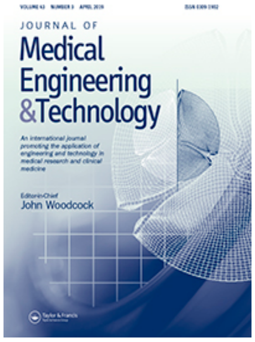

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INNOVATION

A robust algorithm for heart rate variability time series artefact correction using novel beat classification

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ABSTRACT

Purpose: Heart rate variability is a commonly used measurement to evaluate functioning of autonomic nervous system, psychophysiological stress, and exercise intensity and recovery. HRV measurements contain artefacts such as extra, missed or misaligned beat detections, which can produce significant distortion on HRV parameters. In this paper, a robust automatic method for artefact detection from HRV time series is proposed.
Methods: The proposed detection method is based on time-varying thresholds estimated from distribution of successive RR-interval differences combined with a novel beat classification scheme. The method is validated using simulated extra, missed and misaligned beat detections as well as real artefacts such as atrial and ventricular ectopic beats.
Results: The sensitivity of the algorithm to detect simulated missed/extra beats was 100%. The sensitivity to detect real atrial and ventricular ectopic beats was 96.96%, the corresponding specificity being 99.94%. The mean error in HRV parameters after correction was <2% for missed and extra beats as well as for misaligned beats generated with large displacement factors. Misaligned beats with smallest displacement factor were the most difficult to detect and resulted in largest HRV parameter errors after correction, largest errors being <8%.
Conclusions: The HRV artefact correction algorithm presented in this study provided comparable specificity and better sensitivity to detect ectopic beats as compared to state-of-the-art algorithms. The proposed algorithm detects abnormal beats with high accuracy, is relatively easy to implement, and secures reliable HRV analysis by reducing the effect of possible artefacts to tolerable level.

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Heart rate variability; HRV; ectopic beat; artefact correction; beat classification

1. Introduction

Heart rate variability (HRV) is a commonly used measurement to evaluate autonomic nervous system (ANS) function, widely used in scientific studies and self-monitoring purposes. For measuring HRV various devices exist, ranging from clinical purpose electrocardiogram (ECG) devices to low cost heart rate monitors and optical pulse measurement devices. Decreased HRV has been found to associate with many clinical scenarios such as mortality after myocardial infarction [1,2], congestive heart failure [3] and diabetic neuropathy [4]. In addition to these clinical applications, HRV is widely used in various medical, well-being and behavioural research settings [5–7]. For self-monitoring purposes, the two biggest applications of HRV are probably evaluation of psychophysiological stress and monitoring of exercise intensity and recovery.

Analyses of HRV require time intervals between successive normal-to-normal RR intervals. However, almost always the RR time series includes artefacts (abnormal RR interval values), especially when measuring HRV for a longer period of time outside laboratory settings. Typical sources of artefacts include extra, missed or misaligned beat detections as well as ectopic beats. Such artefacts within the RR interval time series are observed as sharp peaks or large changes between successive beat intervals, and can produce significant distortion on HRV analysis parameters.

Ectopic beats can typically be detected by visual inspection of ECG or by automatically detecting missing P-waves or abnormal QRS complex morphology, this is however often time consuming or is not always applicable for example due to poor signal quality. In addition, most heart rate monitors and other wearable technology devices detect heartbeats automatically and store only the HRV time series for later use. Such wearable devices are used in conditions where

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frequent motion artefacts and higher incidence of ectopic events is expected. For example, when monitoring HRV during sports activities or even normal daily activities, the number of artefacts is typically high compared to controlled laboratory measurements. Thus, there is a clear need for scientifically validated, robust and automatic algorithms, which can reliably detect and correct extra, missed and misaligned beat detections as well as ectopic beats. Such algorithms should be able to run inside the wearable devices or in external analysis software.

Automatic approaches for the detection of erroneous beats can be divided into two categories, statistical methods [8–11] and modelling based approaches [12,13]. Statistical methods detect erroneous beats from their different statistical properties and these methods are often robust, their time complexity (i.e., number of operations) is low, and implementation for different set-ups is easy. However, the detection accuracies of previously proposed statistical methods are poor when compared to modelling based approaches [12]. The modelling approaches have typically higher time complexity and their implementation is often difficult.

In this paper, a robust automatic method for artefact detection and correction from HRV time series is proposed. Detection of artefacts is based on two variable thresholds. The first threshold is estimated from distribution of successive RR-interval differences and the second one is estimated from distribution of differences between individual RR-intervals and median RR interval. The method is validated using resting ECG measurements with simulated extra, missed and misaligned detections. Detection accuracy and impact of correction on time-domain and frequency-domain HRV parameters are reported. In addition, detection accuracy of ectopic beats is validated using measurements with real atrial and ventricular premature beats. Finally, we tested the proposed algorithm with a clinical exercise test measurement, to see how the method adapts to non-resting heart rates.

2. Methods

The proposed method for detecting and removing artefacts from HRV time series is presented next. Three most common artefact types in HRV time series are extra, missed and ectopic beats, which generate short, long and sequences of short and long beat interval values, respectively.

Previous publications have shown that difference between two successive RR intervals (dRRs time series) is a robust way to separate ectopic and misaligned beats from the normal sinus rhythm [9,10]. dRRs time series is defined as

$$dRRs(j) = RR(j) - RR(j-1), \; j = 2 \ldots N \tag{1}$$

where N is the number of RR intervals and dRRs(1)=0. To identify artefact beats from the normal ones, a threshold Th1 is adopted. To ensure adaptation to different HRV levels, the threshold is estimated from the time-varying distribution of the dRRs series. Th1 is defined as α times quartile deviation (QD) of the 91 surrounding beat interval differences

$$\mathrm{Th1(j)} = \alpha \ \mathrm{QD}\Big[\ \big|\mathrm{dRRs(j{-}45} \ldots \ \mathrm{j}+45)\big|\Big], \; j = 1 \ldots N \tag{2}$$

where α is a scaling factor and $|\cdot|$ denotes absolute value. dRRs series is then normalised with Th1

$$\mathrm{dRR(j)} = \frac{\mathrm{dRRs(j)}}{\mathrm{Th1(j)}}, \; j = 1 \ldots N \tag{3}$$

After normalisation, |dRR|>1 is used to detect ectopic beats and single missing, short or long beats.

Extra beats and detector errors where every second beat is missing cannot be easily detected from dRR series. Therefore, we define mRRs series, which is the difference between individual RR intervals and an 11-beat median RR interval (medRR). Thus, mRRs is defined as

$$\mathrm{mRRs}(j) = \mathrm{RR}(j) - \mathrm{median}[\mathrm{RR}(j{-}5 \ldots j+5)], \; j = 1 \ldots N \tag{4}$$

For heart rate of 60 bpm, mRRs is close to -0.5 s for extra beats (assuming the extra detection divides the normal beat interval in half) and mRRs is close to 1 s for missing beats. To be able to apply equal threshold for extra and missed beats, mRRs is scaled as follows

$$\mathrm{mRRs}(j) = \begin{cases} 2\ mRRs(j), & if\ \ mRRs(j) < 0 \\ mRRs(j), & if\ \ mRRs(j) \geq 0 \end{cases}, \; j = 1 \ldots N \tag{5}$$

The value of mRRs for 60 bpm HR is then close to 0 s for normal beats, close to 1 s for missed beats and close to -1 s for extra beats (dividing the normal interval in half). To identify artefact beats from normal beats, a threshold Th2 is adopted. The threshold is estimated from the time-varying distribution of the mRRs series to ensure adaptation to different HRV levels. The threshold Th2 is defined as α times quartile deviation (QD) of the 91 surrounding beat differences

$$\mathrm{Th2(j)} = \alpha \ \mathrm{QD}\Big[\big|\mathrm{mRRs(j{-}45} \ldots \ \mathrm{j}+45)\big|\Big], \; j = 1 \ldots N \tag{6}$$

mRRs is then normalised with Th2 to have

$$mRR(j) = \frac{mRRs(j)}{Th2(j)}, \quad j = 1 \ldots N \tag{7}$$

The scaling factor α is selected to be 5.2 (for both dRR and mRR series). Beats within this range cover 99.95% of all beats if RR series is normally distributed. However, RR interval time series is not often normally distributed and thus, also some of the normal beats exceed these thresholds. Therefore, decision algorithm is needed to detect artefact beats.

2.1. Decision algorithm

The decision algorithm discriminates beats into different types of erroneous beats, which guides how the erroneous beat is corrected. A schematic presentation of the proposed decision algorithm is presented in Figure 1.

Ectopic beats form negative positive negative (NPN) or positive negative positive (PNP) segments to the dRR series. This pattern is used for differentiating ectopic beats from the missed or extra beats or the sudden drop or increase of heart rate. A two-dimensional space S_1 is calculated as follows

$$S_{11}(j) = dRR(j), \quad j = 1 \ldots N \tag{8}$$

$$S_{12}(j) = \begin{cases} \max[dRR(j-1), dRR(j+1)], & if\ dRR(j) > 0 \\ \min[dRR(j-1), dRR(j+1)], & if dRR(j) < 0 \end{cases} \tag{9}$$

In this space, S_{12} and $-S_{11}$ get simultaneously large values only for segments of NPN and small values for

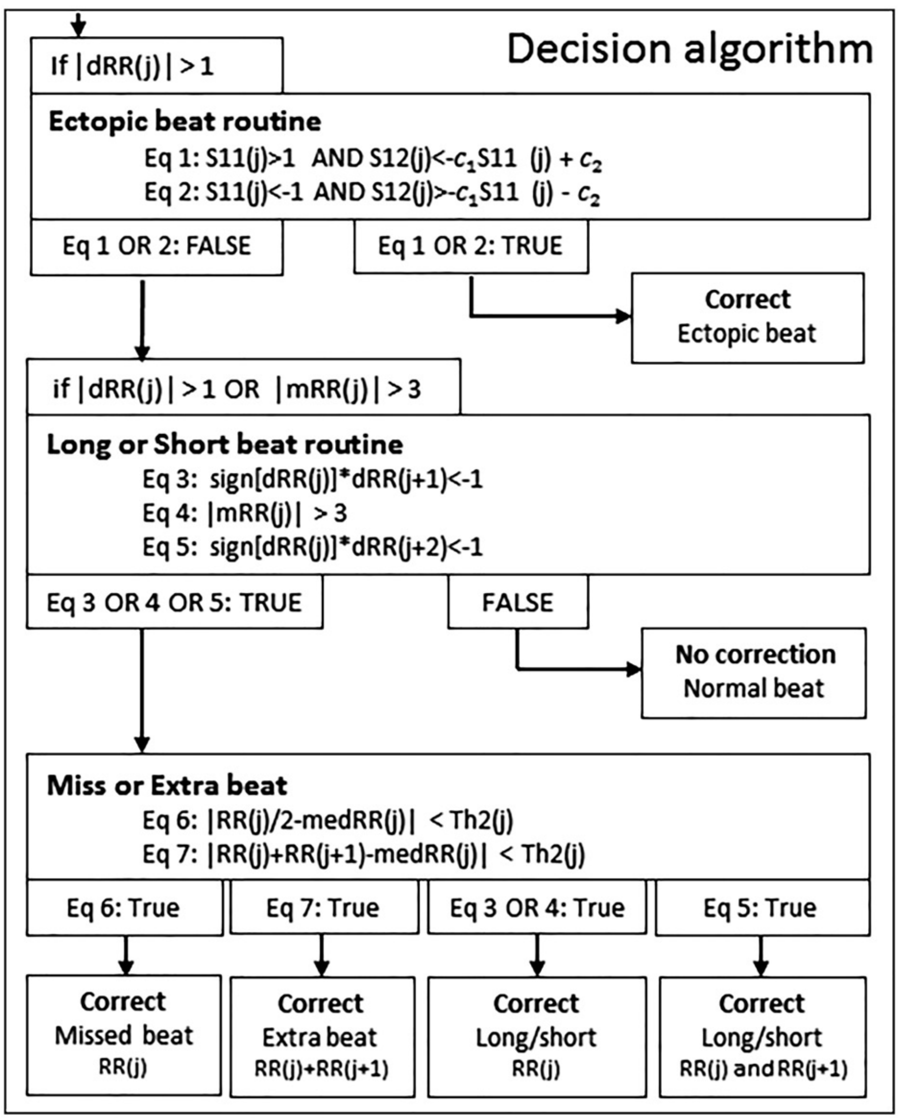

Figure 1. Schematic presentation of the decision algorithm for detecting real artefacts and removing extra detections. Firstly, RR interval is tested against the ectopic beat criterion and secondly against the long or short criterion if beat is classified long or short then missed and extra beat criterions are tested. If criterions are not fulfilled beat is classified as a normal rhythm.

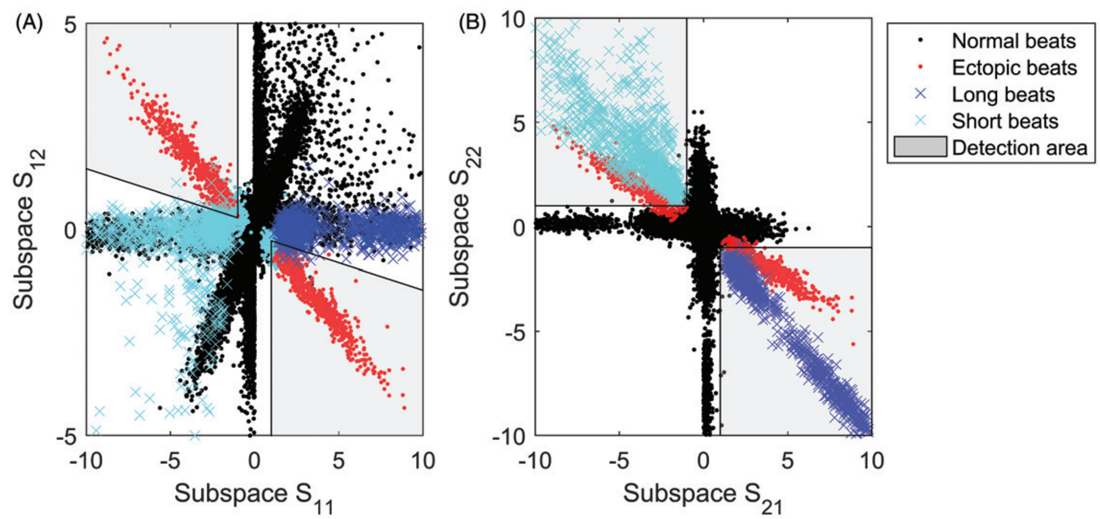

Figure 2. Subspaces S_1 and S_2 and detection area of the ectopic beats in subspace S_1 and detection area of the long, short, extra and missed beats in subspace S_2.

PNP segments. Figure 2(A) shows an example how normal and ectopic beats are positioned in this subspace. The figure also illustrates the decision boundaries for ectopic beat detection. The j'th beat is classified as an ectopic beat if it satisfies the following conditions

$$Ectopic\ beat = \begin{cases} S_{11}(j)>1 \text{ AND } S_{12}\ (j)<-c_1\ S_{11}(j)-c_2 \\ OR \\ S_{11}(j)<-1 \text{ AND } \ S_{12}(j)>-c_1\ S_{11}(j)+c_2 \end{cases} \tag{10}$$

where the values of c_1 and c_2 ($c_1 = 0.13$ and $c_2 = 0.17$) were estimated using simulated artefacts and by optimising false classification of ectopic and short/long beats.

Long beats (including missed beat detections) form positive negative (PN), short beats form negative positive (NP), and extra beats form NNP or NPP segments to the dRR series. To ensure that all long, short, missed, and extra beats are detected, a two-dimensional space S_2 is constructed using dRR time series.

$$S_{21} = dRR(j),\ \ j = 1 \dots N \tag{11}$$

$$S_{22} = \begin{cases} \min[dRR(j+1), dRR(j+2)], & if\ \ dRR(j) \geq 0 \\ \max[dRR(j+1), dRR(j+2)], & if\ \ dRR(j) < 0 \end{cases} \tag{12}$$

The j'th beat (as well as the following beat $j+1$ if $|dRR(j+1)| < |dRR(j+2)|$) is classified as long or short beat if it satisfies following conditions

$$Long\ \ OR\ \ Short = \begin{cases} S_{21}>1 \text{ AND } S_{22}<-1 \\ OR \\ S_{21}>1 \text{ AND } S_{22}<-1 \\ OR \\ |mRR>3 \end{cases} \tag{13}$$

Figure 2(B) shows how long and short beats are positioned in subspace S_2. The figure illustrates also the decision boundaries for detecting long and short beats.

A missed or extra beat is detected if the beat is first classified as a long or short beat respectively and in addition if the RR interval satisfies following conditions

$$\text{Missed beat} = \left|\frac{RR(j)}{2} - medRR(j)\right| < Th2 \tag{14}$$

$$\text{Extra beat} = |RR(j) + RR(j+1) - medRR(j)| < Th2 \tag{15}$$

Correction of missed and extra beats are handled differently than other artefact beats.

2.2. Correction of erroneous heartbeats

After the detection of erroneous beats, invalid RR interval times are corrected. Correction strategy depends on the type of the erroneous beat.

Extra beats are corrected by removing the extra R-wave detection corresponding to the detected short RR interval and RR interval series is then recalculated.

Missed beats are corrected by adding new R-wave occurrence time so that it divides the detected long RR interval into two equal halves and RR interval series is then recalculated.

Long or short beats, are corrected by interpolating new values to the RR time series.

Ectopic beats are corrected by replacing corrupted RR times by interpolated RR values.

3. Materials

The performance of the proposed artefact detection and correction algorithm was tested using ECG data from the *Fantasia database* [14] and *MIT-BIH arrhythmia database* [15], both available at the PhysioNet archive [16]. In addition, a clinical exercise test data measured at University of Eastern Finland was used to test how the algorithm performs for non-resting heart rates.

The Fantasia database consist of 120-min resting ECG measurements from 20 young and 20 elderly subjects with beat annotations. The recordings with not more than 6 non-normal heartbeats (9 recordings) were selected for analysis. These nine recordings with normal sinus rhythm were then passed though the proposed algorithm and the number of beats triggering false alarm (False Positives) were calculated. Secondly, the performance to detect missed, extra and misaligned beats was studied by generating these artefacts on the recordings similarly as in [12]. Missed beats were simulated by removing beat detections at indexes $k = 100n$, where $n = \{1, 2, 3, \dots\}$. Extra detections were simulated by inserting an extra beat after every beat index k. Misaligned beats were simulated by moving beat detections at indexes k by record-dependent temporal displacement Δt. Detectability of the misaligned beats depends on the level of normal RR variability within the measurement. Therefore, Δt was calculated by $\Delta \mathrm{t} = \mathrm{q}^{*}\mathrm{RMSSD}$, where RMSSD is the square root of the mean squared differences of successive RR intervals of each individual measurement [17]. Misaligned beats were simulated at three displacement levels $q = \{2, 4, 8\}$. By using record specific (RMSSD dependent) displacement, comparability of artefacts generated with equal q value was achieved.

The MIT-BIH arrhythmia database was utilised for testing the detection performance on real ectopic beats [15]. The database contains 48 half-hour measurements with reference annotations for every beat. Every recording was first classified in 20-s time windows to acceptable (less than 10 artefact corrupted RR intervals) or non-acceptable (more than 10 artefacts) time periods, and from each recording two longest acceptable segments (had to be at least 5-min) were selected for final analysis. This resulted in 37 segments from 28 measurements, total beat count >47 000 with 559 abnormal beats.

Finally, one bicycle exercise ECG measurement from healthy male subject was used to test how the proposed artefact correction method adapts to varying heart rate. For the analysis, chest lead V5 was chosen and the ECG was visually checked not to have missed, extra or ectopic beats. The sampling rate of the ECG was 500 Hz and QRS-complexes were detected using the Kubios HRV software [18]. In the measurement, subject first lay supine for 3 min, and then sat up on the bicycle for the next 3 min. After this, subject started the incremental exercise test with starting load of 40 W and the load was increased with 40 W every 3 min. Subject continued exercise until exhaustion, after which a 10-min recovery period was measured.

4. Results

4.1. Detection of simulated artefacts (fantasia database)

Examples of simulated misaligned beats with different displacement ($\Delta t = \mathrm{q}^{*}\mathrm{RMSSD}$) as well as missed and extra beats are illustrated in Figure 3. It can be noted that misaligned beats generated with the smallest displacement ($q = 2$) are very small and detection of these smallest displacements is difficult. The overall performance of the proposed correction algorithm for the simulated artefacts is reported in Table 1. The data consisted of 61 757 normal beats and 610 simulated abnormal beats for each artefact type. The accuracy of the algorithm to detect normal beats was 99.963%, that is, only 2–4 normal beats per one-hour recording were classified as artefacts. Missed, extra and misaligned beats with factor $q = 8$ were all detected, and even misaligned beats produced by factor $q = 4$ were detected by 99.3% accuracy.

4.2. Detection of real ectopic beats (MIT/BIH database)

Figure 4 shows an example of a 20-min RR interval time series with real ectopic and other abnormal beats, data taken from the MIT-BIH arrhythmia database. From this recording, the algorithm correctly detects and corrects all ectopic beats except the two smallest misaligned beats (see topmost panel in Figure 4).

The overall performance of the proposed algorithm for the MIT-BIH arrhythmia data is presented in Table 2. The used dataset contained 46 895 normal beats and 559 abnormal beats. Most of the abnormal beats were atrial or ventricular ectopic beats. Normal beats were classified as normal ones with 99.94% accuracy. All nodal, blocked and loss of signal artefacts were correctly detected by the algorithm. Atrial ectopic beats were detected with 98.27% and ventricular beats with 96.23% accuracy. The overall accuracy to detect abnormal beats was 96.96%.

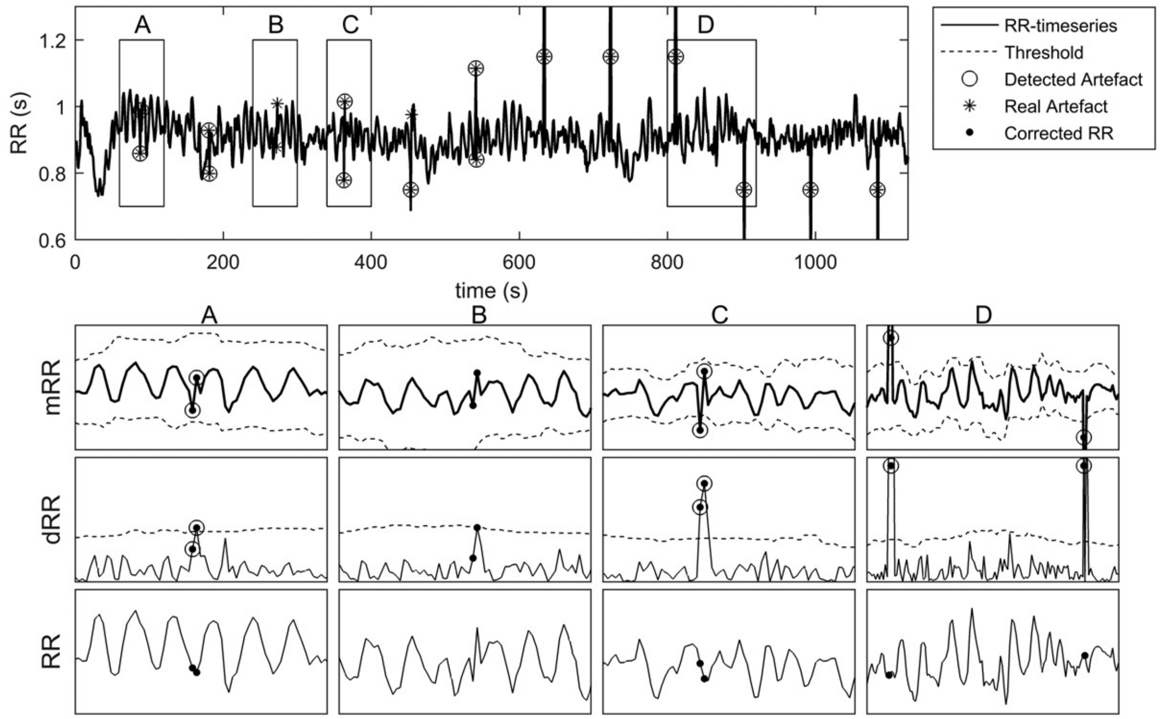

Figure 3. A representative recording taken from Fantasia database with simulated artefacts. RR intervals are presented as black line and detection thresholds (Th1 and Th2) as dashed lines. Simulated artefacts are presented as black stars and detected artefacts as black circles. In panels A and B, ectopic peaks are generated with $q = 2$, in subfigure B, algorithm could not detect the artefact correctly. In panel C, ectopic peaks are generated with $q = 4$. Panel D demonstrates a single missed beat and extra beat.

Table 1. Performance of presented algorithm to classify normal sinus beats and simulated artefacts; missed, extra and misaligned beats (mb).

Beat types	Nbr of beats	Mean Δt (ms)	Classification (%)	Detection (%)
Normal	61 757	–	–	99.963
missed	610	–	100	100
extra	610	–	99.8	100
mb, $q = 2$	610	58	53.3	53.9
mb, $q = 4$	610	119	98.8	99.3
mb, $q = 8$	610	238	100	100

The table summarises the different beat types, number of beats in each class, mean displacement of simulated ectopic beats (mean Δt), and the detection and classification accuracies for different beat types. The classification accuracy gives the percentage of beats which have been detected as artefacts and classified into correct class (missed, extra or misaligned beat).

4.3. Exercise ECG measurement

Figure 5 shows an example of exercise ECG measurement, demonstrating how the time-varying thresholds reliably adjust to the changing HRV levels during the exercise test. The algorithm is able detect misaligned beats even from the peak exercise where HRV is very small. The exercise measurement had altogether 4491 normal beats (no artefacts), of which all except two were correctly identified as normal beats. The two beats incorrectly identified as artefacts are presented in Figure 5(C).

4.4. HRV parameters

Table 3 summarises how different simulated artefacts effect on five commonly used HRV parameters (Mean RR, SDNN, RMSSD, LF power, and HF power). The HRV parameters were calculated from 45 5-min samples taken from the Fantasia database. Artefacts (missed, extra, and ectopic beats) were generated as presented in Materials section.

It was observed that Mean RR was not sensitive to artefacts, showing on average a 0.9% increase when the RR series included missed beats. However, all other HRV parameters were hugely increased (2–80 times higher values) when computed from time series including missed or extra beats, compared to their original values (computed from artefact free RR data). After applying the artefact correction algorithm, the mean absolute errors for these HRV parameters were between 0.2–1.9% compared to original their values.

Ectopic beats simulated with smallest displacement ($q = 2$) produced on average 1.2–16.6% increase to HRV parameters. Artefact correction decreased the error observed in SDNN, RMSSD and HF power, mean absolute error being between 1.2–7.8% after correction. Ectopic beats generated with higher displacements ($q = 4$ and 8) produced 3–250% increase to HRV parameters. After correction, the error was only −1.2–0.4%.

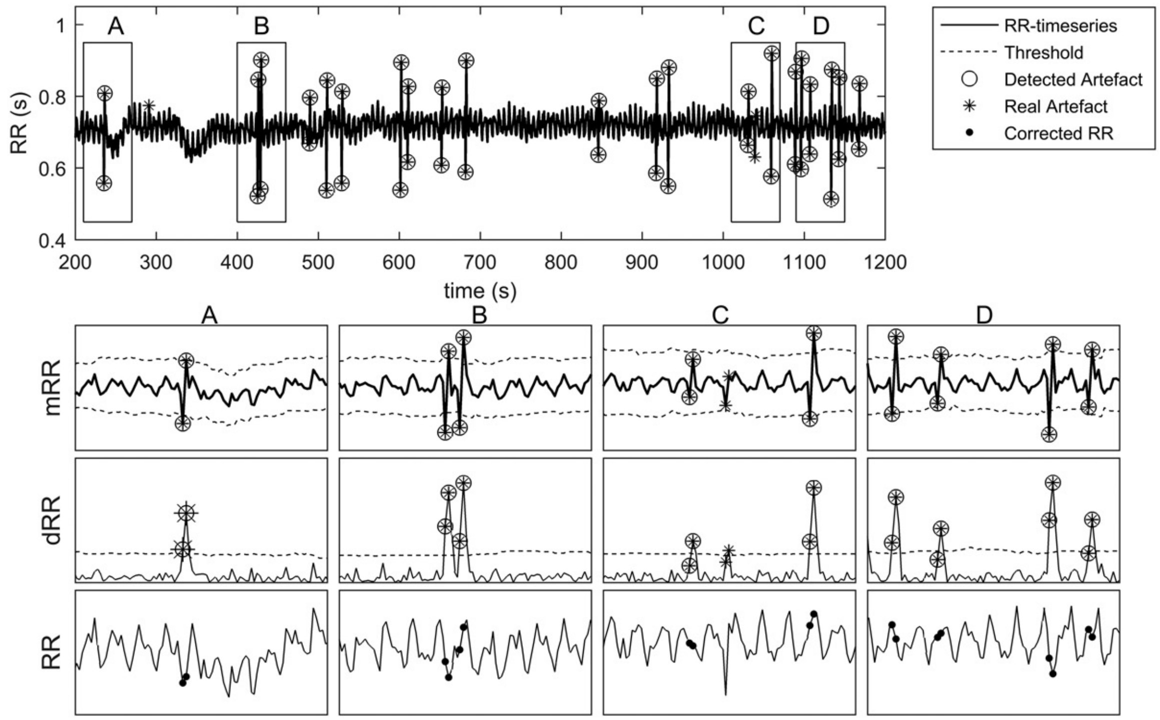

Figure 4. Representative recording with real ectopic beats taken from MIT-BIH arrhythmia database. RR intervals are presented as black line and detection thresholds (Th1 and Th2) as dashed line. Real misaligned beats are presented as black stars and detected artefacts as black circles.

Table 2. Detection results of real artefacts from MIT-BIH arrhythmia database.

	Nbr of beats	False Detection	Correct Detection	Percentage
Normal	46 895	28	46 870	99.940
Abnormal	559	17	542	96.959
Atrial	173	3	170	98.265
Ventricular	371	14	357	96.226
Nodal	3	0	3	100
Blocked	7	0	7	100
loss of signal	5	0	5	100

Atrial (atrial premature beats, aberrated atrial premature beats and atrial escape beats), ventricular (premature ventricular contraction), nodal (nodal/junctional escape beats), blocked (non-conducted P-wave).

5. Discussion

In this paper, a robust method for artefact correction from HRV time series was presented. The algorithm consists of a robust and accurate classification scheme, which enables artefact beat classification to ectopic, long, short, missed and extra beats. The algorithm was validated using real and simulated data. The accuracy of the algorithm to detect real artefacts such as atrial and ventricular ectopic beats was high with overall detection accuracy of 96.96%. In addition, normal beats were classified as normal with 99.94% accuracy. Furthermore, artefacts were observed to have significant effect on HRV parameters, but after correcting the RR interval series with the proposed method the error was in most cases below 2%. Misaligned beats with the smallest displacement ($q = 2$) were hardest to detect, and therefore, also showed highest errors in HRV parameters computed from the corrected RR series.

The Fantasia database and similar procedure to produce simulated artefacts was used in one previous study [12]. They compared four different methods for HRV artefact correction, that is, the methods presented in Citi et al. [12], Mateo et al. [13], Rand et al. [11] and Berntson et al. [9]. Although the analysed dataset is not identical (our dataset contained 61,757 normal beats, whereas Citi et al. had 60,017 normal beats in their dataset), the results should be comparable because the analysed samples are selected from the same database and artefacts are simulated using similar methodology. The detection accuracy for normal beats was higher in Citi's method (99.985% accuracy) when compared to our algorithm (99.963%). The methods proposed in [9,11,13] had slightly lower accuracy in detecting normal beats (99.880–99.938%). The detection accuracy for extra or missed beats was near to 100% in all compared algorithms. The accuracy of our algorithm to detect ectopic beats generated with the smallest displacement ($q = 2$) was 53%,

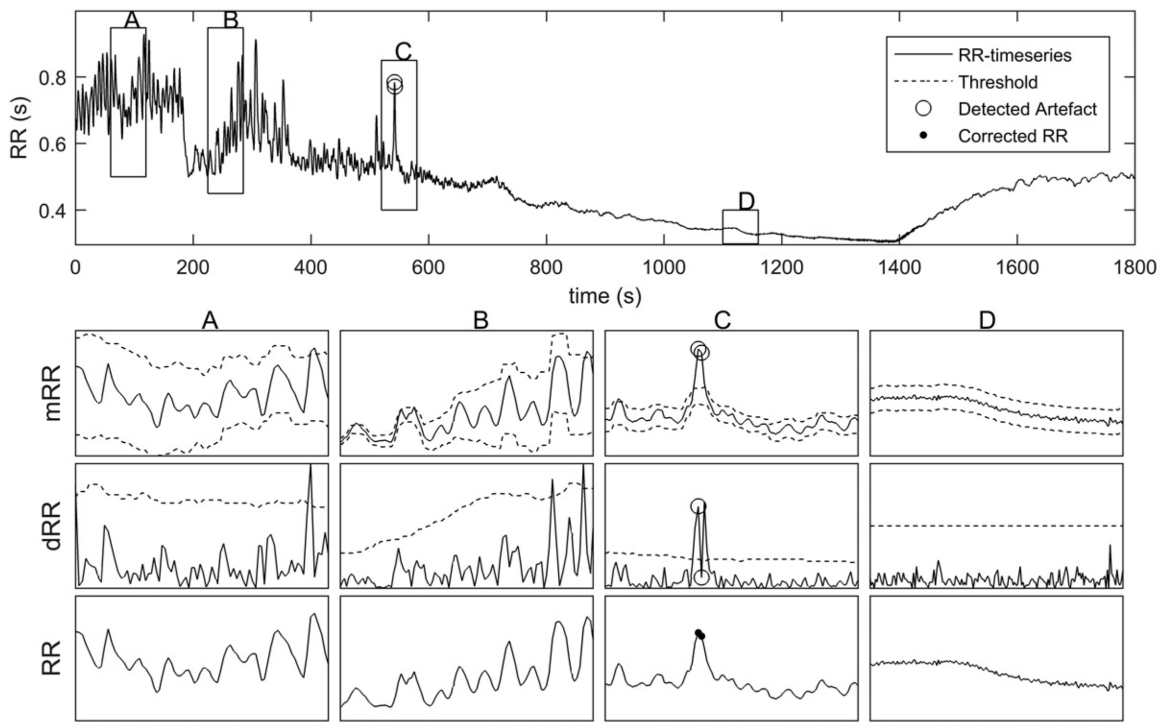

Figure 5. Example of exercise ECG measurement. RR intervals are presented as black line and detection thresholds (Th1 and Th2) as dashed line. Detected artefacts are presented with black circles.

Table 3. Effect of simulated artefacts and artefact correction on HRV parameters. Each parameter is presented as mean ± standard deviation (mean absolute error in percent's).

Parameter	Original	missed	extra	Ectopic $q = 2$	Ectopic $q = 4$	Ectopic $q = 8$
HRV parameters from original RR series and RR series with simulated artefact						
Mean RR (ms)	1020 ± 85	1029 ± 86 (0.9%)	1011 ± 84 (−0.9%)	1020 ± 85 (−0.0%)	1020 ± 85 (−0.0%)	1020 ± 85 (−0.0%)
SDNN (ms)	30.9 ± 13.2	97.8 ± 11.4 (216.2%)	120.3 ± 102.9 (289.0%)	32.1 ± 13.4 (3.8%)	20.7 ± 3.9 (13.6%)	44.9 ± 17.2 (45.1%)
RMSSD (ms)	27.7 ± 12.2	138.2 ± 16.9 (398.5%)	146.9 ± 145.0 (430.1%)	31.1 ± 13.0 (12.3%)	39.3 ± 15.7 (41.8%)	61.3 ± 23.7 (121.2%)
LF power (ms^2)	684 ± 664	6505 ± 2568 (850.2%)	1737 ± 2260 (153.8%)	692 ± 671 (1.2%)	709 ± 684 (3.5%)	780 ± 749 (14.0%)
HF power (ms^2)	287 ± 287	6298 ± 1777 (2088%)	24 ± 9010^3 (8363%)	335 ± 325 (16.6%)	464 ± 425 (61.2%)	1032 ± 963 (258.7%)
HRV parameters from corrected RR series						
Mean RR (ms)	1020 ± 85 (0.0%)	1020 ± 85 (0.0%)	1020 ± 85 (0.0%)	1020 ± 85 (0.0%)	1020 ± 85 (0.0%)	1020 ± 85 (0.0%)
SDNN (ms)	30.9 ± 13.2 (−0.2%)	30.8 ± 13.2 (−0.5%)	30.9 ± 13.2 (−0.2%)	31.4 ± 13.6 (1.5%)	30.8 ± 13.3 (−0.3%)	30.8 ± 13.2 (−0.3%)
RMSSD (ms)	27.6 ± 12.3 (−0.4%)	27.5 ± 12.2 (−0.7%)	27.6 ± 12.3 (−0.4%)	29.0 ± 13.2 (4.6%)	27.4 ± 12.2 (−1.2%)	27.4 ± 12.2 (−1.1%)
LF power (ms^2)	684 ± 664 (−0.0%)	680.9 ± 658.7 (−0.5%)	684 ± 664 (−0.0%)	692 ± 673 (1.2%)	687 ± 668 (0.4%)	686 ± 666 (0.2%)
HF power (ms^2)	287 ± 287 (−0.3%)	282 ± 280 (−1.9%)	287 ± 287 (−0.3%)	310 ± 323 (7.8%)	286 ± 289 (−0.6%)	287 ± 292 (0.0%)

which is better than algorithms presented in Citi's paper (5–41%). Similarly, ectopic beats produced by displacement factor $q = 4$ were detected by our algorithm at 99% accuracy, whereas the corresponding accuracy was 97% in Mateo et al., 96% in Citi et al., 94% in Rand et al., and 18% in Berntson et al.

The accuracy of the proposed algorithm in detecting real artefacts was tested using selected sections from MIT-BIH arrhythmia database. The analysed dataset contained 46 895 normal beats and 559 abnormal beats. Our algorithm identified normal beats with 99.940% accuracy and detected abnormal beats with 97% accuracy. In Citi's paper MIT-BIH arrhythmia database was also used to evaluate algorithm performance. Their algorithm showed slightly better accuracy in detecting normal beats (99.985%), but lower accuracy in detecting abnormal beats (84–94%) [12].

Large artefacts such as missed, extra or ectopic beats with large displacement error induce huge errors into HRV parameters. As can be seen in Table 3, the parameter values can be several times higher than true values if artefacts are not corrected. However, by using an accurate algorithm, large artefacts are easily detected and corrected. After artefact correction, HRV parameters showed on average only −1.9–0.4% error compared to the original correct values. Small errors (such as ectopic beats produced with $q = 2$) are more difficult to detect even for state-of-the-art artefact correction algorithms, only 5–53% detection accuracies have been reported. Table 3 shows that due the low detectability, small displacements errors cause's highest errors in HRV parameters after correction. The error after correction is however relatively low (<8%).

Two previous publications have shown that the difference of two successive beat intervals is a robust way to separate ectopic and misaligned beats from the normal sinus rhythm [9,10]. However, decision thresholds and classification of different types of artefacts was poorly implemented and thus detection and correction results of these algorithms were low [12]. In our algorithm, a time-varying threshold and a novel classification scheme were implemented, which increased detection and classification results significantly. Compared to more recently published modelling based erroneous beat detection approaches [12,13], our simple and robust correction algorithm provided comparable or even better results.

In conclusion, the proposed artefact correction algorithm detects abnormal beats with high accuracy, is relatively easy to implement, and secures reliable HRV analysis by reducing the effect of possible artefacts to tolerable level.

Disclosure statement

Mika P. Tarvainen and Jukka A. Lipponen are founders of Kubios Ltd. and have an equity interest in the company. The authors state that there are no conflicts of interest.

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References

[1] Schmidt G, Malik M, Barthel P, et al. Heart-rate turbulence after ventricular premature beats as a predictor of mortality after acute myocardial infarction. Lancet. 1999;353:1390–1396.

[2] Carney RM, Blumenthal JA, Stein PK, et al. Depression, heart rate variability, and acute myocardial infarction. Circulation. 2001;104:2024–2028.

[3] Ponikowski P, Anker SD, Chua TP, et al. Depressed heart rate variability as an independent predictor of death in chronic congestive heart failure secondary to ischemic or idiopathic dilated cardiomyopathy. Am J Cardiol. 1997;79:1645–1650.

[4] Schroeder EB, Chambless LE, Liao D, et al. Diabetes, glucose, insulin, and heart rate variability: the Atherosclerosis Risk in Communities (ARIC) study. Diabetes Care. 2005;28:668–674.

[5] Acharya UR, Joseph KP, Kannathal N, et al. Heart rate variability: a review. Med Biol Eng Comput. 2006;44: 1031–1051.

[6] Thayer JF, Åhs F, Fredrikson M, et al. A meta-analysis of heart rate variability and neuroimaging studies: implications for heart rate variability as a marker of stress and health. Neurosci Biobehav Rev. 2012;36:747–756.

[7] Jarczok MN, Jarczok M, Mauss D, et al. Autonomic nervous system activity and workplace stressors—a systematic review. Neurosci Biobehavio R. 2013;37:1810–1823.

[8] Cheung MN. Detection of and recovery from errors in cardiac interbeat intervals. Psychophysiology. 1981;18: 341–346.

[9] Berntson GG, Quigley KS, Jang JF, et al. An approach to artifact identification: application to heart period data. Psychophysiology. 1990;27:586–598.

[10] Sapoznikov D, Luria MH, Mahler Y, et al. Computer processing of artifact and arrhythmias in heart rate variability analysis. Comput Methods Programs Biomed. 1992;39:75–84.

[11] Rand J, Hoover A, Fishel S, et al. Real-time correction of heart interbeat intervals. IEEE Trans Biomed Eng. 2007;54:946–950.

[12] Citi L, Brown EN, Barbieri R. A real-time automated point-process method for the detection and correction of erroneous and ectopic heartbeats. IEEE Trans Biomed Eng. 2012;59:2828–2837.

[13] Mateo J, Laguna P. Analysis of heart rate variability in the presence of ectopic beats using the heart timing signal. IEEE Trans Biomed Eng. 2003;50:334–343.

[14] Iyengar N, Peng C-K, Morin R, et al. Age-related alterations in the fractal scaling of cardiac interbeat interval dynamics. Am J Physiol. 1996;271:1078–1084.

[15] Moody GB, Mark RG. The impact of the MIT-BIH arrhythmia database. IEEE Eng Med Biol Mag. 2001;20: 45–50.

[16] Goldberger AL, Amaral LAN, Glass L, et al. PhysioBank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals. Circulation. 2000;101:e215–e220.

[17] Task Force of the European Society of Cardiology, and Task Force of the European Society of Cardiology the North American Society of Pacing and Electrophysiology. Heart rate variability: standards of measurement, physiological interpretation and clinical use. Circulation. 1996;93.5:1043–1065.

[18] Tarvainen MP, Niskanen JP, Lipponen JA, et al. Kubios HRV-heart rate variability analysis software. Comput Methods Programs Biomed. 2014;113:210–220.