Heart Beat Detection Method with Estimation of Regular Intervals between ECG and Blood Pressure

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Abstract

Heart beat is a fundamental cardiac activity which is easily found with various measurements. In the worst case, unexpected noise or contaminated signals can affect ECG signal in the practical conditions, then, we hardly find the heart beat for a while. To deal with these problems, PhysioNet/CinC suggests a challenge for developing robust heart beat detection method with multimodal data.

In this paper, we proposed two models which process EEG and a pair of ECG and BP signals to compensate the limitation of QRS detection. At first, we extract candidates of heart beat using QRS detector. As supplementation, we estimated regular interval between ECG and BP signal. When we miss heart beats on ECG, we can estimate the locations of heart beat using detected characteristic BP signal and regular interval. At last, we decomposed EEG signal which contains ECG signal as cardiac artefact. Adaptive filtering model in cascade was proposed for this purpose.

We utilized the model to identify the locations where the cardiac artifacts are occurred on EEG signal. Then, voting module generated the suggested locations of candidate heart beats. Our proposed method achieved the overall score with 82.01% at phase III.

1. Introduction

The QRS complex is typical target to detect heart beat, since the amplitude of R-peak is the highest level on ECG signal waveform. If the measured signals are clean, we can easily distinguish the positions of heart beat. In this manner, QRS detection is known to be very useful in assessing heart beat detection method.

However, a noise with similar amplitude on QRS complex is one of the major causes of accuracy degradation in the heart beat detection. In this situation, we cannot decide whether the measurement device is broken or a patient is in serious status

The aim of this year's PhysioNet/CinC challenge was to develop robust heart beat detection method with multimodal data [1]. In response to this challenge, we developed a method for combination of signals which are associated with cardiac activity directly and indirectly. The proposed method is further extended to statistically select reliable positions of heart beat candidates.

2. Methods

In this research, we proposed methods of QRS complex detector, estimation of BP-ECG interval, and adaptive filters in cascade.

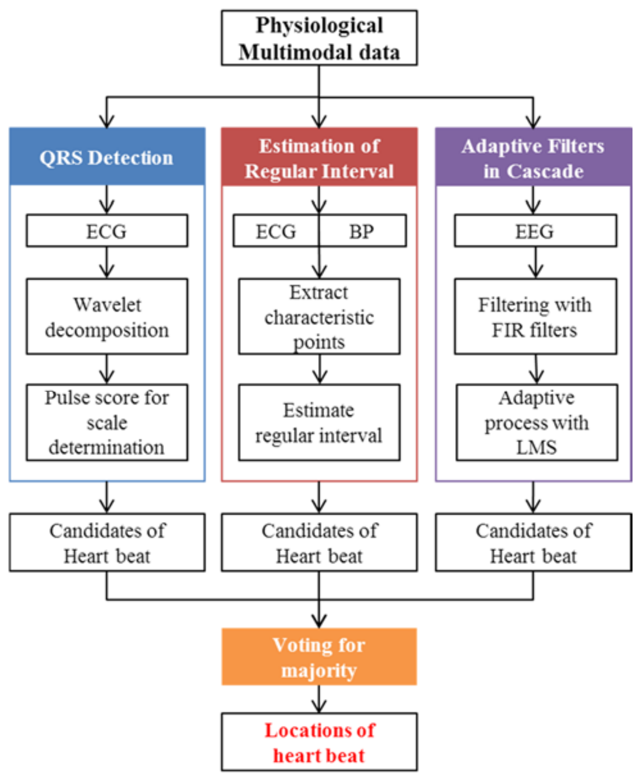

Figure 1. Overall procedure of proposed method.

Figure 1 shows that the overall procedure of our methods. We process multi parameter signals with three sub-modules. Basically, we find heart beats using QRS complex detector for easy and normal cases. Based on detected QRS complexes, BP-ECG regular interval is estimated with regular intervals from characteristic points on ECG and BP signals as directly associated with cardiac activity. At the last, we extract location of heart beat using adaptive filtering process for EEG, EOG and EMG for indirectly associated with cardiac activity. These results for candidate locations of heart beats are merged through a voting for majority.

2.1. QRS detection

We have tested QRS detection method of our previous work [2]. This method is based on wavelet decomposition and pulse score for scale determination. At first, we decomposed input ECG signals with Daubechies wavelet with filter length of 8. Then, approximation coefficients are eliminated to remove wandering baseline. Each detail coefficient has a corresponding pulse score; the score is used to determine the wavelet scale for protruding shape of ECG. Finally, we can detect the QRS complexes with the peak points where the largest drop of consecutive scales.

We compare this method with SQRS and WQRS detection methods which provided from PhysioNet as open sources. SQRS detection method is based on slope detection using predefined filters for five slopes (P, Q, R, S, and T waves). WQRS method analyses on ECG signal, detecting QRS onsets and J-points, using nonlinearly-scaled ECG curve length feature. Using these QRS detection methods, we can determine the temporal location of the assumed QRS candidate.

2.2. Estimation of regular intervals between BP and ECG signals

In this research, we proposed estimation of regular interval between blood pressure and ECG signals for heart beat detection. As mentioned before, QRS detection methods have limitations which cannot determine the temporal location of the assumed QRS candidate for the abnormal cases. Thus, we model the association between ECG and BP signals using estimation of regular intervals.

We extracted characteristic points from ECG and BP signals for the estimation. The locations of assumed QRS candidate on ECG signals are used as the characteristic points. Also, the locations of local maximum and minimum points on BP signals are used as the characteristic points. According to observations on the waveform and the characteristic points of ECG and BP signals, the signals show regular interval for each consecutive heart beat caused by blood circulation from cardiac activity. The QRS candidates are followed by the maximum points of BP signal.

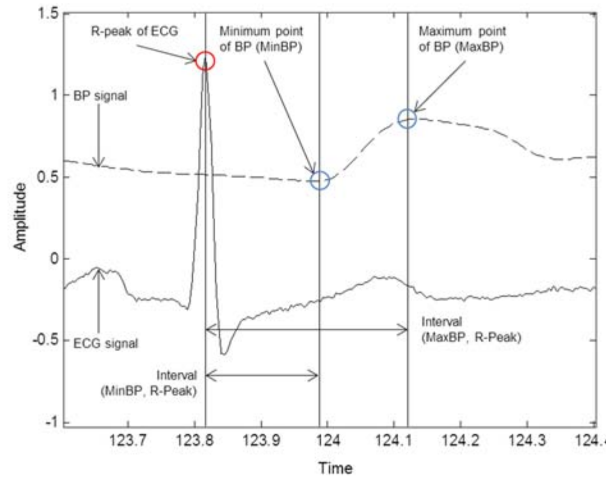

Figure 2. Characteristic points and intervals on ECG and BP signals.

Figure 2 shows the characteristic points and interval from ECG and BP signals. In this work, we selected interval between the QRS candidate and the maximum point of BP signal. The maximum points of BP signals guarantee steady interval than the minimum points. Using the extracted QRS candidate, we calculate local intervals for each heart beat as follow:

$$Interval_{\mathrm{local_i}} = \mathrm{t}_{\mathrm{maxBP_i}} - \mathrm{t}_{\mathrm{maxECG_i}}, \quad (1)$$

where $\mathrm{maxECG_i}$ is the maximum point of extracted i-th QRS candidate on ECG signal and $maxBP_i$ is the maximum point of BP signal which is followed by extracted i-th QRS candidate.

From the first beat of each record, consecutive 50 local intervals are used to estimate a regular interval as follow:

$$\mathrm{Interval_{regular}} = \frac{1}{\mathrm{k}} \cdot \sum_{\mathrm{i=1}}^{\mathrm{k}} \mathrm{Interval_{local_i}}. \quad (2)$$

After the first 50 heart beats, we used estimated regular interval and extracted characteristic points of BP signal to detect heart beats.

2.3. Adaptive filters in cascade for indirectly associated group

We proposed estimation of regular interval between ECG and BP signals. However, there are still existing difficult cases for the proposed estimation methods. The BP signal is also able to have noises and missing signals. To fill the gap of directly associated group, we extract the locations of heart beats from indirectly associated group which contains EOG, EEG, and EMG.

From the point of view of EEG analysis, it can be seen that EEG signal is contaminated by the QRS complexes

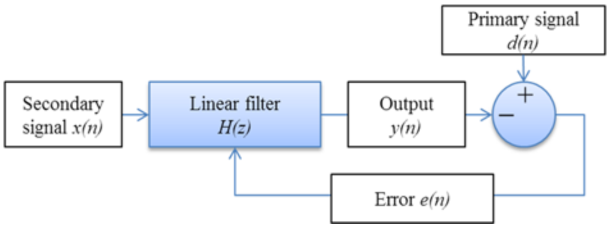

Figure 3. Structure of adaptive filter with linear filter *H(z)*.

which appear as spikes at the same time in ECG record. The ECG signal increases the difficulty in analyzing from the EEG signal and obtaining clinical information. Therefore, a lot of researches have been proposed to correct, or remove the artifacts from the EEG signal [3-5]. In other words, we can extract the QRS complexes from the set of EOG, EEG, and EMG signals. Usually, those physiological signals have similar frequency spectrum. The adaptive interference cancellation scheme has been proposed to remove or extract signals and interferences from polysomnography (PSG).

The structure of a general adaptive filter can be seen at figure 3. There is a primary signal *d(n)* and secondary signal *x(n)*. The linear filter *H(z)* produces an output *y(n)* which is subtracted from *d(n)* to compute an error *e(n)*. The main objective of an adaptive filter is to model the reliable coefficients of the linear filter *H(z)*. With successful adaptation to secondary signal *x(n)*, linear filter *H(z)* generates similar output *y(n)* with secondary signal *x(n)*. In this paper, we used EEG signal for primary signal *d(n)*, generated normal ECG signal for secondary signal *x(n)*, and FIR filters for linear filter *H(z)*. We concatenated adaptive filters with different order values of 16, 32, and 64. The result of this process can be found with output *y(n)* as QRS candidates.

2.4. Voting for majority

From previous processes, we have obtained several locations of QRS candidates. For the simplicity, we generate final decision of QRS candidate using voting for majority. The QRS candidates are lying on the one-dimensional vectors, then we split ten sections from the first QRS candidate to the last QRS candidate on each heart beat. Then, the spliced sections are voted from the locations of QRS candidates.

3. Results

3.1. Data set

The data for the challenge consists of ten-minute multi parameter signals. Each recording includes four to eight signals; the first four are ECG, BP, EEG, Resp, the others are stroke volume (SV), SO2, EMG and EOG [CinC2014]. A set of reference beat annotation for each recording was produced by expert opinions about the locations of the observed QRS complexes in the ECG signal. Two data sets were provided for evaluating challenge entries; training data set (100 records with 10min length and 250Hz sampling rate) and hidden test data set (300 records with various lengths and between 120 and 1000 Hz sampling rate).

We divide the data set into two groups according to the contents; directly and indirectly associated with cardiac activity. Directly associated group is consist of BP, SV, So2 and Resp. Indirectly associated group is consist of EEG, EMG, and EOG. We extracted three candidate locations of heart beat from ECG, directly associated group, and indirectly associated group. Finally, these locations will be merged through voting for majority.

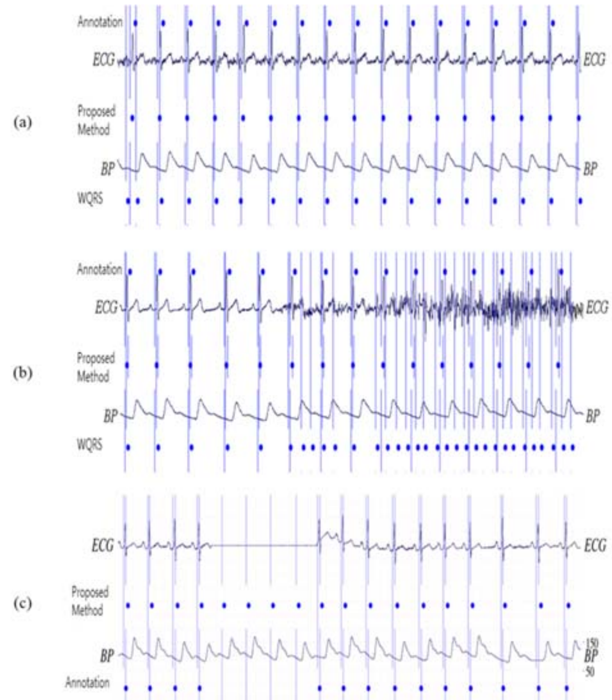

Figure 4. Example results of proposed method: (a) normal ECG signal, (b) unstable ECG signal, and (c) missing ECG signal.

3.2. Evaluation

We tested QRS detection methods with given training data set. Our QRS detector outperformed SQRS and WQRS detection methods. The evaluated overall scores with reference annotation are like follow: our work with 99.64%, SQRS with 60.39%, and WQRS with 96.77%. In this paper, we used the results from our QRS detector for other processing modules.

Figure 4 shows representative example result of proposed method. Our method successfully captured heart beats on unstable ECG signal. If there exist missing ECG section, our method occasionally lost the anchor point for the estimation module with ECG and BP signals.

4. Discussion

In this paper, we introduced heart beat detection method by estimation of the QRS complexes with regular interval and QRS extraction from EEG signal. The final results indicate that the method worked well in various noisy scenarios and conditions. Furthermore, the proposed work can be improved with integration of multi-cue detectors based on machine learning techniques.

Acknowledgements

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