Identification of a signal for an optimal heart beat detection in multimodal physiological datasets

Roman Schulte, Johannes Krug, Georg Rose

Department of Medical Engineering,
Otto-von-Guericke University of Magdeburg, Magdeburg, Germany

Abstract

This work describes an algorithm for the robust detection of heart beats in multimodal physiologic data, developed for the PhysioNet/Computing in Cardiology Challenge 2014. Depending on which physiological signals were available in the provided datasets, the proposed algorithm uses a combination of the ECG, the continuous blood pressure (BP) or the stroke volume (SV) signals. Due to the temporal dynamics of the signal distortions, each record was divided into several subsegments of the same length. Different peak detection algorithms were applied to the different signals of each subsegment. Each signal was rated with a quality index. It was used to identify one signal to be used for the heart beat detection. The quality index was estimated from the signal statistics and the number of peaks and their location within each subsegment. Once each signal of a subsegment was rated with the quality index, the best rated signal was considered for the final peak detection. This identification procedure was then repeated for every new subsegment.

In the challenge, the proposed method achieved an overall score of 90.04 % in phase I, 83.79 % in phase II and 84.31 % in phase III.

1. Introduction

In modern patient monitoring systems different physiologic signals are recorded simultaneously. The quality of one or more of these signals can be temporarily decreased by improper sensor placement, abrupt body movements or environmental noise. The aim of the PhysioNet/Computing in Cardiology Challenge 2014 is to improve the detection of heart beats in such records. An algorithm should identify such signal segments where a reliable heart beat detection is not possible. The robustness of the detection is increased by utilizing or combining the information of several different signals which are available in a record.

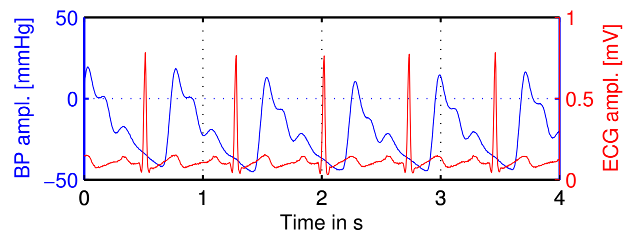

Figure 1. Typical BP and ECG signal morphologies.

2. Used material and methods

During the development of the heart beat detection algorithm several specific methods and different databases were used. This chapter describes their characteristics, origins and usages.

2.1. Signals used for heart beat detection

Each record of the training dataset included several physiological signals. A short description signals utilized for the heart beat detection and and their attributes is given in the following.

The most obvious choice for heartbeat detection was the Electrocardiogram (ECG). The specific, steep form of the QRS-complexes allows an identification of the beats and their differentiation from other distortions. For the precise beat localization many different beat detection algorithms were tested. The *gqrs* function written in C++ turned out to be fitting in both, sensitivity and computation time [1].

The blood pressure (BP) signal was also included in most of the training records. The representation of the cardiac activity in the BP signal is not as steep and precise as in the ECG signal and it appears with a short delay with respect to the ECG's QRS-complex (see figure 1). The *wabp* was used for peak detection in the BP signals [1].

Stroke volume (SV) signals were available in a few training records. The SV signal represents a continuous measurement of the ejected blood volume. As the BP signal, the SV is directly linked to the cardiac activity. The

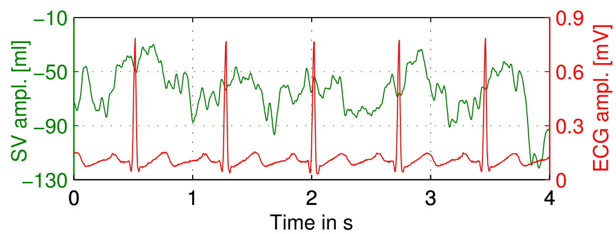

Figure 2. Typical SV and ECG signal morphologies.

relatively noisy signal characteristics shown in figure 2 and the varying delay with respect to the ECG signal complicated the SV analysis. The SV signals were preprocessed using a moving average filter with a window length of 333 ms and by taking the first derivative. A maximum peak detector was used for detecting the peaks in the SV signal.

Other signal types provided in the training dataset (e. g. electromyography (EMG), electroencephalography (EEG), respiration) were not taken into account.

2.2. The challenge training dataset

The training dataset provided for the development of the algorithms contained 100 ten minute records. All of the records in this set were sampled at a frequency of 250 Hz. However, the sampling frequencies of the test records ranged from 125 Hz to 1 kHz which needed to be considered by the algorithms. For a verification of the developed algorithm, a set of reference QRS annotations was provided.

2.3. Other datasets used for the development of the algorithms

An additional training dataset was generated to include a broader spectrum of signal artefacts. The Massachusetts General Hospital/Marquette Foundation Waveform Database (MGHDB) is a collection of records of stable and unstable patients in critical care units, operating rooms, and cardiac catheterisation laboratories, further described in [2]. The database contains records of 250 patients (each 12 to 86 minutes) and includes a wide range of physiologic health problems. The records are consisting of up to three ECG leads and also up to three different BP signals. Thus, this database fitted the challenge requirements. Due to the huge amount of data only manually selected segments with low signal quality – each with a length of 10 minutes – were used for the analysis and development of the algorithms.

2.4. The developed algorithm

To fit the challenge requirements the algorithm was developed using *Octave*. Due to the fact that the algorithm was developed on a 32-bit system and also had to work on the 64-bit system running on the challenges server, instead of using the already implemented functions for reading and writing annotation files in the PhysioNet format, they were written manually in C++. Beside these necessary functions, the work was focused on three ideas which are explained in the following.

2.5. Data segmentation and beat detection

In a first step, each record was divided into several shorter segments which were analysed separately. The length of these segments was optimized using the training dataset. Segment lengths were varied between 2 s and 10 s. An overlap of 1 s was used between adjacent segments. After the signal was segmented, the annotated heartbeats in each segment were stored in arrays. It was examined how often a beat was found in the ECG or BP signals. A window of 100 ms was used. If several signals are showing heartbeats in one window the amount of detected beats is saved together with the mean time of all beats in this window. Arrays of double, triple and more often appearing beats are generated.

2.6. Parameters used for the quality estimation of a signal

A central requirement for the development of the algorithms was the signal quality estimation in each of the segments. Several quality parameters described in literature were analysed and tested [3–5]. Finally, four parameters with upper and/or lower boundary values were used to determine the quality value of a signals segment (see table 1). The quality of a signal was defined as high when all the parameter values were inside the strict and soft boundaries. A high quality segment describes a signal with normal variance and regular annotations. If a signal segment satisfied the strict but violated the soft boundaries, its quality was defined as average. This signal was then only used if no other signals was judged as high in this segment. If even the strict boundary values were violated, the signal quality was judged as low. This signal was not taken into account in this segment.

Due to the fact, that the heartbeat frequency differs between 40 and 120 beats per minute, the fundamental frequency (f_1) of the signals was used to estimate the corresponding boundary values. This frequency provided a rough estimation of the average heart rate even though it could vary over the length of the record. The fundamental frequency was calculated for each signal. To lower the in-

Parameter	low boundary		up boundary	
	strict	soft	soft	strict
# of beats	$5.6 \cdot f_1$	-	-	$2.4 \cdot f_1$
RR-var.	-	-	0.03	0.09
Sig-var.	$5 \cdot 10^{-4}$	0.05	5	500
RR-int	-	$2/f_1$	$0.5/f_1$	-

Table 1. Quality indices and their boundary values.

fluence of noise and baseline fluctuation the first derivative of the signal was used, normalized to one and filtered by a 5 Hz low-pass filter. The signal was split up into several segments of 12 s length. For each segment a Fast Fourier Transformation (FFT) was executed. The fundamental frequency was estimated from the averaged frequency spectra.

The quality parameters summarized in table 1 were used for the following purposes:

- The *number of annotations* in a segment indicated if a reliable peak detection was possible or if more or less than the expected number of beats were detected.
- The *variance of the peak distance*, e. g. of the RR interval, was a criterion for the robustness of the detection. For a normal (healthy) record, the peak distance should have a low variance. A high variance indicated one or more missed beats. However, the variance could also increase during arrhythmic episodes. Using the training datasets, such arrhythmic episodes were considered for the definition of the strict boundary values.
- The *signal variance* was used as another quality indicator. All signals were normalized to a total variance of one before the variance was measured in each segment. Low signal variances indicated segments where the signal to noise ratio was very low or the signal was completely switched off. High signal variances indicated external disturbances.
- The *peak distance*, e. g. the RR interval length, was only used as a soft quality criterion. If two adjacent beats were too close or too far away from each other the signal quality was judged as low. This parameter should detect segments with one or more wrong annotations.

2.7. Recombination of detected beats

Before all beats detected in the different signals were prepared for recombination, it was necessary to estimate the delays between the ECG's QRS-complex and the BP or SV peaks. Therefore, only segments were taken into account in which the ECG and the signal for which the displacement was calculated were marked as good quality. The calculated displacement was subtracted from all annotations in a record. If no suitable segments of sufficient quality were identified to estimate the delay between the ECG and the other signals, the default delay value was set to 200 ms.

After all signals were prepared for the recombination, their quality indices were used to determine which signal was used in the current segment. In a first run, only those segments with a good signal quality were taken into account. In a second run, possible missing parts were filled up with average quality segments. All signal segments marked as low quality were not used for the beat detection. In both runs, the detected beats and signals qualities were used in the following relevance order to build the final annotation vector. If the same beat was found in several signals (e. g. in the ECG and the BP signals), and the quality of the corresponding signal was defined as good or average, these beat locations were used for the annotation. If a beat was not found twice or more often, the beats found in the ECG and BP signals were considered next. In this case, the variance of the heartbeat intervals was estimated in order to decide which signal should be finally used for the beat detection. If no other signal was rated as high as or higher than the SV signal, the SV signal was used. This low relevance of the SV signal was based on their low quality observed in the training records.

Table 2. Results for the challenge training dataset depending on different segment lengths.

length [s]	Average Se	Average +P
2	99.31	99.81
3	99.91	99.97
4	99.95	99.98
5	99.90	99.98
10	99.02	99.98

3. Results

Table 2 shows the how the length of the segments affected the detection results. Based on these results, the records were divided into segments with a length of 4 s. Taking into account an overlap of 1 s, a 10 min record consisted of 200 segments.

The algorithm used in each phase of the challenge and the octave sample entry were evaluated using the MGH training dataset. The averaged results are shown in table 3.

The results achieved in the training dataset and in phases I, II and III of the challenge are presented in table 4. The results of the octave sample entry are shown for comparison.

4. Discussion

Using the training dataset which was provided for the challenge, a high detection quality was achieved when compared to the results obtained in the test datasets of the different challenge phases. Hence, an additional training

Table 3. Results for the MGH dataset.

Algorithm	Se (%)	P+(%)
Phase 1	81.96	91.08
Phase 2	95.78	96.73
Phase 3	96.92	96.79
Octave sample entry	65.57	81.74

Table 4. Results for the different challenge test datasets.

Dataset	Results	Octave sample entry
Training	99.96	99.61
Phase 1	90.04	88.89
Phase 2	83.79	83.74
Phase 3	84.31	79.28

datasets was defined from the MGH database. The aim was to include more records with low signal quality and different signal properties. Records from the MGH database were selected in a way that they provided disturbances as well as arrhythmic signal data. Comparing the results of the sample entry in octave in the MGH dataset with its results in the test dataset, it can be assumed that the records of the MGH traning dataset more difficult than the official test datasets. Comparing the results of the developed algorithm the opposite assumption has to be made. This contradiction can be explained by the fact that some of the quality indices were (over)fitted to the MGH training dataset. Hence, the training dataset did not sufficiently represent the signal qualities, possible artefacts are arrhythmic episodes contained in the three test datasets (phase I-III).

The developed algorithms were extended during the different phases of the challenge which explains the different results in the MGH training dataset. Although the quality was improved during the different phases using the MGH training dataset, the detection quality decreased on the different test datasets.

For the further development of the algorithms, more or other parameters describing the quality of different signals will be considered. In addition, more training records with different signal and quality properties are required to be able to respond appropriately in different scenarios.

5. Conclusion

An algorithm for the robust detection of heart beats in multimodal data has been developed. The algorithm is based on open source software and makes use of two public available beat detectors. It considers ECG, BP and SV signals contained in a record, divides them into shorter segments and determines the signals quality in each segment based on different parameters. Information about the detected beats in each signal was combined in order to estimate their correct positions.

For the final phase III, the algorithm achieved a place in the midfield of the challenges (average score for phase III: 84.31 %). Further improvements of the existing algorithm are required for a more reliable beat detection. This could be achieved using more complex training data and extended algorithms.

References

[1] Goldberger AL, Amaral LA, Glass L, Hausdorff JM, Ivanov PC, Mark RG, Mietus JE, Moody GB, Peng CK, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. Circulation Jun 2000;101(23):215–220.

[2] Welch J, Ford P, Teplick R, Rubsamen R. The Massachusetts General Hospital-Marquette Foundation hemodynamic and electrocardiographic database–comprehensive collection of critical care waveforms. Clinical Monitoring 1991;7(1):96–97.

[3] Moody B. Rule-based methods for ECG quality control. Computing in Cardiology 2011;38:361–3.

[4] Clifford G, Behar J, Li Q, Rezek I. Signal quality indices and data fusion for determining clinical acceptability of electrocardiograms. Physiol Meas 2012;33(9):1419.

[5] Behar J, Oster J, Li Q, Clifford G. A single channel ECG quality metric. Computing in Cardiology 2012;381–384.

Address for correspondence:

Johannes Krug
Department of Medical Engineering
Universitaetsplatz 2 // 39106 Magdeburg // Germany
johannes.krug@ovgu.de