrected series are so small that we do not identify any practical relevance in such results. Frequency-domain parameters correction with DEL brought the highest median errors for all parameters, whereas corrections with NPI presented the lowest median error values. For nonlinear parameters, the median error showed a variable behavior. In general, scaling exponents of DFA ($\alpha 1$ and $\alpha 2$) present little median error for mMAW and NPI. Indices calculated from MSE (MSE1 and MSET) showed a lower median error for series corrected by DEL or NPI. Symbolic dynamic indices (0V and 2UV) presented lower median error values for series corrected by NPI.

DISCUSSION

It is worth noting that the absence of difference between HRV indices calculated from original and a corrected time series does not always imply that the corrected method used is the best approach. The lack of difference means that there is no reliable statistical evidence that the HRV indices calculated from original (reference) and corrected series are different. It may happen, for example, when there is a high variation in the population. Therefore, the calculation of the error provides an additional measure for the evaluation of the correction methods reliability.

Results showed that the correction techniques assessed here affect in different ways the HRV indices. While the simple deletion of spurious values (DEL) seems to be one of the best approaches for all time-domain indices, at the same time, it is the worst method for frequency-domain. In the latter case, all other techniques provide similar performances, with emphasis to NPI. For nonlinear methods, the correction techniques are quite variable regarding accuracy.

In general, NPI seems to be the best overall approach. One can observe from Tables 2, 3 and 4 that this technique has the least number of statistical differences, and from Figures 2, 3 and 4 it presents the lowest median error value in most situations. However, the simplest method, DEL, can also be used as an excellent correction approach in many cases (see Figure 3).

One could expect that the performance of the correction methods be worse when the number of beat losses is higher. Accordingly, the median error values tend to be higher for corrections after 5% of losses in comparison with 2.5%. However, the impact on increasing the number of missing beats was greater for frequency-domain and nonlinear HRV indices than for time-domain.

CONCLUSION

Through the simulation of beat losses that mimic real situations in experimental settings, different RR time series correction methods were analyzed. The method with the best overall performance was the NPI. However, for studies on specific HRV indices, other correction techniques can provide quite good performances as well. While for time-domain analysis the deletion technique seems to be an excellent option, it should be avoided for frequency-domain. Moreover, the rate of losses, i.e. 2.5% or 5% of total beats, has less impact on the time-domain indices when compared to the frequency-domain and nonlinear indices.

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Tables:

Table 1: Mean percentage of spurious values calculated over the entire database. The spurious values were quantified according to their distribution ranging from 1 single beat to 10 consecutive beats.

Number of consecutive spurious values	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Percentage	1.29	0.41	0.19	0.11	0.11	0.13	0.14	0.13	0.13	0.17

Table 2: Median values with [1st; 3rd] quartiles for time domain indices calculated for the time series without the presence of spurious values (control group) and after application of each correction method on both level of correction (2.5 and 5.0%). In these results are indicated if statistical differences were found using p-value criteria less than 0.05 (* $p < 0.05$).

Correction Method	**AVRR (ms)**	**SDNN (ms)**	**RMSSD (ms)**
Reference series (Control)	199.2 [188.8; 215.6]	6.9 [2.7; 4.6]	3.6 [2.7; 4.6]
2.5 % of Corrected values:			
Deletion	199.2 [188.8; 215.2]	6.9 [5.5; 10.5]	3.6 [2.7; 4.6]
LI	199.2 [188.7; 215.6]	6.9 [5.5; 10.4]*	3.5 [2.6; 4.5]*
CI	199.2 [188.7; 215.6]	6.9 [5.5; 10.4]	3.5 [2.6; 4.5]
mMAW	199.2 [188.7; 215.6]	6.9 [5.5; 10.4]*	3.6 [2.4; 4.5]*
NPI	199.2 [188.8; 215.6]	6.9 [5.5; 10.4]*	3.6 [2.7; 4.6]*
5% of Corrected Values			
Deletion	199.2 [188.8; 215.6]	6.9 [5.5; 10.4]	3.6 [2.7; 4.6]*
LI	199.2 [188.8; 215.6]	6.9 [5.5; 10.4]*	3.5 [2.6; 4.4]*
CI	199.2 [188.8; 215.6]	6.9 [5.5; 10.4]*	3.5 [2.6; 4.4]
mMAW	199.2 [188.8; 215.6]	6.8 [5.5; 10.4]*	3.5 [2.6;4.5]
NPI	199.2 [188.8; 215.6]	6.9 [5.5; 10.4]*	3.6 [2.7; 4.5]*

LI: linear interpolation, CI: cubic spline interpolation, mMAW: moving average windowing, NPI: non-linear predictive interpolation.

Table 3: Median values with [1st; 3rd] quartiles for frequency domain indices calculated for the signals without the presence of spurious values (control group) and after application of each correction method on both level of correction (2.5 and 5.0%). In these results are indicated if statistical differences were found using p-value criteria less than 0.05 (* $p < 0.05$).

Correction Method	**VLF (ms^2)**	**LF (ms^2)**	**HF (ms^2)**	**LF/HF**
Reference series (Control)	44.6 [22.0; 103.4]	1.3 [0.6; 2.2]	3.8 [2.4; 7.0]	0.4 [0.1; 0.6]
2.5 % of Corrected values:				
Deletion	44.6 [22.5; 104.4]*	1.9 [0.8; 2.9]*	4.5 [3.7; 7.8]*	0.4 [0.9; 0.6]
LI	44.6 [22.5; 103.4]	1.3 [0.6; 2.3]*	3.7 [2.3; 6.7]*	0.4 [0.2; 0.6]*
CI	44.6 [22.5; 103.4]	1.3 [0.6; 2.3]*	3.7 [2.3; 6.7]*	0.4 [0.2; 0.6]*
mMAW	44.6 [22.4; 103.3]	1.3 [0.6; 2.2]*	3.7 [2.3; 6.7]*	0.4 [0.1; 0.6]
NPI	44.6 [22.5; 103.4]	1.3 [0.6; 2.2]	3.8 [2.3; 6.8]*	0.4 [0.1; 0.6]
2.5 % of Corrected values:				
Deletion	44.9 [22.4; 103.1]	2.3 [1.0; 3.6]*	5.6 [4.5; 8.5]*	0.4 [0.2; 0.5]
LI	44.6 [22.5; 103.4]	1.4 [0.7; 2.4]*	3.6 [2.2; 6.4]*	0.4 [0.2; 0.6]*
CI	44.6 [22.5; 103.5]	1.4 [0.7; 2.4]*	3.6 [2.2; 6.4]*	0.4 [0.2; 0.6]*
mMAW	44.5 [22.4; 103.2]*	1.2 [0.6; 2.1]*	3.6 [2.3; 6.5]*	0.4 [0.2; 0.6]
NPI	44.5 [22.4; 103.3]	1.3 [0.6; 2.3]	3.8 [2.4; 6.8]*	0.4 [0.2; 0.6]

LI: linear interpolation, CI: cubic spline interpolation, mMAW: moving average windowing, NPI: non-linear predictive interpolation.

Table 4: Median values with [1st; 3rd] quartiles for nonlinear indices calculated for the signals without the presence of spurious values (control group) and after application of each correction method on both level of correction (2.5 and 5.0%). In these results are indicated if statistical differences were found using p-value criteria less than 0.05 (* $p < 0.05$).

Correction Method	**α_1 (a.u)**	**α_2 (a.u)**	**MSE_1 (a.u)**	**MSE_T (a.u)**	**0V (%)**	**2UV (%)**
Reference series (Control)	0.7 [0.6; 0.9]	1.1 [1.0; 1.2]	1.4 [1.0; 1.9]	19.9 [16.4; 22.2]	24.3 [11.8; 37.0]	28.7 [23.9; 48.0]
2.5 % of Corrected values:						
Deletion	0.8 [0.6; 0.9]	1.1 [1.0; 1.2]	1.5 [1.0; 1.9]*	20.2 [16.6; 22.5]*	24.8 [12.0; 37.1]	28.9 [24.1; 47.7]
LI	0.8 [0.6; 1.0]*	1.1 [1.0; 1.2]*	1.4 [1.0; 1.8]	20.2 [16.6; 22.6]*	25.7 [12.8; 38.1]*	27.6 [22.6; 46.0]*
CI	0.8 [0.6; 1.0]	1.1 [1.0; 1.2]	1.5 [1.0; 1.8]	20.2 [16.6; 22.7]	26.1 [12.7; 38.3]	27.4 [22.5; 45.9]
mMAW	0.8 [0.6; 1.0]*	1.1 [1.0; 1.2]*	1.5 [1.0; 1.8]	20.2 [16.6; 22.7]	26.1 [12.7; 38.3]*	27.4 [22.5; 45.9]*
NPI	0.8 [0.6; 1.0]	1.1 [1.0; 1.2]	1.4 [1.0; 1.9]	20.1 [16.4; 22.3]*	25.1 [11.8; 37.0]	29.1 [23.0; 47.7]
2.5 % of Corrected values:						
Deletion	0.8 [0.6; 0.9]	1.1 [1.0; 1.2]*	1.5 [1.0; 1.9]*	20.3 [16.9; 22.4]*	27.2 [12.5; 37.6]*	28.7 [22.6; 47.4]*
LI	0.8 [0.6; 1.0]*	1.1 [1.0; 1.2]*	1.5 [1.0; 1.8]	20.4 [17.3; 22.8]*	27.9 [15.0; 39.2]*	26.8 [21.3; 45.1]*
CI	0.8 [0.6; 1.0]*	1.1 [1.0; 1.2]*	1.5 [1.0; 1.8]	20.4 [17.3; 22.9]*	27.5 [15.0; 39.3]*	26.7 [21.7; 44.9]*
mMAW	0.8 [0.6; 0.9]*	1.1 [1.1; 1.2]*	1.4 [1.0; 1.8]*	20.0 [16.3; 22.4]	27.0 [13.5; 39.1]*	27.5 [22.9; 46.9]*
NPI	0.8 [0.6; 0.9]*	1.1 [1.0; 1.2]	1.4 [1.0; 1.9]	20.1 [16.6; 22.4]*	26.6 [12.5; 37.4]*	27.8 [22.8; 48.4]

LI: linear interpolation, CI: cubic spline interpolation, mMAW: moving average windowing, NPI: non-linear predictive interpolation.

Figures:

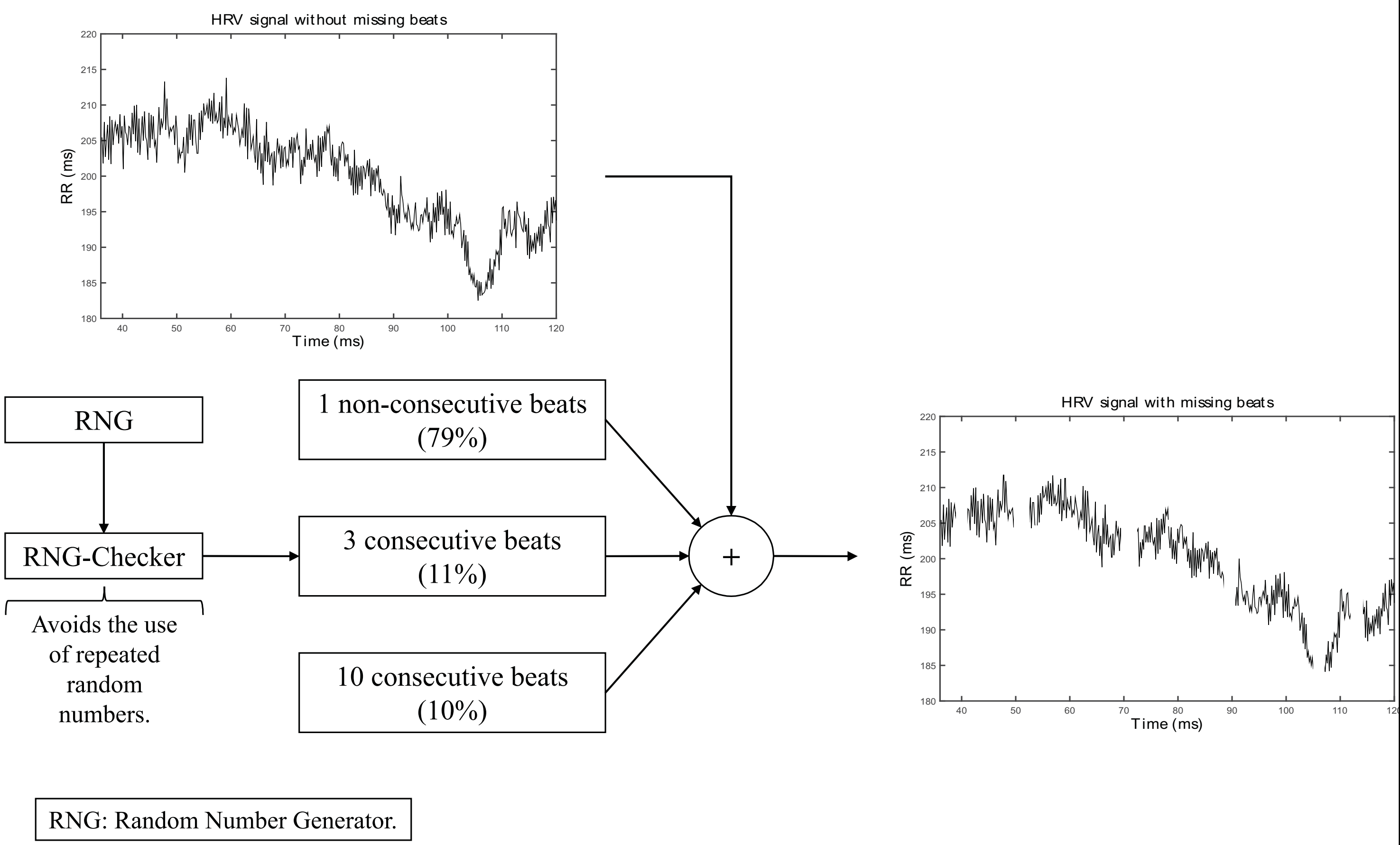
Figure 1: Illustrating scheme describing the simulation of losses. Given a reference RR time series (top left corner), the simulation uses a random number generator to produce 1 beat losses with 79% probability, segments of 3 beats with 11% probability and segments of 10 beats with 10% probability. In total, 2.5% or 5% of the reference time series are randomly removed, resulting in the RR series illustrated on the bottom right.

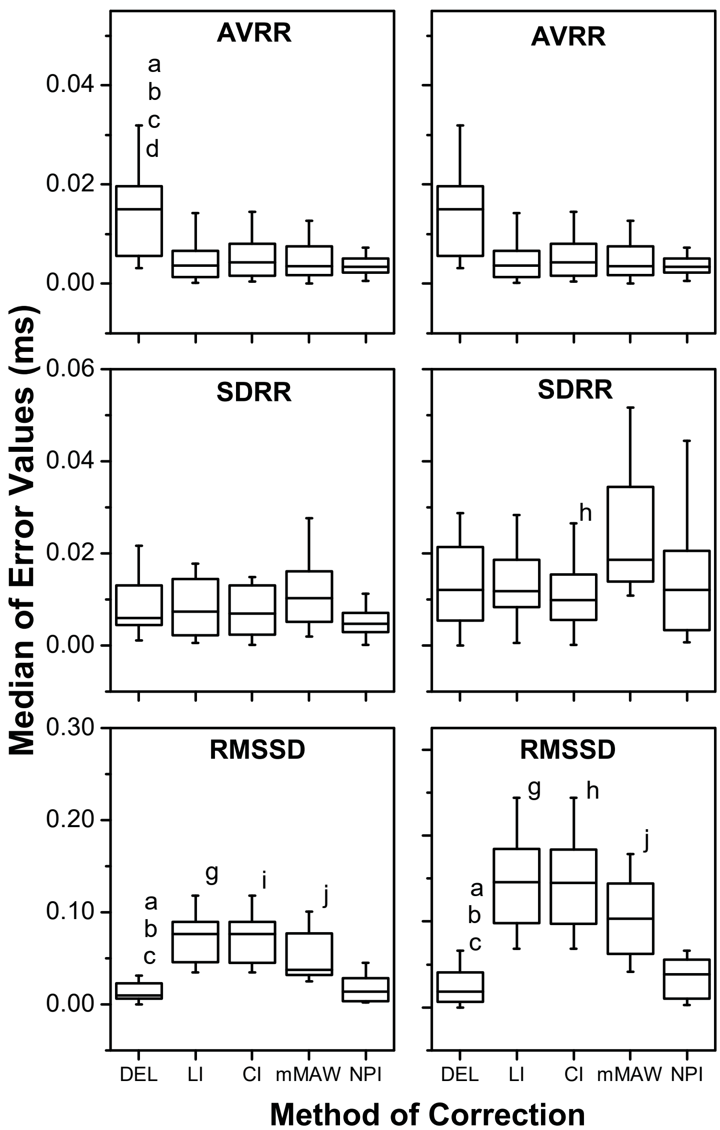
Figure 2: The mean errors for the time-domain HRV measures calculated from corrupted-corrected time series and reference (original) series for different correcting methods over the two levels of correction, i.e. 2.5 and 5%. LI: Linear Interpolation; CI: Cubic Interpolation; mMAW: modified Moving Average Window; NPI: Nonlinear Predictive Interpolation; The letters on the top of the bars represent statistical differences, as inferred with ANOVA on ranks, found between correction methods as follows. a: between DEL and LI; b: between DEL and CI; c: between DEL and mMAW; d: between DEL and NPI; e: difference between LI and CI; f: difference between LI and mMAW; g: differs between LI and NPI; h: difference between CI and mMAW; i: difference between CI and NPI; j: difference between mMAW and NPI.

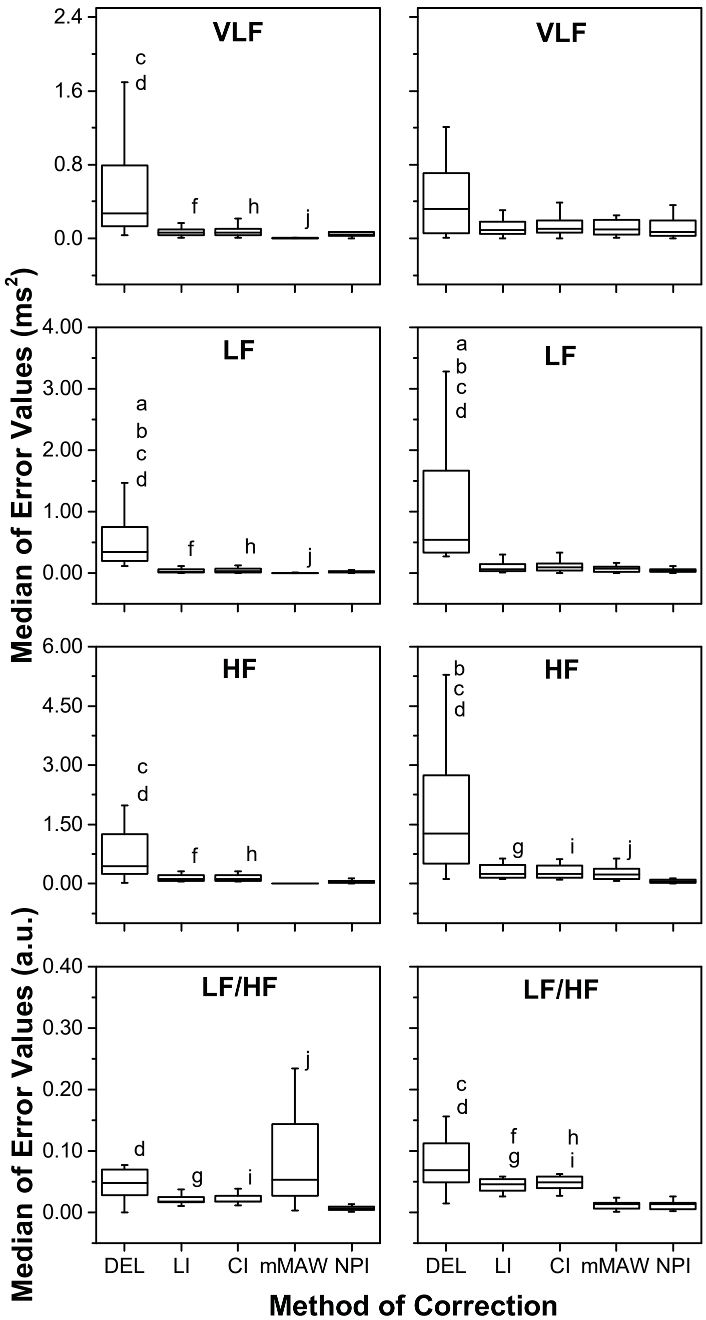
Figure 3: The mean errors for the frequency-domain HRV measures calculated from corrupted-corrected time series and reference (original) series for different correcting methods over the two levels of correction, i.e. 2.5 and 5%. LI: Linear Interpolation; CI: Cubic Interpolation; mMAW: modified Moving Average Window; NPI: Nonlinear Predictive Interpolation; The letters on the top of the bars represent statistical differences, as inferred with ANOVA on ranks, found between correction methods as follows. a: between DEL and LI; b: between DEL and CI; c: between DEL and mMAW; d: between DEL and

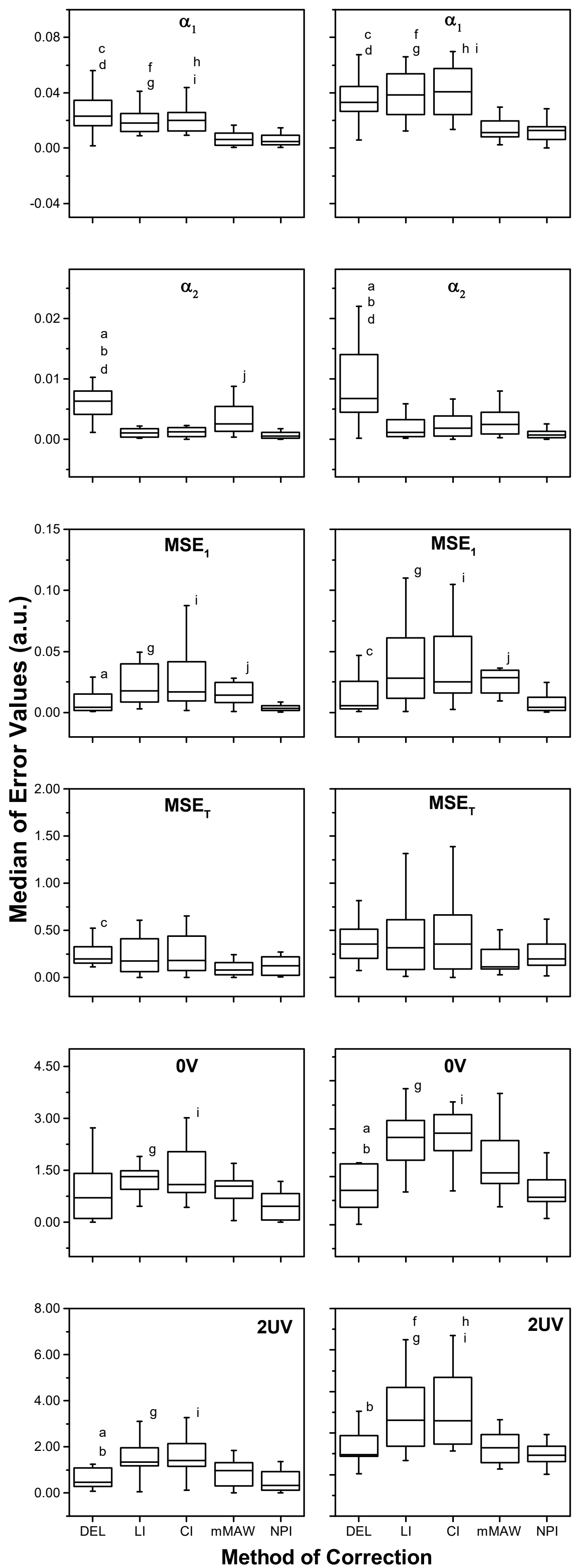
NPI; e: difference between LI and CI; f: difference between LI and mMAW; g: differs between LI and NPI; h: difference between CI and mMAW; i: difference between CI and NPI; j: difference between mMAW and NPI.

Figure 4: The mean errors for the nonlinear HRV measures calculated from corrupted-corrected time series and reference (original) series for different correcting methods over the two levels of cprrection, i.e. 2.5 and 5%. LI: Linear Interpolation; CI: Cubic Interpolation; mMAW: modified Moving Average Window; NPI: Nonlinear Predictive Interpolation; The letters on the top of the bars represent statistical differences, as inferred with ANOVA on ranks, found between correction methods as follows. a: between DEL and LI; b: between DEL and CI; c: between DEL and mMAW; d: between DEL and NPI; e: difference between LI and CI; f: difference between LI and mMAW; g: differs between LI and NPI; h: difference between CI and mMAW; i: difference between CI and NPI; j: difference between mMAW and NPI.


HRV signal without missing beats
RR (ms)
Time (ms)
RNG
RNG-Checker
Avoids the use of repeated random numbers.
1 non-consecutive beats (79%)
3 consecutive beats (11%)
10 consecutive beats (10%)
+
HRV signal with missing beats
RR (ms)
Time (ms)
RNG: Random Number Generator.


AVRR
AVRR
SDRR
SDRR
RMSSD
RMSSD
Median of Error Values (ms)
Method of Correction
DEL
LI
CI
mMAW
NPI
0.00
0.02
0.04
0.06
0.10
0.20
0.30


VLF
VLF
LF
LF
HF
HF
LF/HF
LF/HF
Median of Error Values (ms^2)
Median of Error Values (a.u.)
DEL LI CI mMAW NPI
DEL LI CI mMAW NPI
Method of Correction


Median of Error Values (a.u.)
Method of Correction
DEL
LI
CI
mMAW
NPI
α1
α2
MSE1
MSET
0V
2UV