

# Heart Rate Variability Discovery: Algorithm for Detection of Heart Rate from Noisy, Multimodal Recordings

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## Abstract

*Starting point for the heart rate variability analysis is the ECG signal, which ensures the most precise way of detecting heartbeats. However, very often devices used to record ECG also record at the same time many other physiological signals containing useful information about heart rate. In the case of the poor ECG quality or its absence information about beats is lost. This raises the need for robust algorithms which could locate heartbeats in continuous long-term data from bedside monitors, allowing reliable, automatic analysis.*

*We analyzed multi-channel recordings from PhysioNet Challenge 2014 database. Our algorithm focuses on detecting the most prominent part of a QRS complex i.e. RS slope in four of the channels provided: ECG, EMG, EEG and EOG. Similar algorithm was developed for blood pressure signal. First we remove long-range trends. Then, we localize decelerations with the required characteristics (adequate amplitude and slope). Note, that algorithm is adaptive and finds by itself optimal slope characteristics for every recording. After this final steps of a “fine-tuning” are done, i.e. removal of incorrect detections and in the case of missing ones re-check with lower requirements.*

*These steps allowed us to obtain accurate and reliable results of R peak detection.*

## 1. Introduction

Electrocardiography (ECG) is the most frequently used heart rate variability registering method in the world [1]. It enables the analysis of the action potential spread in the heart muscle and provides the determination of abnormal cardiac activities. ECG as an electrical signal is susceptible to noises, which prevents from accurate QRS complex detection.

One of the best methods to fill the gaps which occur from undetected heart beats might be the usage of HR

information included in other physiological signals measured by bedside monitors in hospitals. These records might be directly correlated with cardiovascular system, such as blood pressure (BP) or plethysmogram (PLETH), but there are also attempts to get information about HRV from various respiratory signals or electroencephalography (EEG). All mentioned information allows creating a useful tool to locate heart beats in continuous long-term data.

The main goal of implemented methods described in this article was to detect R peaks in adults ECG signal as precise as possible, considering different types of QRS complex morphology and noises affecting the signal. The other aim was to consider the situation in which detecting of the R peak in ECG was impossible, because of the lack of the signal or of some extreme noises. In that case any gaps in detection, were filled thanks to annotations provided by other biological signals. That was the problem to be solved in PhysioNet/Computing in Cardiology Challenge 2014.

## 2. Data

Signals for analysis were provided by the PhysioNet/Computing in Cardiology Challenge 2014. While preparing successive entries we analyzed 100 multi-channel recordings from PhysioNet Challenge 2014 database. Each recording included 3 to 6 channels of different physiological signals such as ECG, blood pressure, plethysmogram or electroencephalography, with sampling rate of 250 Hz and duration of approximately 10 min. Detected RR interval peaks were compared with reference annotations. In phase I our entry was examined on 100 recordings (available for users). In the next stages of the challenge this number increased with 100 additional unknown signals (up to 200 recordings in phase II and 300 in phase III).

To verify how our program does on low-quality signals we used recordings from MIMIC II Waveform Database [2].

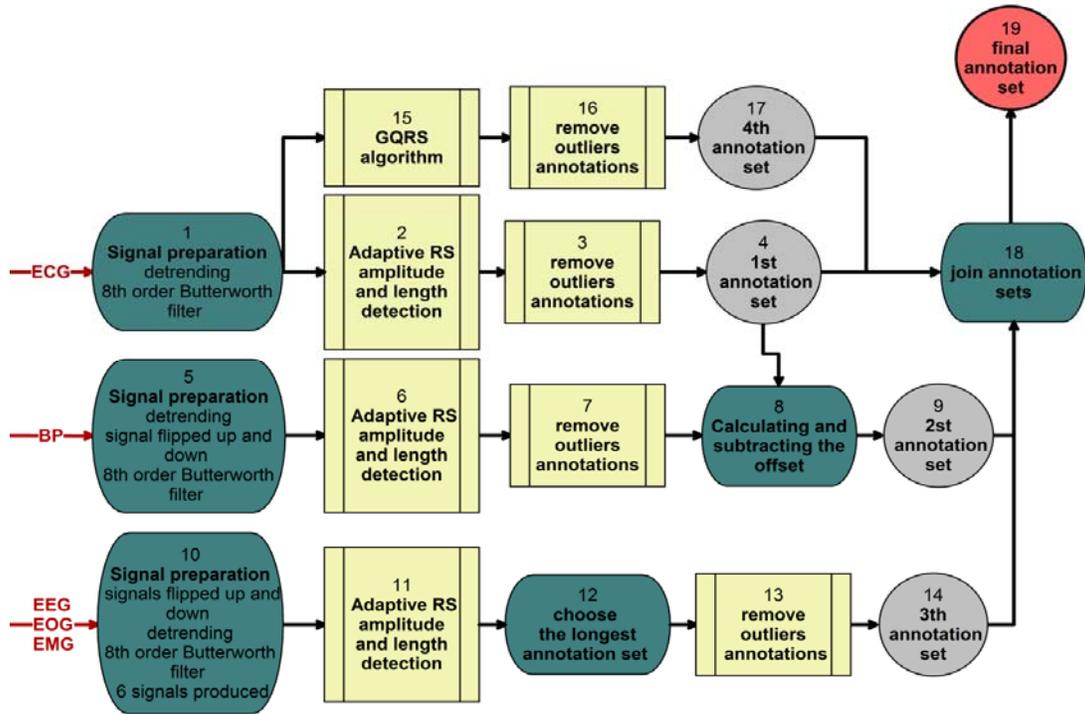


Figure 1. Flow chart of algorithm analyzing heart rate from noisy, multimodal recordings. All signals of each recording are processed in 19 steps, briefly described in section 3.

### 3. Methods and results

The characteristic feature of our algorithm is creation of annotation sets, created in couple of iterations, which include detected annotations. In several steps they are constructed for each available type of signal, then modified and joined in the one final annotation set. Searching for QRS complex is based on detecting RS slope, as the most characteristic part of heart rate record. This is an analogical solution, as used in our 2013 PhysioNet/CinC Challenge entry, which received one first and two second places in the three of five categories of the 2013 Challenge [3]. Below the successive parts of the algorithm are described in detail.

#### 3.1. Preparation and analysis of the signals

To assess whether the information received from any channel is useful, a quality check of the recording was implemented. It consists of two criteria, involving calculation of the distribution of the full annotation set for the particular channel before removing outliers, then finding the maximum of it and checking whether it is higher than 500 ms. This requirement ensures that

correct RR intervals are able to stand out from the noises, which means that the channel carries actually useful information.

The second criterion verifies the number of the annotations. Channel is rejected, when less than  $N/6$  annotations has been found in it, where  $N$  is the length of recording in  $s$ . This indicates that this recording contains noisy information.

- ECG

Step 1: First, detrending on analyzed signal is performed using moving median with a window of 250 ms. This particular width of the window is chosen to include full QRS complex. As a next step we use 8<sup>th</sup> order Butterworth low pass filter to minimize noise impact (with frequency limit parameter set to 40 Hz).

Step 2: Then we initialize the algorithm to detect RS slopes with the specially prepared adaptive procedure. First, a signal from the test set available for users is employed to assess the amplitude range of the QRS complex from 3% of the signal distribution as a lower boundary to upper boundary set at the level of 97%. The other requirements say that RS slope interval length should be concerned between 5 and 38 samples for 250 Hz sampling and that S peak position should be situated below isoelectric line in the detrended signal.

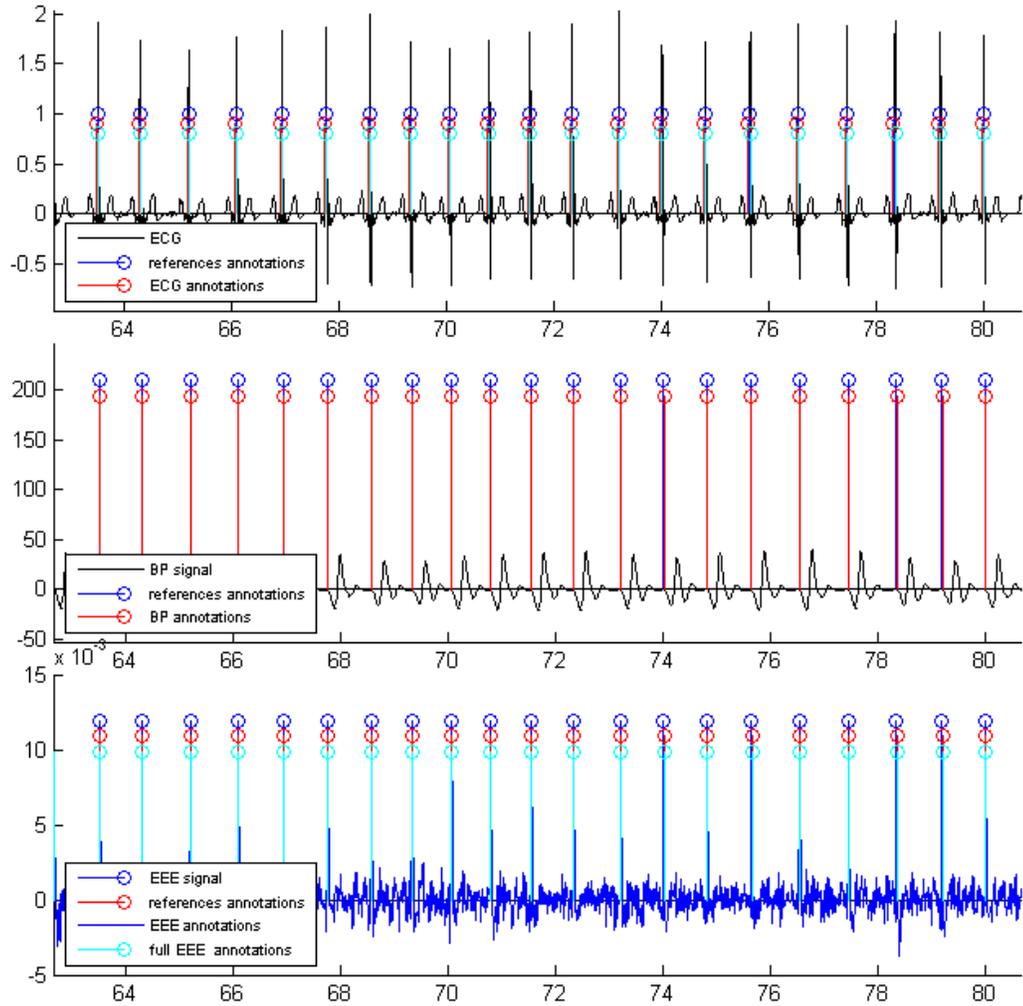


Figure 2. Example of algorithm performance on ECG (top), BP (middle) and EOG (bottom) signals for the test recording.

All of the parameters above, need to be adaptively chosen for each signal. To do that we change amplitude range with steps of 2% and then we find locations that comply with criteria of amplitude and length boundary described previously. In the next step we calculate mean interval between R peaks and leave only these RS locations for which RR interval is within 75 ms from the mean value. The best values for amplitude range of the QRS complex are estimated due to the largest number of the matching location. The same process is provided to estimate RS slope length. As a results we obtain first annotation set with a large number of all annotations of the QRS complex locations.

- BP

Step 5: We use the same algorithm as for adaptive RS detection. The BP signal is reversed in time to detect the pressure rise with a downward-slope detection algorithm. Then, we use moving mean with a window of 87 samples (350 ms) to detrend the signal. In the end we use 8<sup>th</sup> order Butterworth filter – as in the first step..

Step 6: In this step we perform the same RS slope detection algorithm as we did in the ECG part, but with different boundaries. Based on the well known test set we found that upper boundary is not higher than 90% of the signal distribution, and lower boundary is equal to 10%. Deceleration length may be from 22 to 40 samples (from 90 to 160 ms).

Step 7: For the physiological reasons the offset between ECG and BP signals occurs, which we calculate basing on the ECG record. We determine mean value of the distance between annotations obtained from ECG and BP signals, which designate the same heart beats. If there is no ECG signal in the recording we set the offset for BP as 280 ms, determined on the test set. Subtracting the offset provides the second annotation set.

- EEG, EOG, EMG

Step 10: If any of EEG, EOG or EMG recordings are available, we create array with them and also with the signals flipped upside down (recordings in the array are

not distinguishable from each other). Then on every signal we perform the same steps as in the ECG part.

Step 11: Firstly we check quality of each recording in the array. We perform RS slope detection without adaptive procedure using values according to the assumptions as follow: upper boundary does not exceed 95% of the signal distribution, lower boundary is larger than 5% of it and RS interval length is between 4 and 15 samples. In the next steps we use only this signal in which RS slope detection algorithm gives as a result more than 100 annotations.

Then we use adaptive procedure described in the ECG section with the same boundaries as in the checking quality part of the algorithm.

### 3.2. Fine-tuning

Step 3,7,13, 16: At this point there are annotation sets from each signal including all possible annotations. In this step the algorithm imposes some physiological restrictions. It eliminates annotations which RR intervals are not long enough – as a fixed limit of 150 ms was set. Example of produced annotation sets is depicted in Fig. 2

### 3.3. Joining annotation sets

Step 18: In the annotation sets after fine tuning remain only the annotations which are assumed as certain by the algorithm. During that step more annotations than necessary might be eliminated, but our point is to create very restrictive annotation sets. In the next stage quality of the signals is determined. If the ECG signal is present, it will always be recognized as the most important one, because of its precision in registering heart rate variability. Secondly, BP signal will be examined, which is considered as an indicator of cardiac activity. Next the EEG record will be included. In that order the annotation sets are joined, but they still need to meet physiological requirements to prevent duplication of detected annotations. In the next step of the algorithm it is verified, whether any gaps remained. In case of that situation, the *gqrs* function from WFDB library is included in the algorithm. In the final step the annotation set of the annotations detected by the *gqrs* function is combined with our annotation set. This way the final annotation set is achieved, which is free from unnecessary annotations and also has high sensitivity to different types of QRS complex morphology.

## 4. Results

The best result achieved in the PhysioNet Challenge 2014 was in the final, third phase with the score 86.40. Phase III included 300 unknown recordings.

## 5. Discussion and conclusions

The algorithm presented in this paper is a successful approach for detecting normal heart rate. It might be applied for finding heart beats not only using ECG recording, but also other cardiac signals. This method may be especially useful when some problems occur, such as noises or lack of signal, what is possible situation also when using advanced devices.

Described approach is based on detecting the RS slope in QRS complex as the most characteristic part of the heart rate recording. The idea of registering the longest decelerations is also employed in blood pressure records as pulsatile signal and electroencephalogram in which it is possible to find ECG signal presence.

Implemented algorithm is also well-adapted to the recordings including morphologically changed parts (e.g. from patients with pathological abnormalities in the cardiac muscle structure and some kind of cardiac dysrhythmias). One of the important elements which enables correct detection in such situations is *gqrs* function from WFDB library, which combined with our own algorithm gives a prominent effect.

However, human heart rate may change significantly even during a few minutes recording. Thus an optimal approach to improve functioning of our program would be implementing window analysis. Signal parameters would be calculated progressively for short fragments and step-by-step analyze of the recording would be much more effective.

Additionally, analysis of EEG, EOG, EMG signals should be expanded by considering features of the signals that has not been considered yet in our algorithm.

## References

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