# Robust Multichannel QRS Detection

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## Abstract

*The task of the CinC Challenge 2014 was to develop an algorithm for robust detection of a QRS complex throughout different measurement data.*

*Our proposed approach starts with filtering and detection of the QRS complex in channel with electric activity using standard deviation and defines preliminary QRS annotations. The averaged shape (length of 640 ms) for each channel is found by accumulating data close to preliminary annotations through the whole record (max. 10 minutes). The weight of each averaged shape is computed by average correlation of the shape with its original signal through all preliminary QRS annotations. The correlation of each averaged shape to the corresponding channel is multiplied by its weight and forms a new channel containing the total correlation response channels. The resulting QRS annotations are found by tresholding this total correlation response.*

*The final version of our method leads to results of SE+ = 99.87 and P+ = 99.96 for the Challenge Training data set containing 100 records. The overall score was 73.85 at the end of stage I (using an early version of this method) and 83.73 at the end of stage III.*

## 1. Introduction

The method for locating heart beats in long-term data expresses several challenges linked with one another. One challenge is dealing with the technical quality of signals (as in the presented data sample – Figure 1), another is dealing with irregularities (as extra-beats), one of the requirements for this method, or a possible change of QRS shape, and the last concerns speed. According to the "CinC Challenge 2014", each recording consists of several types of signals and this fact can help us in solving the task (for example, when the patient moves there are usually noisy parts on the ECG, though the blood pressure remains undamaged. On the other hand, a photoplethysmograph needs recalibration from time to time which damages data in the blood pressure channel (Figure 1). Generally, in this method any kind of data can be used to help us recognize and detect heartbeats.

The maximum processing time is limited to 40 seconds per recording file on a dedicated virtual machine (two cores without specified power and 2 GB RAM).

The presented method was developed in the C# language, but to meet the requirements of the "CinC Challenge" it was translated into Java™. It is a command-line application which takes the name of the file to process as the only parameter. The result annotation list is written to standard output (as required by the Challenge).

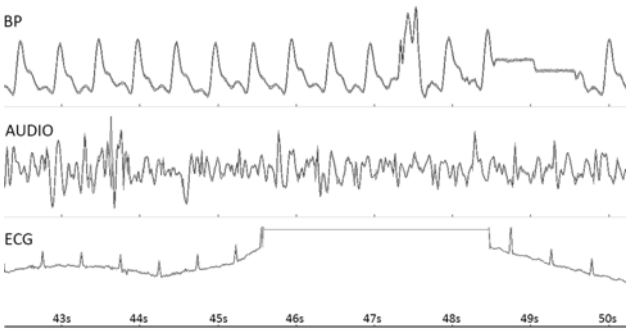


Figure 1. Sample of tested data. Channels (from the top): BP – blood pressure, AUDIO – heart sounds and ECG.

## 2. Tested groups

The CinC Challenge 2014 offers a public "Training data set" containing 100 recordings up to 10-minutes long with sampling frequencies at 250 Hz. Each recording consists of 4–8 channels (ECG, BP and others). However, the set does not contain issues regarding signal-to-noise ratio or channel drop-outs and it is without diversities of sample frequencies (the Challenge requirement was to process sampling frequencies in a range of 120–1,000 Hz). Therefore, a second testing group of data (measured at FNUSA-ICRC, Czech Republic) was prepared and included data from bioimpedance (45-minute recordings measured with different types of load, sampled at 500 Hz) and ultra-high-frequency ECG measurements (recordings measured in supine position, length 15 minutes, sampled at 5 kHz). The sample data for the figures in this article comes from bioimpedance measurements. Some were artificially damaged and converted to different frequencies. For the purposes of comparison, the Physionet MIT-BIH-Arrhythmia database [1] (47 recordings, length 30 minutes, sampled at 360 Hz, 2-ECG channels) was processed with our method.

## 3. Method

The elementary idea behind the presented method is to find what the shape of each channel usually looks like in time of QRS complex and search back in the whole record to find a correlation between the signals and the averaged multichannel shape (Figure 2).

The method distinguishes between channels carrying electrical activity (ECG, EOG, EMG etc. signed as ExG), channels with blood pressure (BP) and general channels (with any other type of signal). Signal type is recognized by channel name.

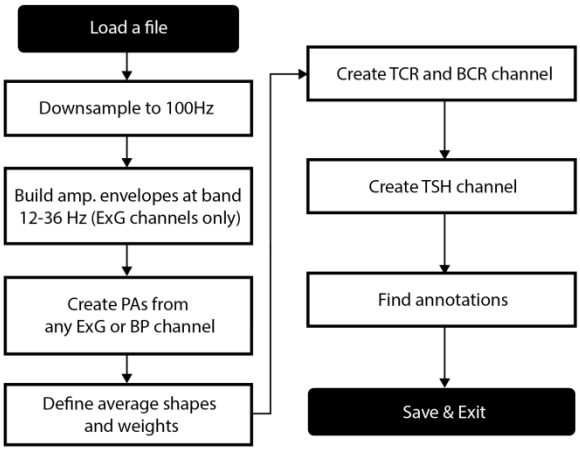


Figure 2. Workflow of presented method. ExG – channels carrying an electrical activity, PA – preliminary QRS annotation, BP – blood pressure channel, TCR – Total Correlation Response, BCR – Best Correlation Response, TSH – Threshold Channel.

### 3.1. Downsampling and filtering

After loading a file, all channels are processed by a FIR low-pass filter ($40^{th}$ order, 35 Hz) for antialiasing before decimation to 100 Hz (to decrease method processing time).

A deeper view inside the elementary idea of the method shows its weakness – such an algorithm will probably give unsatisfactory results when the QRS shape changes during measurement and its ability to catch extrasystoles will be very limited. Therefore, all ExG channels are converted to envelopes in the 12–36 Hz band using FFT.

### 3.2. Preliminary annotations and average shapes

To find an averaged shape (ASH) of a QRS complex in time in each channel, a certain number of preliminary QRS annotations (PAs) has to be found (Figure 3). Any channel carrying electrical activity (i.e. ExG channel) can be used for this task. PAs are derived as the middle of positive peaks from the SSD channel:

$$SSD[i] = \sigma_{SHORT} - \sigma_{LONG}$$

where $i$ is sample index, $\sigma_{SHORT}$ is standard deviation value from the selected ExG channel (± 160 ms around the $i$) and $\sigma_{LONG}$ is the standard deviation value from the selected ExG channel (± 2000 ms around the i). Using differences of standard deviations emphasize parts of signal with high s/n ratio. If a sufficient number of PAs is not found, the next ExG channel is selected and the process repeated. If all the ExG channels have been tested and a sufficient number of PAs cannot be found, the method tries to detect PAs using BP channels (160 milliseconds before diastole). If a sufficient number of PAs cannot be found, the program exits.

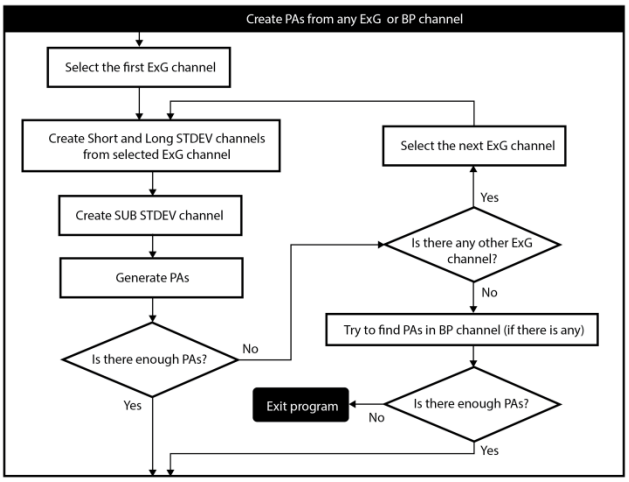


Figure 3. Creating preliminary annotations (PAs)

The averaged shape (Figure 4) for each channel is computed by accumulating the area surrounding each PA (± 320 ms). The weight of each individual ASH is determined as an average correlation of the ASH in place of each PA. Shapes with a weight lower than 0.1 are omitted from the next processing.

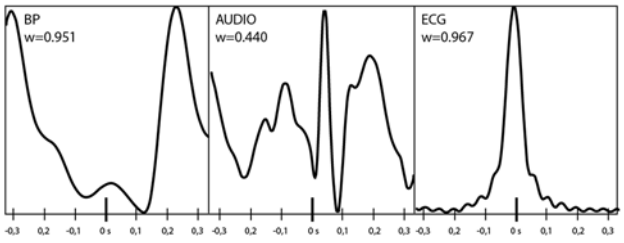


Figure 4. Averaged shapes. In the top left corner of each box is the name and weight (w) of an individual averaged shape. The ECG channel is transformed into an envelope.

### 3.3. Correlation response and finding final annotations

ASH is moved through the whole record and the Total Correlation Response channel (TCR) and Best Correlation Response channel (BCR) are calculated as

$$TCR_i = \sum_n C_i[n] * weight[n]$$

$$BCR_i = Max\ C_i$$

where *i* is the index of the sample, *n* is the index of the channel (and index of averaged shape) and $C_i$ $[n]$ is the Pearson correlation coefficient between ASH and the corresponding channel in time of sample *i*. Annotations are found at maximums on the TCR channel. When one of the channels with a high weight drops, there are still maxima made by other channels (see Figure 5).

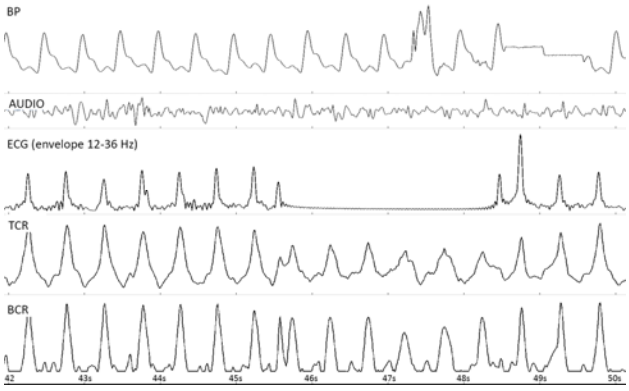


Figure 5. Signal and correlation (TCR, BCR) channels.

The threshold is needed to select a valid TCR maximum. This work started with a fixed threshold, but it proved unsatisfactory in situations such as a longer ECG drop-out. Instead the Threshold channel (TSH) is computed as

$$TSH_i = AVG_i - STD_i$$

where *i* is the sample index, *AVG* is the average and *STD* the standard deviation value from the ± 1 seconds area around *i*. If $TCR_i > TSH_i$ and *i* are far enough from the previous annotation (0.25 seconds in the case of the human heart) the $TCR_i$ is compared to the TCR of the previous annotation (Fig. 6, middle). The significantly higher ratio means significantly lower similarity between the tested and preview QRS complex. Such a situation occurs when the majority of signals drop. In this case, the BCR channel is used to detect correlation maxima in any channel with significant weight.

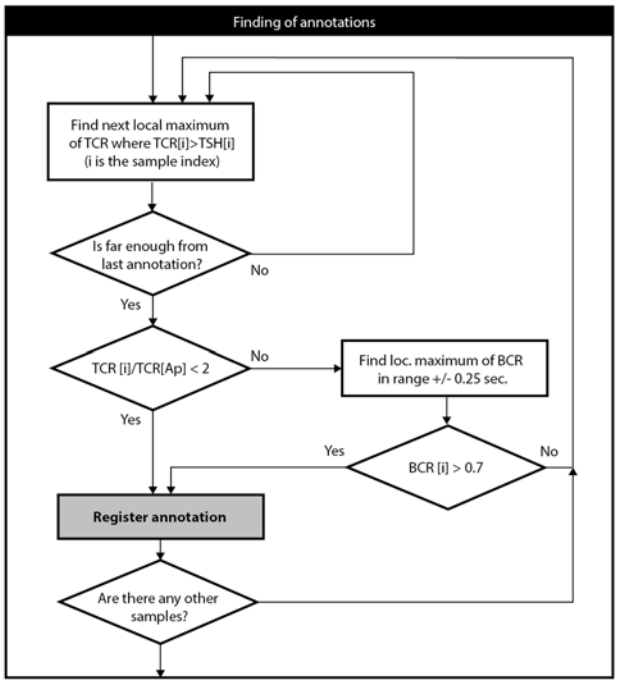


Figure 6. Principle of finding annotations. TCR[Ap] is the TCR value of the previously accepted QRS annotation

Each annotation mark holds information about the corresponding TCR value (i.e. validity), but is available only in the original C# implementation of the method.

## 4. Results and conclusion

As seen in Figure 7, the presented method is able to detect the QRS complex in signals where valid ECG is partially (or fully) absent. The success of detection depends on the type and quality of additional channels.

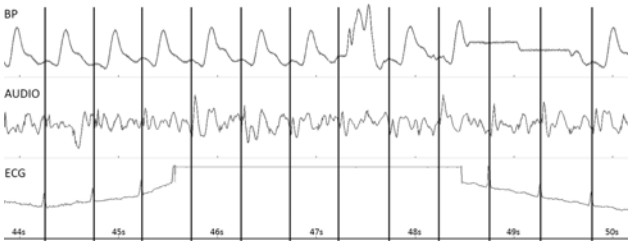


Figure 7. QRS Annotations (vertical lines) within demonstration data sample

### 4.1. Method features

The ability to use any type and any number of signals is the major feature (at least one ExG or BP channel is necessary for the PAs recognition process).

A significant feature is the ability to catch extra beats, even with different shapes, thanks to conversion of ExG channels to envelopes (Figure 8). This also applies to cases where the QRS shape changes during measurement.

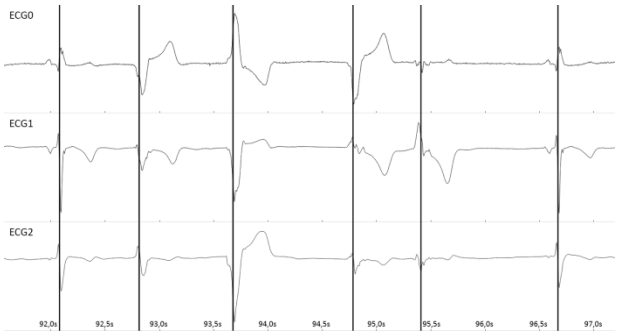

Figure 8. Correctly captured extra beats (from another sample data). Verticals are detected QRS annotations.

## 4.2. Method limitations

There is a risk of creating false positives when the signal is noisy in all channels with higher weight. Also, false positives are likely to occur when the T-wave is too sharp and steep.

## 4.3. Speed

The "CinC Challenge 2014" requirement for processing speed was 40 seconds per 10-minute file (up to 1 kHz and eight channels). Our method achieved an average processing time on the Challenge training set and dedicated virtual machine of 0.47 seconds (loading and saving time excluded).

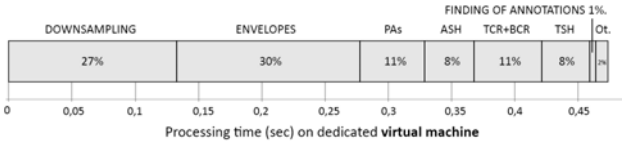

Figure 9. Processing performance of consecutive blocks.

Because of decimation block, the processing time is independent of sampling frequency, but dependent on the recording length, number of channels and quality of ExG signals. Low-quality ExG signals can lead to a longer search for a reliable PAs source.

## 4.4. Performance comparison

Table 1. Detection performance with MIT-BIH Arrhythmia db. (comparison values adopted from [2]).

| Method | Beats | SE+ | P+ |
|---|---|---|---|
| This method | 107230 | 99.77 | 98.99 |
| Elgendi | 109985 | 99.78 | 99.87 |
| Ghaffari | 109837 | 99.91 | 99.72 |
| Benitez et al. | 109257 | 99.13 | 99.31 |
| Li et al. | 104182 | 99.89 | 99.94 |

The method was tested with the MIT-BIH Arrhythmia database and the performance compared to some of existing methods. Our approach was disadvantaged because the tested database contains only two ECG signals and no other type of signal. The full potential of the presented method could not, therefore, be used. It follows from Table 1 that the presented method is not as powerful as the best detection method available if only ECG signals are in use.

Performance with Challenge Training data set was SE+ = 99.87 and P+ = 99.96. Final score for Challenge Phase 3 was 83.73 (SE+ = 83.60, P+ = 84.83).

## 5. Discussion

The presented method can also be used for non-human signals. Successful detection requires a change of coefficient describing the minimal allowed QRS distance and change of frequency band for the computing of ExG envelopes.

The method can be parallelized in large scale and our facility uses this improved form. The maximum of two cores (a limitation of the CinC Challenge) allows very small space for using the power of contemporary technology. Parallelization is easily applied in the case of filtering and correlation tasks which can then be computed simultaneously.

The presented method is in frequent use for off-line processing of bioimpedance (project PRECEDENCE) and ultra-high-frequency measurements in our facility. Less positive predictivity is compensated by a post-processing method which also sorts individual beats to groups based on their shapes. The program in this form uses parallel processing and works with original sampling frequencies.

## Acknowledgement

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## References

[1] Goldberger AL. PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation 101: e215–e220.

[2] Elgendi M. Fast QRS detection with an optimized knowledge-based method: evaluation on 11 standard ECG databases. PLOS ONE 2013; Volume 8.

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