

Multimodal Information Fusion for Robust Heart Beat Detection

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Abstract

QRS detection based on ECG signal is the most straightforward method for heart beat detection. However, existing QRS detection methods do not work well when ECG signal is contaminated or missing. Other physiological signals also contain information about cardiac activity and ECG. Their information can be explored for robust heart beat detection.

As part of the PhysioNet/Computing in Cardiology Challenge 2014, this study proposed a multimodal information fusion framework for robust heart beat detection. The framework consisted of three steps: 1) QRS detection. 2) Remove spurious QRS detection using pulsatile signal if it is available. 3) Refine the remaining beat detection and interpolate missed beats. Results show that the algorithm can sufficiently reduce spurious QRS detection and accurately fill in missed beats.

1. Introduction

Electrocardiography (ECG) has been widely used in healthcare systems to record the heart's electrical activity for its simplicity and non-invasiveness. In ECG analysis, especially computerized ECG analysis, heart beat detection is always the first step. Therefore, the accuracy of heart beat detection is of great importance since it determines the performance of ECG analysis.

QRS detection, i.e., detecting R wave based on ECG signal, is an intuitive and straightforward solution for heart beat detection. Many methods have been developed for QRS detection [1-5], and they all achieve more than 99% accuracy on the MIT/BIT arrhythmia database [6]. However, they operate on ECG signal only and their performance heavily relies on the quality on the ECG signal. In the case of large noise, disturbance, and artifacts, or even when ECG signal is missing, these methods cannot accurately detect the heart beat.

In addition to ECG, other pulsatile signals such as

blood pressure (BP) and photoplethysmogram (PPG) also indicate cardiac activity, and thus can fill in the gap when ECG is contaminated or missing. For example, the relationship between ECG-pulse wave delay time and arterial blood pressure (ABP) was studied in [7]. This relationship can be used for QRS detection when the onset of ABP pulses can be accurately detected [8]. Non-pulsatile signals such as electroencephalography (EEG) and electromyography (EMG) are not directly related to cardiac activity, but they are usually contaminated by ECG components. Even though there is no currently available approach to derive ECG from EEG or EMG signal, their relationship can be explored as well for heart beat detection.

The PhysioNet/Computing in Cardiology Challenge 2014 aims to encourage exploration of robust methods for heart beat detection using ECG as well as other physiological signals. In this paper, we propose a multimodal framework that efficiently fuses information from different signals for robust heart beat detection.

2. Methods

2.1. Dataset

The dataset of ECG and a wide range of other pulsatile and non-pulsatile signals recorded simultaneously was provided by PhysioNet/Computing in Cardiology Challenge 2014. A training dataset was available for the study, while a testing dataset was hidden for evaluating the Challenge entries.

The training dataset consisted of 100 records of human adults, including patients with various problems as well as healthy subjects. All the records had ECG signal and three to seven simultaneously recorded physiological signals. Each record was 10-minute long or occasionally shorter, sampled at a uniform 250 samples/second. For the training dataset, a set of reference heart beat annotations was available. These reference heart beats

represented the locations of the QRS complexes in the ECG signal. They were annotated by several experts and therefore were considered as the ground truth. A 10-second excerpt of a record from the training dataset is shown in Figure 1 (viewed in LightWAVE [9], available at <http://physionet.org/lightwave/>), where the blue marks are the reference heart beat annotations.

The hidden testing dataset consisting of 300 records was similar to the training dataset, except that the

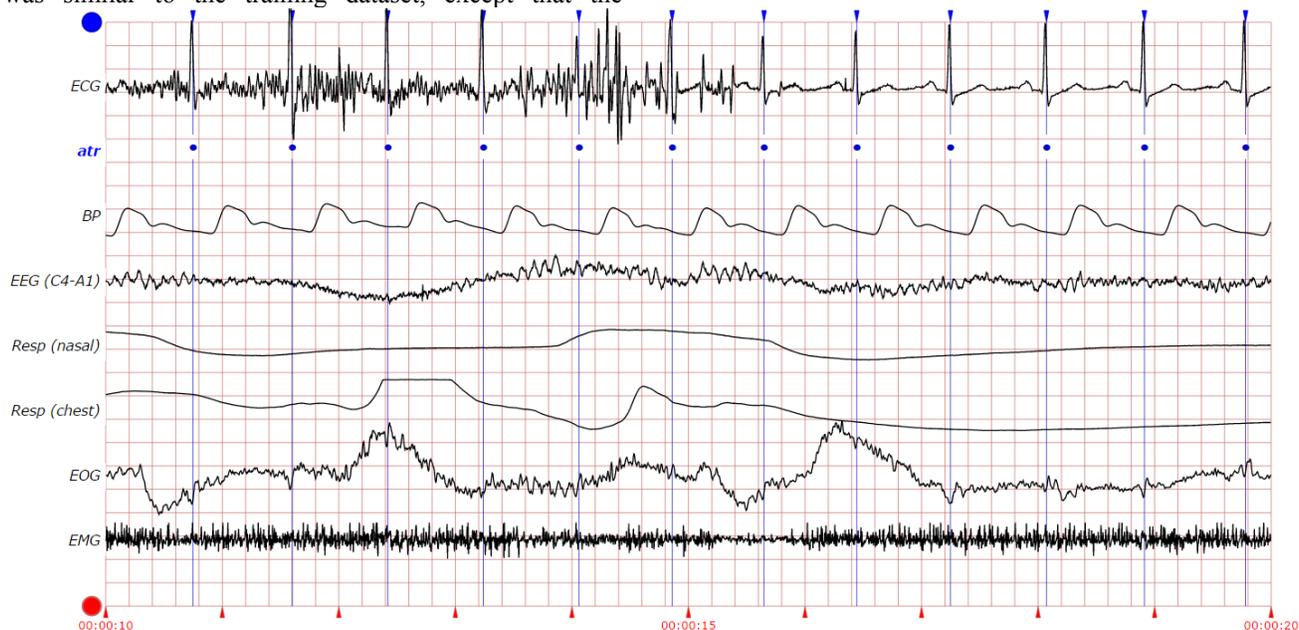


Figure 1: A 10-second excerpt of a record from the training dataset.

2.2. Performance Evaluation

For each record in the testing dataset, sensitivity (Se) and positive predictivity (+P) are defined by

$$Se = TP/(TP+FN)$$

$$+P = TP/(TP+FP)$$

where TP is the number of true positives or correctly detected beats, FN is the number of false negatives or missed beats, and FP is the number of false positives or detections of non-beats. Se measures the proportion of actual positives which are correctly identified, and +P measures the percentage of detections that are true positives. To be considered as a true positive, a test annotation must be located within 150 ms of a reference annotation, and must also be the nearest annotation to this reference annotation.

Gross Se and gross +P are derived from the sum of all TP, FN, and FP over the testing dataset. Average Se and average +P are the averages of individual Se and individual +P, respectively. The average of gross Se, gross +P, average Se, and average +P, is the overall score for ranking.

sampling frequency ranged from 120 to 1000 samples/second.

The goal of the challenge was to develop an algorithm that takes a record as the input, and outputs the detected heart beat annotations. The output annotations were compared with the reference annotations for performance evaluation.

2.3. Multimodal Information Fusion

Since the goal of the Challenge was to explore robust methods, the characteristics of the available training dataset were very different from those of the hidden testing dataset. This meant that any method specifically designed for the training dataset was not expected to perform well on the testing dataset. The model had to be general enough so that it could incorporate difficult situations not observed in the training dataset.

A multimodal information fusion framework for robust heart beat detection consisting of the following three steps was proposed.

- 1) QRS detection.
- 2) Remove spurious detections or false positives using information from pulsatile signal if it is available.
- 3) Refine the remaining beat detection and interpolate missing beats.

Such a flowchart is shown in Figure 2.

For step 1), QRS detection was based on ECG signal. An open-source algorithm QRS from PhysioNet

(available at <http://physionet.org/physiotools/wag/gqrs-1.htm>) was used for this purpose. Examples of GQRS results, when operated on the Challenge dataset, were plotted in Figure 3. It was observed that, when the ECG signal was clean, the GQRS algorithm was almost perfect since the results matched the reference annotations, as shown in Figure 3(a). But when the ECG signal was severely contaminated, the performance of GQRS decreased dramatically. False positives (spurious detection) and false negatives (missed beats) were seen in Figure 3(b). Therefore, step 2) followed to reduce false positives using information from pulsatile signal.

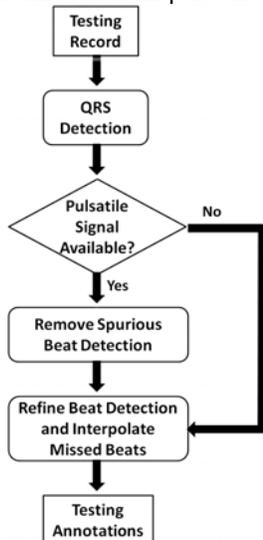
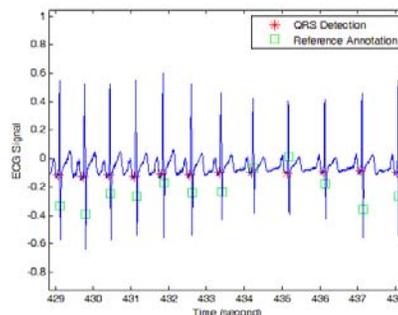


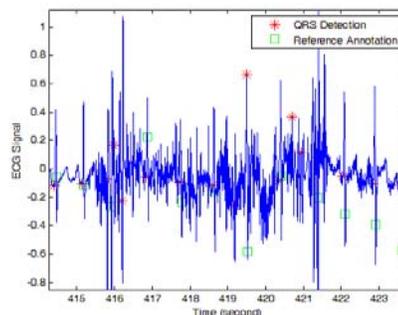
Figure 2: Flowchart of the multimodal information fusion framework for robust heart beat detection.

Since BP was the most common pulsatile signal in this Challenge, it was used in step 2). Note that the framework is not limited for BP but for any pulsatile signal. The idea was intrigued by the work in [10]. It used R wave position in ECG signal to verify intracranial pressure (ICP) peak detection. Similarly, the delay between the QRS complex and the BP peak could be exploited (see Figure 1). For this Challenge, we used peaks in BP signal to verify QRS detection. First of all, the BP signal was band-pass filtered by a finite impulse response (FIR) filter. The cut-off frequencies corresponded to the 30th and 70th percentiles of the RR intervals obtained from the QRS detection. This heart-rate dependent filtering was to reduce the inherent noise and baseline variations in BP signal, while keeping the same frequency components as the heart rate. Next, we needed to determine if the BP was of a good quality for us to verify QRS detection. For each QRS detection in step 1), a short window of BP signal at the R wave location was selected. The Fisher's g -statistic was performed on the short window to test for periodicity of the BP signal [11]. This test indicated the quality of the BP signal. If the BP signal was periodic, we then searched for a local maximum over a narrow delayed

window corresponding to QRS detection. The range of the narrow window was $[\text{pre_Delay}-\Delta/2, \text{pre_Delay}+\Delta/2]$, where pre_Delay was the delay between the previous QRS complex and its corresponding BP peak, and Δ was the window length. If a local maximum was found in the BP window, it indicated that the QRS detection was a true positive. On the other hand, if a local maximum did not exist in the BP window, it implied that the QRS detection was spurious. Finally, all the spurious QRS detections were removed.



(a) ECG is clean.



(b) ECG is contaminated.

Figure 3: Examples of the results of GQRS.

Note that even though step 2) could remove most of the spurious QRS detections, it may not be able to detect all of them. Also, it may occasionally remove some true positives. Therefore, step 3) would refine the remaining QRS detections in step 2), and fill in the missed beats.

In step 3), RR intervals from the remaining QRS detections were calculated. These RR intervals included both true and false RR intervals. For the RR intervals within a predefined normal range, their mean RR_{avg} and standard deviation σ were obtained. As a result, $[RR_{\text{avg}} - 3\sigma, RR_{\text{avg}} + 3\sigma]$ was considered as the refined subject-dependent normal range of RR intervals, because the predefined normal range was wide enough to cover subjects of different conditions. For RR intervals too small ($RR < RR_{\text{avg}} - 3\sigma$), the corresponding QRS detections were removed. Finally, for the remaining RR intervals that were too large ($RR > RR_{\text{avg}} + 3\sigma$),

additional R waves were interpolated according to the nearest normal RR intervals.

Note that our approach required some predefined parameters such as the predefined normal range of RR intervals and the narrow window length Δ to search for a local maximum in BP signal. Since the characteristics of the testing dataset were different from those of the training dataset, these parameters were empirically estimated from the training dataset and manually adjusted to incorporate possible testing cases not observed in the training dataset.

3. Results

The performance statistics of our approach on the training and testing datasets are summarized in Table 1. The difference in performance implies that the signals are much cleaner in the training dataset. Since the training dataset is too easy, it is difficult to evaluate the performance in each step of our method. Instead, we created a more difficult dataset by adding white Gaussian noise (WGN) to the ECG signals randomly. The performance statistics in each step of our method are summarized in Table 2. We can see that step 2) dramatically increases +P by removing the spurious QRS detection, and slightly reduces Se since it occasionally removes some true positives. Similarly, step 3) increases Se by interpolating the missed beats, and slightly reduces +P since it occasionally fills in false positives.

Table 1. Performance statistics of our approach on the training and testing datasets.

		Se (%)	+P (%)
Training	Gross	99.97	99.32
	Average	99.96	99.29
	Overall	99.64	
Testing	Gross	83.31	79.84
	Average	83.84	77.77
	Overall	81.19	

Table 2. Performance statistics in each step of our approach on a simulated dataset corrupted by WGN.

		Se (%)	+P (%)
Step 1)	Gross	86.32	65.24
	Average	86.41	64.85
	Overall	75.71	
Step 2)	Gross	80.19	87.78
	Average	80.54	87.43
	Overall	83.99	
Step 3)	Gross	88.90	86.11
	Average	89.12	85.99
	Overall	87.53	

4. Conclusions

Even the state-of-the-art QRS detectors cannot accurately estimate the QRS locations when ECG signal is contaminated or missing. Other physiological signals contain cardiac information and can be used for robust heart beat detection. We have developed a multimodal information fusion framework using any pulsatile signal for robust heart beat detection. Overall accuracies of 99.64% and 81.19% were achieved on the training and testing datasets, respectively. Each step in our method was verified on an artificial dataset corrupted by WGN.

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