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Signal Quality Index-Based Two-Step Method for Heart Rate Estimation by Combining Electrocardiogram and Arterial Blood Pressure Signals

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Accurately monitoring heart rate (HR) is important in intensive care unit (ICU) application, which is usually performed by electrocardiogram (ECG) analysis. However, the contamination of ECG is common and this may lead to the erroneous estimation of HR. In this study, an improved HR detector, named as signal quality index (SQI)-based two-step method, was proposed. This method consists of two steps: (1) HR estimation by SQI-based Kalman filter for single channel signal, (2) SQI-based HR estimation by fusing the results from ECG and ABP signals. First, two QRS detectors, GQRS and SQRS, were used to obtain SQI and HR from ECG signal, and the wabp algorithm and a fuzzy logic analysis method were used to obtain SQI and HR values from ABP signal. Then, HR values derived from ECG and ABP were separately processed by Kalman filter. HR after Kalman filter were fused based on the signal SQIs, to obtain the fused HR. The method was evaluated on the set-p (with good signal quality) and set-p2 (with poor signal quality) databases from the PhysioNet/CinC Challenge 2014. For set-p, mean absolute errors from the fusion of ECG and ABP signals were 0.233, 0.289, 0.417, 0.456, 0.440 and 7.865 beat/min for the six SQI levels (0.9–1.0, 0.8–0.9, 0.7–0.8, 0.6–0.7, 0.5–0.6, and 0–0.5) respectively. As comparison, for set-p2, the signal quality was relative low, mean absolute errors from the fusion of ECG and ABP signals were 0.191, 0.391, 0.688, 1.135, 0.921 and 13.32 beat/min for the six SQI levels respectively. As expected, the fusion method performed better than the single channel signal (ECG or ABP).

Keywords: Electrocardiogram (ECG), Heart Rate Estimation, Signal Quality Index, Pulse Signal, Kalman Filter.

1. INTRODUCTION

ECG is a time-varying signal reflecting the electrical activity of heart which is generated by depolarization and repolarization of the atria and ventricles.[1] HR estimation, derived from ECG or other cardiovascular signals, is important in clinical environments, such as intensive care unit (ICU) monitoring. The alarms are triggered when HR exceeds the specified thresholds.[2,3] Therefore, the accuracy of the alarms is important for prompt treatment and health care of ICU patients. However, ECG can be severely contaminated by noise and artifacts or even missing completely.[4–6] Therefore, it is difficult for clinicians to believe the HR estimation from ECG signal without personal confirmation. This can also easily lead to alarm fatigue, desensitization and confusion of clinical staff.[7–10]

Many methods have been used to enhance the accuracy and robustness of ECG HR estimation. On the occasion when ECG may be of poor quality or even missing entirely, HR information can be obtained from other physiological signals, such as pulsatile signal, typical as arterial blood pressure (ABP) signal.[9,10] For ECG signal, HR information can be obtained by performing the common R-peak detectors, such as gqrs, jqrs, differential threshold method, etc.[11–14] For ABP signal, wabp algorithm and derivative-based search approaches were commonly used.[14,15] There were also other ways for heart beat detection, such as hidden semi-Markov model (HSMM), data coupling method, association models, video-based method, etc.[14,16–18] Reliable estimation of HR can be obtained by 'information fusion' after

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heart beat detection from ECG and ABP separately.[19–21] To determine the weights of HR derived from ECG and ABP, signal quality index (SQI), therefore, plays a vital role in fusion of multimodal signals.[8,9,22–24] Li et al. proposed a modified approach for fusing HR derived from ECG and ABP waveforms, weighted by the Kalman filter and SQIs, and was evaluated on the open-access database–Multi-Parameter Intelligent Monitoring for Intensive Care II (MIMIC II) database.[9] This work provided a continuously updating estimation of HR that automatically rejects untrustworthy data.

However, researchers are further interested in the quantitative relationship between HR estimation errors and the SQI levels, and this information lacks in the previous studies. So in this study, we proposed a SQI-based two-step algorithm for HR estimation from multimodal ECG and ABP signals. We tested the new method on the open-access multimodal database used for the PhysioNet/CinC Challenge 2014,[13,15] etc. also used the data from the PhysioNet/CinC Challenge 2014. Sensitivity, positive predictivity, and the accuracy index induced from them, were usually used for evaluating the QRS detection results.[11,12,18,22,25] However, they only focused on the overall performances. In this study, we used mean and standard deviation (SD) of HR errors to evaluate the effectiveness of HR estimation. We especially focus on quantifying how the estimated HR error changes with the decreases of the signal quality by dividing the signal quality into six different ranges.

2. METHODS

2.1. Data

Data are from the PhysioNet/CinC Challenge 2014, which includes two databases: training database (set-p) and the extended training database (set-p2).[20,25] The set-p includes 100 records with high signal quality, while set-p2 includes 100 records but the signal quality is relative poor. Data were sampled at 250 Hz or 360 Hz. Each record contains four to eight signals; the first is an ECG signal in most cases, the others are a variety of simultaneously recorded physiological signals. In this study, we focused on the HR estimation from ECG and ABP signals. However, there are 27 records in set-p2 without ABP signal. Thus these 27 records were excluded for the analysis. The data profile is shown in Table I.

A SQI-based two-step method for robust HR estimation from the combination of ECG and ABP signals was proposed. Firstly, the QRS complexes of ECG signal and the onsets of ABP signal were detected.[26] Then, signal quality was evaluated for ECG and ABP respectively. Then, HR derived from ECG and ABP were separately processed by Kalman filter. Finally, HR was fused using a SQI-weighted method. The absolute error between the estimated HR and the reference HR was calculated to evaluate the effectiveness of the proposed algorithm. Figure 1 shows the flow chart of the proposed method. The detailed methodological explanations were given later.

Table I. Data profile of the PhysioNet/cinC challenge-2014 databases.

Variables	Set-p	Set-p2
Used records	100	73
Beats	72415	78618

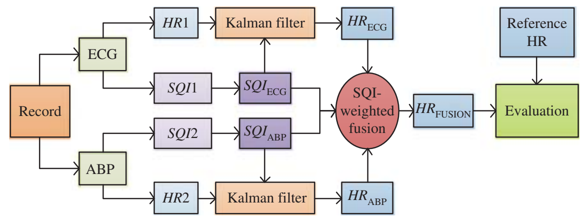

Fig. 1. Flow chart of proposed method.

2.2. ECG Processing

2.2.1. HR Estimated from ECG

First, HR1 was calculated from the RR intervals within a 5-s time window:

$$\mathrm{HR1} = \frac{60}{\mathrm{median[RR\ interval]}} \tag{1}$$

where the median RR interval was used to avoid the influence of the extreme RR interval values due to the false detected beat or missed beat detections.

Then, the derived HR1 was processed by Kalman filter. The filter combines the past measurement estimation errors with the new measurement errors to estimate future errors. When the value of SQI1 in Eq. (7) was greater than or equal to 0.7, or the value of SQI1 was less than 0.7, there were different filtering methods The detailed process of the Kalman filter for ECG signal is shown in Figure 2.

2.2.2. SQI for ECG Signal

QRS complexes were detected by GQRS and SQRS, provided by the WFDB toolbox.[27,28] Then, the ECG signal quality was evaluated. Firstly, bSQI within a window of ω seconds ($\omega = 8$ s in this study) is defined as:

$$\mathrm{bSQI} = \frac{\mathrm{num\_match}}{\mathrm{num\_GQRS} + \mathrm{num\_SQRS} - \mathrm{num\_match}} \tag{2}$$

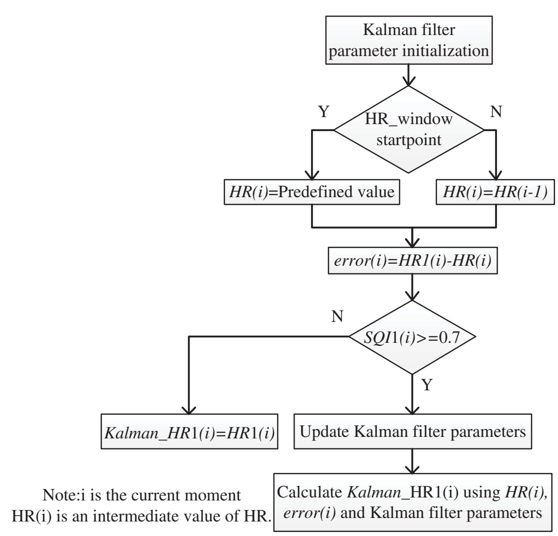

Fig. 2. The running process of the Kalman filter for ECG.

where num_GQRS and num_SQRS are the numbers of QRS complex detected by GQRS and SQRS respectively, num_match is the number of beats detected synchronously. The beat detections from the two algorithms were set to have agreed on a beat location if they fell within a 150 ms window. bSQI values were updated every second.

In addition, sSQI and kSQI, were also calculated. The energy of QRS complex is mainly centered around 10 Hz and concentrated in a 10 Hz frequency band width. Thus sSQI is defined as

$$\mathrm{sSQI} = \begin{cases} 1 & 0.5 \le \mathrm{SDR} \le 0.8 \\ 0 & \text{else} \end{cases} \tag{3}$$

where SDR is the distribution ratio of power spectral density (PSD) of 5–14 Hz against 5–50 Hz:

$$\mathrm{SDR} = \frac{\int_5^{14} P(k, w)\, df}{\int_5^{50} P(k, w)\, df} \tag{4}$$

From the central limit theorem, we know that random uncorrelated processes tend to have Gaussian distributions.[9] The fourth-order *kurtosis* was used to evaluate the similarity between the signal and Gauss signal, which measures the relative peakedness of a distribution with respect to a Gaussian distribution. The *kurtosis* of the signal x is defined as:

$$kurtosis = \frac{1}{M}\sum_{i=1}^{M}\left(\frac{x-\mu}{\sigma}\right)^4 \tag{5}$$

where μ and σ are the mean and SD of x, respectively, M is the sample number of the signal. The ECG signal with normal sinus rhythm usually has a *kurtosis* larger than 4.8. So, kSQI is given by

$$\mathrm{kSQI} = \begin{cases} 1 & kurtosis > 4.8 \\ 0 & \text{else} \end{cases} \tag{6}$$

Thus, we can define the final signal quality for the ECG signal as:

$$\mathrm{SQI1} = \begin{cases} \mathrm{bSQI} & \mathrm{kSQI} = 1 \text{ and } \mathrm{sSQI} = 1 \\ \mathrm{bSQI} \times \eta & \text{else} \end{cases} \tag{7}$$

where $\eta = 0.7$ is a penalty factor, for reducing SQI1 by 30% if spectral or statistical noise appears.

Finally, we collected Kalman_HR1 and SQI1 every 2 s within the length of ECG signal, and used the smallest two as the representative HR and SQI of the 2 s interval. The obtained $\mathrm{HR}_{\mathrm{ECG}}$ and $\mathrm{SQI}_{\mathrm{ECG}}$ will be used for the fusion work.

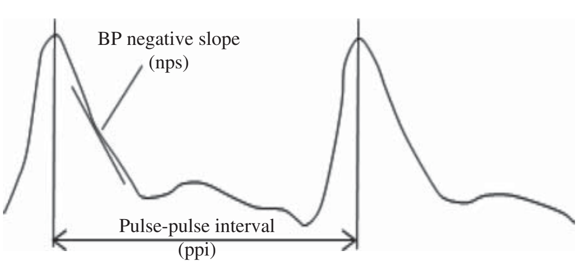

Fig. 3. ABP waveform parameters.

2.3. ABP Processing

The wabp algorithm was used to locate the onsets of the ABP signals.[26] The waveform parameters were extracted from the onset detection of ABP waveforms.[29,30] These parameters are shown in Figure 3.

2.3.1. HR Estimated from ABP

We also used a 5-s time window to calculate the values of HR from ABP signal:

$$\mathrm{HR2} = \frac{60}{\mathrm{median[onset\ interval]}} \tag{8}$$

The derived HR2 should be processed by Kalman filter to obtain Kalman_HR2 as well. The Kalman filtering method is similar to the previous one used for ECG signal processing, except for a special parameter setting, detailed as follows: $\mathrm{SQI2} \le 0.7$ replace $\mathrm{SQI1} \ge 0.7$.

2.3.2. SQI for ABP Signal

A 8-s time window was also used to align with the ECG signal. Firstly, the first 20 beats with good signal quality were selected for the waveform parameters for determining the initial values of the waveform parameters.

In order to obtain SQIs of ABP signal, i.e., jSQI and wSQI, a fuzzy logic analysis algorithm, which can reduce false ABP alarms was used.[31] jSQI is a normal/abnormal index. If the value of waveform parameters mentioned above were in the range as shown in Eq. (9), jSQI is 0, which indicates the normal beats. Otherwise, jSQI is 1, which indicates the abnormal beats.

wSQI takes a continuous value between 0 and 1 as signal quality for each beat. In order to obtain wSQI, a group of composite variables was calculated based on the waveform parameters extracted from ABP and the reference values in the base feature set, which reflect signal changes. The value of wSQI was

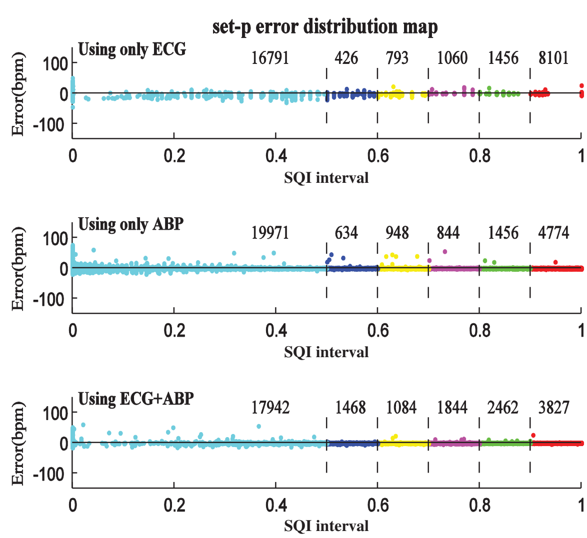

Fig. 4. Estimated HR errors against the SQI values on the set-p database. The number of the signal episodes with 5-s time window are shown for each of the SQI levels.

Table II. Mean and SD values (unit: beat/min) of estimated HR errors on the set-p database at the different SQI levels.

	ECG		ABP		FUSION	
SQI level	Mean	SD	Mean	SD	Mean	SD
[0.9 1.0]	0.398	0.551	0.335	0.443	0.233	0.478
[0.8 0.9]	0.367	0.703	0.411	0.934	0.289	0.460
[0.7 0.8]	0.345	1.054	0.506	2.154	0.417	0.715
[0.6 0.7]	1.217	1.691	0.738	2.764	0.456	1.002
[0.5 0.6]	2.208	2.464	0.840	2.712	0.440	0.575
[0 0.5]	7.628	7.311	8.659	8.369	7.865	7.468

determined by the values of these composite variables. Detailed calculations are shown in Ref. [31].

$$\begin{cases} \text{systolic BP(sbp)} < 300, & \text{mmHg} \\ \text{distolic BP(dbp)} > 20, & \text{mmHg} \\ \text{pulse BP} > 20, & \text{mmHg} \\ 30 < \text{mean BP} < 200, & \text{mmHg} \\ 20 < \text{HR2} < 200, & \text{bpm} \\ \text{mean nps} > -40, & \\ |\text{sbp(i)} - \text{sbp(i}-1)| < 20, & \text{mmHg} \\ |\text{dbp(i)} - \text{dbp(i}-1)| < 20, & \text{mmHg} \\ |\text{ppi(i)} - \text{ppi(i}-1)| < 2/3, & \text{seconds} \end{cases} \tag{9}$$

where i is the current moment. The first column is the decision parameters of jSQI value. The second column is the unit corresponding to these parameters.

The final signal quality for the ABP signal is defined as

$$\text{SQI2} = \begin{cases} \text{wSQI} & \text{jSQI} = 0 \\ \text{wSQI} \times 0.7 & \text{jSQI} = 1 \end{cases} \tag{10}$$

At last, use the similar collecting method as in ECG to obtained HR_{ABP} and SQI_{ABP} for the fusion work.

2.4. Fusion Method

The obtained HR values from ECG and ABP respectively were fused to obtain the fused HR. $\text{HR}_{\text{FUSION}}$ is defined as:

$$\text{HR}_{\text{FUSION}} = \frac{\text{SQI}_{\text{ECG}}^2 \times \text{HR}_{\text{ECG}}}{\text{SQI}_{\text{ECG}}^2 + \text{SQI}_{\text{ABP}}^2} + \frac{\text{SQI}_{\text{ABP}}^2 \times \text{HR}_{\text{ABP}}}{\text{SQI}_{\text{ECG}}^2 + \text{SQI}_{\text{ABP}}^2} \tag{11}$$

2.5. Evaluation Method

The absolute HR errors between estimated HR and reference HR were calculated. Reference HRs were obtained from the expert annotations, derived from a 5-s time window and updated for each 2-s time window. The results were divided into 6 classes according to the SQI levels. For evaluating the fused method, the mean of SQI_{ECG} and SQI_{ABP} corresponding to the same 5-s signal window was defined as the fused SQI value, i.e., $\text{SQI}_{\text{FUSION}}$.

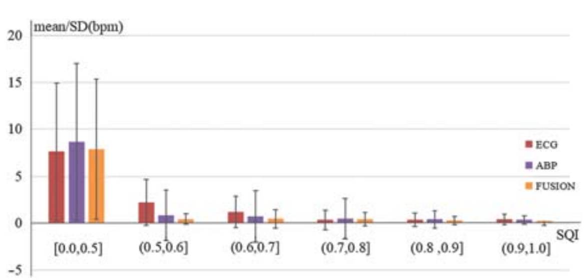

Fig. 5. Boxplots of the mean and SD values of estimated HR errors on the set-p database

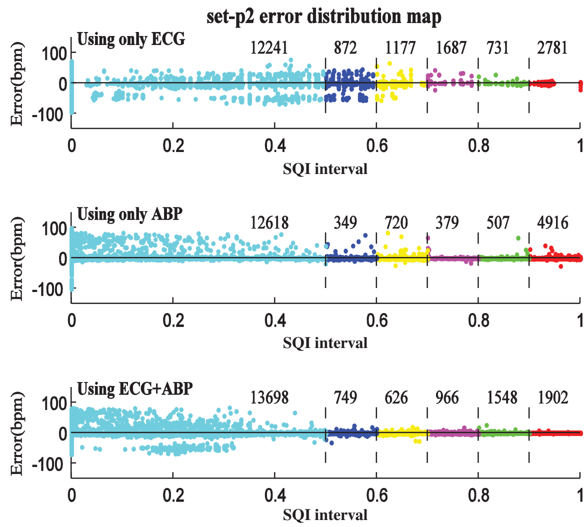

Fig. 6. Estimated HR errors against the SQI values on the set-p2 database. The number of the signal episodes with 5-s time window are shown for each of the SQI levels.

3. RESULTS

3.1. Results on Training Set-p Database

Figure 4 shows the estimated HR errors against the SQI values on the set-p database. Table II and Figure 5 show the numerical results and the boxplots. Mean absolute errors for ECG signal were 0.398, 0.367, 0.345, 1.217, 2.208 and 7.628 beat/min for the six SQI levels respectively, and were 0.335, 0.411, 0.506, 0.738, 0.840 and 8.659 beat/min respectively for ABP signal. Mean absolute errors after fusion were 0.233, 0.289, 0.417, 0.456, 0.440 and 7.865 beat/min respectively. SD values of the estimated HR errors were also shown, with the similar phenomenon as the mean absolute errors.

3.2. Results on Training Set-p2 Database

Then we tested on the relative poor signal quality database, i.e., set-p2 database. Figure 6 shows the estimated HR errors against the SQI values on the set-p2 database by using ECG and ABP separately, as well as using the fusion of these two signals.

Table III. Mean and SD values (unit: beat/min) of estimated HR errors on the set-p2 database at the different SQI levels.

	ECG		ABP		FUSION	
SQI level	Mean	SD	Mean	SD	Mean	SD
[0.9 1.0]	0.317	0.780	0.406	1.218	0.191	0.366
[0.8 0.9]	0.503	1.693	0.775	3.411	0.391	1.076
[0.7 0.8]	0.375	2.351	1.134	4.508	0.688	1.365
[0.6 0.7]	2.450	6.529	1.770	5.411	1.135	2.463
[0.5 0.6]	5.646	12.48	2.263	7.015	0921	2.429
[0 0.5]	17.61	15.91	19.99	19.76	13.32	15.46

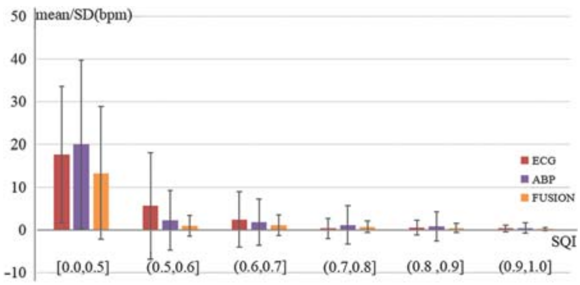

Fig. 7. Boxplots of the mean and SD values of estimated HR errors on the set-p2 database.

Table III and Figure 7 show the numerical results and the boxplots. Mean and SD of absolute errors for ECG, ABP and after fusion show similar phenomenon as in set-p. Both mean absolute errors and their SD values were small at high SQI levels and quickly increased when the SQI decreased. The results showed that the fusion method had potential to reduce the estimated error especially for poor signal quality signals.

4. DISCUSSION

Previous methods for robust HR detection from multimodal signals used beat-to-beat estimation, which performed well in processing bradycardia/tachycardia events, but had difficulties in processing the ventricular tachycardia in the presence of noise and artifacts.[18] Data coupling-based method has advantage that heart beats can be more easily detected in noisy parts of the signal.[11] However, its performance could not achieve high level when dealing with noise-free signal. In addition, HR can also obtain from only photoplethysmogram (PPG) signal.[32–36] PPG-based method has simpler hardware implementation. However, it is sensitive to motion artifacts. Besides,[2, 14] etc. used set-p and set-p2 as a whole to evaluate the HR results. Thus there was no specific estimation for ECG and ABP signals respectively.

The present study proposed a SQI-based two-step algorithm for HR estimation. Mean and SD of the absolute HR errors increase gradually as the signal quality drops, whether in the single channel signal or the fusion of ECG and ABP. Besides, HR estimation after fusion is more accurate than that from the single channel signal in almost every SQI level. Although we expected the mean and SD of the absolute HR error after fusion are smaller than those from the single channel signal, exceptions exist, such as the mean absolute error after fusion in SQI levels of (0.7, 0.8] and [0, 0.5] in set-p database, in SQI level of (0.7, 0.8] in set-p2 database, are a little bit larger than those from the single channel signal. These phenomena may be due to the fact that SQI_{FUSION} is the mean of SQI_{ECG} and SQI_{ABP}. One channel with very small SQI will affect the fusion results. This should be improved in the future. ICU alarm is based on HR estimation in clinical monitoring. The proposed method can serve as an efficient method since it performs well in most cases.

5. CONCLUSION

A simple SQI-based two-step method for heart beat estimation by combining ECG and ABP signals were proposed. A total of 151,033 beats were used for developing and testing the proposed algorithm. Based on the feature detectors for ECG and ABP signals, as well as the signal quality indices, we systematically tested the changes of the calculated HR errors with the changes of signal quality. The results showed that the method enhanced the accuracy of robust HR estimation, especially for the poor signal quality records.

Conflicts of Interest Statement

There is no conflict of interest to this work.

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