Robust Detection of Heart Beats using Dynamic Thresholds and Moving Windows

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Abstract

Background: *This contribution relates to the* PhysioNet/CinC Challenge 2014 *on Robust Detection of Heart Beats in Multimodal Data. The aim is to locate heart beats in continuous long-term data.*

Methods: *The beat detection system is build up of several parts. Preprocessing consists of high pass filtering followed by standardization. Extrema of a moving window were used to capture the heart beat impulse. A windowed approach led to dynamic thresholds. Valid parts of the channels were determined and the locations of beats were extracted. The beat locations of various channels were compared during the multichannel fusion procedure and dynamic delay correction. Doubtful locations were checked using RR distances.*

Results: *The algorithm was tested on the training data set for this challenge (one hundred 10-minute recordings) and on several freely available PhysioNet databases which were annotated by physicians. The algorithm had the best score applied to the hidden Phase I dataset of the 2014 PhysioNet/CinC challenge.*

Conclusion: *The developed algorithm presents a promising approach to detect heart beats in multivariate records.*

1. Introduction

Continuous ECG monitoring (electrocardiography) is widely used in hospitals, especially in critical care units. QRS complexes are mainly used to compute heart rates or heart rate variability (HRV). For diagnostic purposes (myocardial infarction, cardiac dysrhythmias, pulmonary embolism) an accurate detection of QRS complexes is important. Measurement errors and artifacts can distort the clinical calculation. The use of other channels than ECG e.g. continuous blood pressure (BP) or photoplethysmograms (PPG) may help to handle those issues. Beat-by-beat annotation realized by cardiologists is time-consuming and not appropriate for today's clinical practice. Physicians need robust multivariate methods of locating heart beats, which can be implemented in bedside devices.

A classical approach is the real time QRS detector by Pan/Tompkins [1], which consists of digital filtering (high-pass and low-pass), signal transformations and decision rules. A comprehensive review article about recent methods is given by Köhler et. al [2] where detectors were divided into three classes: approaches based on signal derivatives and digital filters, wavelet-based QRS detection or filter-bank methods and approaches using neural networks.

2. QRS detection

A new beat detection system was implemented which consists of several parts.

2.1. Preprocessing

The signal was downsampled to f_s=80 Hz to save computation time. Next, a trimmed moving average filter was applied, which acts as a high pass filter and eliminates both long wave changes and sudden drop-offs / step-ups which may occur when the signal strength rapidly changes.

The α%-trimmed moving average (TMA) [7] with window length w of a time series $(x_t)_{t=1,\dots,n}$ is defined as

$$\text{TMA}_i := \frac{1}{w-2k}\sum_{j=k+1}^{w-k}\tilde{x}_j \text{ with } k=\left\lceil\frac{w\alpha}{2}\right\rceil \text{ and} \\ \text{sorted values } \tilde{x} \text{ of } (x_t), t\in\left[i-\frac{w}{2}, i+\frac{w}{2}\right]. \tag{1}$$

I recommend a trimming value of α=25% and a window length of w_{ECG}=0.2 sec for ECG-like waveforms, w_{BP}=1.0 sec for BP-like waveforms. TMA filtering was also used by Chen [8].

Standardization transformed the signal to a dimensionless waveform of mean 0 and standard deviation 1.

For beat extraction a range filter was used. The range is the difference between local maximum and local minimum in the neighborhood of a particular time point. The neighborhood itself is a window of size l_{ECG}=0.2 sec for ECG-like waveforms and l_{BP}=0.4 sec for BP-like waveforms. Transformation steps are illustrated in Figure 1.

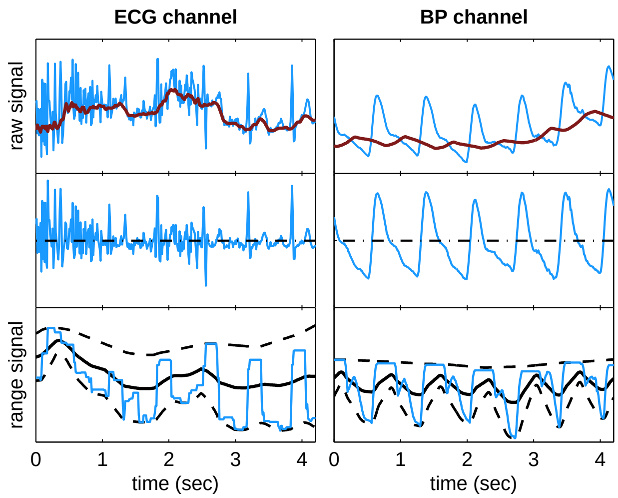

Figure 1. Transformation steps of ECG and BP signals. Top: Raw signal with trimmed moving average (bold line). Middle: Signal after TMA filtering and standardization. Bottom: Range filtered signal with smoothed local maxima and minima (dashed lines) and threshold (bold line).

2.2. Beat extraction

The range signal (r_t) was used to extract the beat positions. Smoothed local maxima (SLmax) and minima (SLmin) were computed (dashed lines in Figure 1). SLmax represents the local amplitude of the signal whereas a high SLmin value indicates noisy data. Hence, an adaptive threshold for beat position i was

$$\begin{aligned} r_i > 0.5(\mathrm{SLmax}_i + \mathrm{SLmin}_i) \text{ and} \\ r_i = r_{i+1} = \ldots = r_{i+f_s/25} \quad (2) \\ \text{as a constancy criterion.} \end{aligned}$$

A new beat position was accepted if there was some j between two subsequent beats with $r_j \leq 0.5(\mathrm{SLmax}_j + \mathrm{SLmin}_j)$. Noisy parts, where SLmax$-$SLmin ≤ 0.4, were kept in a matrix and used for the multivariate fusion part.

2.3. Determine relevant channels

In order to determine whether a channel is suitable for beat detection, independent of a signal description, a short 30 second subset of the time series was taken. All channels ran through the procedures described above. Once with the ECG settings (w_{ECG}=0.2 sec, l_{ECG}=0.2 sec) and once with the BP setting (w_{BP}=1.0 sec, l_{BP}=0.4 sec). Relative RR distances were computed. The RR interval is the time between QRS complexes. The ratio of two consecutive RR intervals is defined as the relative RR interval

$$\mathrm{relRR}_i := \frac{\mathrm{RR}_{i+1}}{\mathrm{RR}_i} \quad \text{for } i{=}1,\ldots,n-1. \quad (3)$$

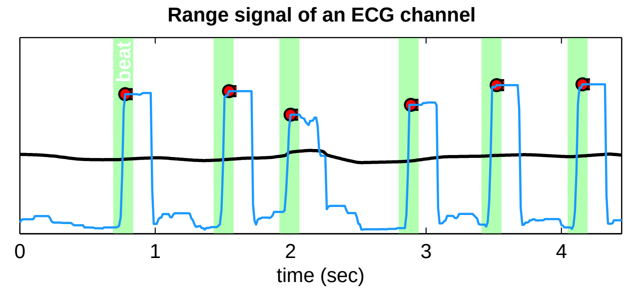

Figure 2. Beat extraction: conditions fulfilled for marked positions. Reference beat positions are shown as vertical bars.

With a healthy heart the values of relRR alternate between 0.8 and 1.2 and can be considered as heart rate variability. Hence an effective channel with appropriate setting fulfills

$$P\left(\mathrm{relRR} \in [0.8, 1.2]\right) \geq 80\%. \quad (4)$$

This means that the extracted beat positions are well-regulated and not chaotic. If both settings were appropriate for the same channel, the channel description (header files) was used for ECG or BP labeling.

3. Multivariate combination

The careful combination of the channel specific annotations has a strong influence on sensitivity and specificity.

3.1. Dynamic delay correction

Pulse transition time [9] and the delay to other devices (e.g. EEGs, EMGs), as illustrated in Figure 3, had to be corrected. The time delay is specific to the device and its distance to the heart. The arrival time is "influenced

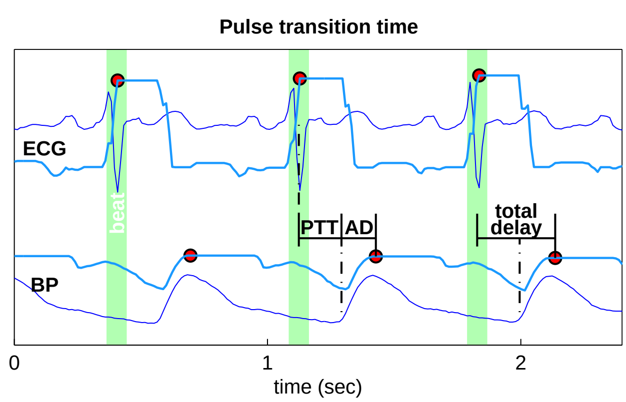

Figure 3. Pulse transition time (PTT) of a BP channel. Total delay obtained by adding the algorithmic delay (AD).

by heart rate, blood pressure changes and the compliance of the arteries" [10]. Due to the variability of transition time (see also [11]), one needs a dynamic delay correction for each channel using a reference ECG electrode. Going through the described QRS detector the delay is of course longer than the usual transition time. For ECG electrodes a static delay of 0.016 sec was assumed (average delay of R-spike to range filter peak). For channels other than ECG a static delay of 0.26 sec was assumed when a ECG reference was missing. Otherwise the time differences to the nearest beat positions of the reference ECG were computed. A dynamic delay correction was given by a median filter with a 20 sec window size (see Figure 4). The following procedures were executed sequentially taking 60 sec subsets of the revised beat positions.

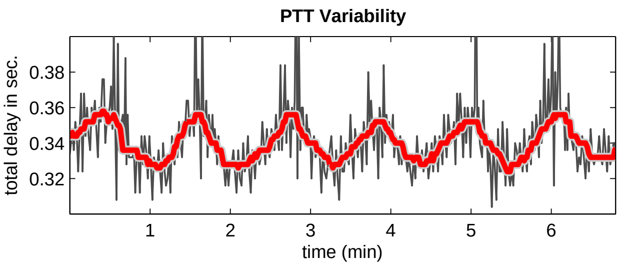

Figure 4. PTT variability. The total delay varies between 320 and 360 ms. The dynamic delay correction is given by a median filter (bold line).

3.2. Merging beats

The beat positions of the different channel origins was sorted. A heart beat was declared as "safe", if there was a sequence of positions coming from all channel origins which were not noisy (see 2.2) and for which the consecutive time differences did not exceed 0.15 sec. The heart beat annotation was defined as the mean of those positions. All other individual positions were declared as "candidates".

3.3. Verifying candidates

There should not be a channel producing more than 70% of candidates or the number of candidates should not exceed a limit of 10% of the number of safe beats.
The candidates were approved by using the concept of relative RR distances. In general, candidates were accepted whenever gaps between two safe beats were filled appropriately. At those positions the relative RR distance function had peaks as shown in Figure 5. Procedures were added to handle cases where two or more candidates were located within two safe beat positions.

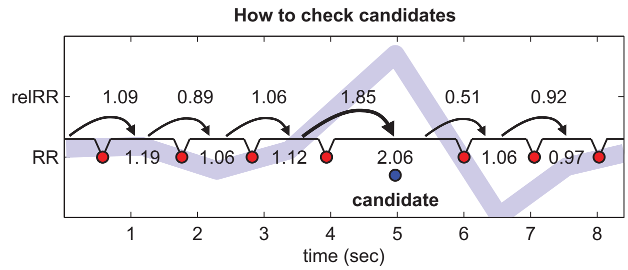

Figure 5. Relative RR distances were used to verify candidates.

3.4. Channel dominance and multivariate subsets

One cannot eliminate the risk of having worse results when merging beats and verifying candidates. Sometimes the information given by a single channel is more accurate than the multivariate pasting. The accuracy of each single channel was derived from quantile ranges of the relative RR distances ($ra_1{=}q_{90\%}{-}q_{10\%}$ and $ra_2{=}q_{80\%}{-}q_{20\%}$). All channels ch for which $ra_1(ch) + ra_2(ch) \leq 1.2\min(ra1 + ra2)$ build up a new multivariate subset. With respect to these ranges, the best channel or multivariate set of channels was picked for writing the annotation file.

4. Performance

The performance was evaluated using freely available standard databases from PhysioNet [12]. Sensitivity and positive predictive value are shown in Table 1 for the MIT-BIH Arrhythmia Database (48 records, 30 minutes each, two-lead ECGs) [13], ST-T Database of the European Society of Cardiology (90 records, 2 hours each, two-lead ECGs) [14], MGH/MF Waveform Database (200 records[1], 12 to 86 minutes each, 3-lead ECGs, ABP, PAP, CVP, respiration, and airway CO2) [15], MIT-BIH Noise Stress Test Database (15 records, 30 minutes each, two-lead ECGs) [16] and the MIT-BIH Polysomnographic Database (18 records, up to 6.5 hours each, various number of channels) [17]. Set-p (100 records, 10 minutes each, various number of channels) was the training database of the PhysioNet/Cinc Challenge 2014.

The evaluation was conducted using MATLAB R2014a on an Intel i7 processor machine. The pure calculation time for QRS detection was about 1 second for a 10 minute record. Hard records detected: MIT-BIH Arrhythmia Database (106, 203, 221, 228, 232), European ST-T (e0604), MGH/MF Waveform Database (040, 072, 074, 075, 120, 122, 130), MIT-BIH Polysomnographic (slp03).

[1] Only the first 200 records were taken, number 026, 041 and 057 were excluded.

Table 1. Results on standard databases

Database	SE	+P
set-p	99.89%	99.93%
MIT-BIH Arrhythmia	98.59%	99.68%
MIT-BIH Noise Stress Test	94.90%	92.02%
European ST-T	99.91%	99.85%
MGH/MF Waveform	98.73%	98.34%
MIT-BIH Polysomnographic	99.90%	99.70%

Noise tolerance was evaluated by the MIT-BIH Noise Stress Test. Excellent results persist even for a signal-to-noise ratio of 6 dB (SE: 99.53%, +P: 95.78%) and for 0 dB (SE: 91.51%, +P: 83.43%). Compared to the robust open-source algorithm by Zong, Moody and Jiang [18] this is more resistant against noise.

The following problems were identified: strong T-waves can cause false positive beats, misplacement by strong P-Waves and false positive beats in noisy sequences.

5. Conclusions

A new detector of heart beats using multivariate records is introduced. Some promising concepts for a fast, simple and robust QRS detection are given.

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