Reducing False Arrhythmia Alarms in the ICU using Novel Signal Quality Indices Assessment Method

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Abstract

The physiological signals such as the electrocardiogram (ECG) and arterial blood pressure (ABP) in the ICU are often severely corrupted by noise, artifact and missing data, producing large errors in the estimation of the characteristics of the signals values, leading to false alarms in ICU. In order to solve this problem, we started with the signal quality assessment of vital signals in intensive care patients using a derived signal quality index (SQI) to reveal the degree of signal quality. And then we use the SQI-weighted residual error of Kalman filters (KF) to complete the date fusion for evaluating the heart rate (HR). Finally, the algorithm of arrhythmia false alarm reduction in ICU monitors was developed based upon the method of combining SQIs and HR estimations derived from ECG waveform and ABP waveform recorded from ICU patients. Results show that the overall True Positive Rate (TPR), True Negative Rate (TNR) and overall score for the Event-1 are respectively 65%, 82%, and 53.19, for the Event-2, the TPR, TNR and overall score are 65%, 87%, and 54.64.

1. Introduction

Physiological signals such as the electrocardiogram (ECG) and arterial blood pressure (ABP) in the intensive care unit (ICU) are often severely corrupted by noise, artefact and missing data, producing large errors in the estimation of the characteristics of the signals, such as the heart rate (HR) and ABP [1,2]. Frequent false alarms due to data corruption will result in not only a serious waste of time, resources, but also sleep deprivation for patients and stress induction for patients and staff, eventually causing a desensitization of clinical staff to real alarms and a consequent decline in the overall level of care [3]. Therefore, a robust method of HR estimation with accurate SQI calculation is essential for ICU monitoring which can reduce false alarms.

Noise and artefact in biological signals can be categorised into two major groups based on their frequency contents: (1) low frequency disturbances such as baseline wander caused conventionally by muscular activities and respiration; (2) high frequency noises such as power-line noise, vibration of vacuum cups of the ECG machine and electronic reactions of the acquisition system. So far many ECG signal denoising methods have been developed, which can be roughly classified into three categories, the classical methods of digital filter and adaptive filter method [4], the wavelet transform method and mathematical morphology and neural network as a representative of modern high-tech filter methods [5]. Considering the denoising result and time, we selected wavelet transform method to deal with the problem.

After filtering the signals with the wavelet transform method, a novel method of signal quality assessment was developed based on modifying Townsend and Tarrasenko's methods to fuse signal quality indices of different types of data from multiple sensors [6-8]. This method provides a continuously updating estimation of the heart rate that would reduce the false alarms in the ICU. Based on the SQI estimation, the disturbance of high levels of noise and artefact in the signal analysis was greatly suppressed. Physiological SQIs were obtained by analyzing the statistical characteristics of each waveform and their relationships to each other. The SQI of ECG signals was obtained by the number of matched QRS complex basing on K-means algorithm [9] and improved Tompkins difference algorithm [10], respectively, while the SQI of ABP signals was obtained by a combination of two algorithms: a beat-by-beat fuzzy logic-based assessment of features in the ABP waveform [11] and heuristic constraints of each ABP pulse [12] to determine normality. After that, we use the SQI-weighted residual error of Kalman filters (KF) [6-8] to complete the date fusion for evaluating the HR.

2. Dataset

The training and test sets were divided into two subsets of mutually exclusive patient populations. The training set contains 750 recordings and the test set contains 500 recordings (which was used for scoring the algorithm only). For data from each patient, no more than three out of total five categories of alarms were used, which were at least 5mins apart (usually longer). An alarm was triggered 5 minutes from the beginning of each record. All signals were resampled to 12 bit, 250 Hz. Each recording contained two ECG leads (which might or might not be the leads that triggered the alarm) and one or more pulsatile waveforms (the photoplethysmogram and/or arterial blood pressure waveform).

3. Method

Figure 1 outlines the flow of our approach. The architecture of our proposed algorithm included signal filtering，calculation and assessment of combined ECG and ABP SQI，data fusion for HR estimation using KF and judgement of false alarms in sequence. Each major step was explained in more detail in the five upcoming subsections.

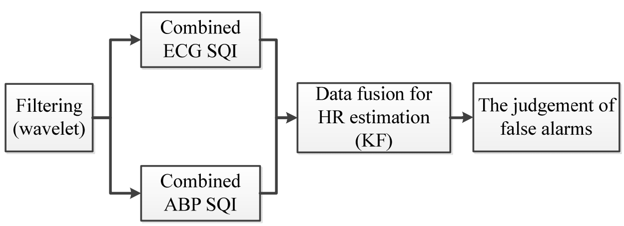

Figure 1. Flow chart of our approach.

3.1. Filtering

For signal denoising, each original ECG signal was decomposed by multi-level discrete wavelet that was equivalent of input ECG signal was divided into low frequency (ai) and high frequency(di) components and then put the low frequency component into the next layer to decompose. In this study, we decomposed original ECG signal into eight scales with coif4 wavelet [13], d1 to d8 are the detail components representing the high-frequency of ECG signals. It was found that the high-frequency noise was mainly determined by d1 to d3. Therefore, values of d1 to d3 were set to zeros to filter the high-frequency noise.

3.2. Combined ECG SQI

After signal denoising, a derived signal quality index (SQI) was applied to evaluate the degree of signal quality for better alarms judgement. In order to evaluate of signal quality of each ECG signal, first, two different algorithms were applied in QRS detection basing on K-means algorithm [9] and improved Tompkins difference algorithm [10], respectively. Then, the number of QRS complex detected by each method was calculated. The SQI of each ECG signal was determined by two factors: (1) the ratio of the number of QRS complex detected by one algorithm to the other (Eq. 1); and (2) the ratio of the number of matched QRS complex detected by both algorithms (Eq.2). Then, the SQI of the ECG was evaluated during both the whole ECG period (globe assessment) and the alarm interval (local assessment) (Eq.3). The final SQI of the ECG was determined by combining the SQIs achieved in global and local assessment (Eq.4). The combined ECG SQI was calculated as follows:

$$SQI_1 = \frac{min(N_1, N_2)}{max(N_1, N_2)} \cdot \eta_1 \quad (1)$$

$$SQI_2 = \frac{N_{matched}}{N_1 + N_2 - N_{matched}} \cdot (1-\eta_1) \quad (2)$$

$$SQI(Global, Local) = SQI_1 + SQI_2 \quad (3)$$

$$ECGSQI = SQI(Global) \cdot \eta_2 + SQI(Local) \cdot (1-\eta_2) \quad (4)$$

where η_1=0.5, η_2=0.4 are the positive coefficients which correspond to the weight of each factor in SQI calculation selected by experiment experience, $N_{matched}$ is the number of QRS complex that both algorithms, N_1 is the number of QRS complex detected by K-means algorithm and N_2 is the number of QRS complex detected by the improved Tompkins difference algorithm. SQI ranges between 0 and 1. Figure 2 shows the detected QRS complex by Tompkins difference algorithm.

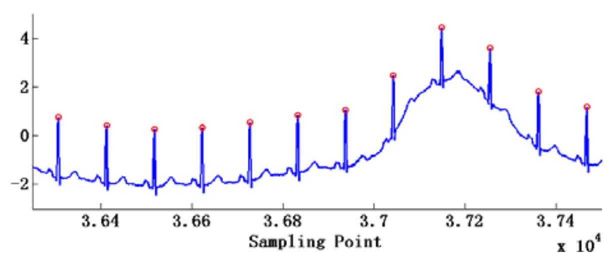

Figure 2. Detected QRS complex by the Tompkins difference algorithm.

3.3. Combined ABP SQI

In order to evaluate of signal quality of ABP signal, ABP SQI calculation was based on a combination of two algorithms: a beat-by-beat fuzzy logic-based assessment of features in the ABP waveform [11] and heuristic thresholding of each ABP pulse [12] which are known as wSQI and jSQI respectively. The wSQI algorithm consisted of an ABP pulse detection routine (using an open-source ABP onset detection algorithm, wabp [14]), a waveform feature extraction routine, a waveform feature fuzzy representation and a fuzzy reasoning procedure. The calculated wSQI ranged between 0 and 1 and values of wSQI above 0.5 indicated that the quality of a given ABP signal was good where reliable heart rate and blood pressure estimation could be made. The same beat detection algorithm was used for jSQI calculation and generated a binary value representing the feature of an ABP signal: 0 for the normal beat and 1 for the abnormal beat. The final ABP SQI was determined by combing wSQI and jSQI [15] as follows:

$$ABPSQI = \begin{cases} wSQI & if \quad jSQI = 0 \\ wSQI * \eta & if \quad jSQI = 1 \end{cases} \tag{5}$$

where η=0.7 is the positive coefficient was selected according to experiment experience. If jSQI indicated a good quality signal (jSQI=0), wSQI was adopted as the ABP SQI. Otherwise, wSQI was less trusted and therefore modified by the coefficient η. Figure 3 shows the detected ABP onset.

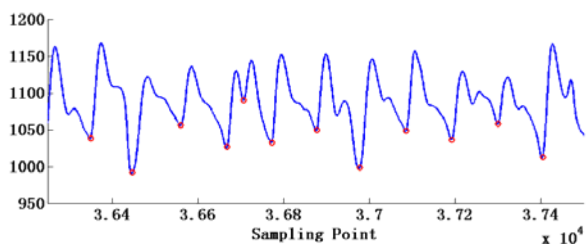

Figure 3. Detected ABP onset.

3.4. Data fusion for HR estimation

As for alarm judgement, in addition to SQI, HR estimation is another crucial factor. In this study, a method of data fusion, which was developed by combining of KF with SQI calculation [15], was used for HR estimation. The KF is an optimal state estimation method for a stochastic signal [16,17] that estimates the state of a discrete time controlled process. First, the ECG and ABP signals were filtered by KF separately. Then, the SQI-weighted residual errors (r) derived from KF were applied to calculate HR using modified Townsend and Tarassenko method [6-8]. The details of HR estimation was shown as follows：

$$HR = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2} HR_1 + \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2} HR_2 \tag{6}$$

where HR_1 is the heart rate derived from the ECG, HR_2 is derived from the ABP, and $\sigma_1^2 = (r_1/SQI_1)^2$ and $\sigma_2^2 = (r_2/SQI_2)^2$ are the weight coefficients corresponding to HR_1 and HR_2 respectively. With this method, when ECG signal is corrupted by artifact and the HR_1 is miscalculated, the derived SQI_1 will be low and the residual error (r_1) will be large due to acute changes of HR_1. Therefore, the weight coefficient of HR_1 ($\sigma_2^2/(\sigma_1^2+\sigma_2^2)$) in total HR estimation will decrease, which means HR_2 rather than HR_1 dominates the total HR estimation in this condition. Therefore, this method of HR estimation reduced the influence of low quality signal on the accuracy of HR estimation.

3.5. The judgement of false alarms

In this challenge, we focused only on life threatening arrhythmias, namely asystole, extreme bradycardia, extreme tachycardia, ventricular tachycardia, and ventricular flutter/fibrillation. In order to reduce the occurrence of false alarm, the standards of false alarms judgement for each arrhythmia were summarized in Table 1. As seen in Table 1, we used RR interval, HR and SQIs to judge false alarms, for each arrhythmia the parameters threshold setting are selected by experiment experience.

Table 1. The judgement of false alarms.

Five type arrhythmias	Sandards of false alarms judgement
Asystole	RR(ECG)max or BB(ABP)max<4s and SQI=max(ECGSQI, ABPSQI)>0
Extreme Bradycardia	HRmin>40 and SQI=max(ECGSQI,ABPSQI)>0.5
Extreme Tachycardia	HRmax<140 and SQI=max(ECGSQI,ABPSQI)>0.9
Ventricular Tachycardia	HRmax<100, QRS(width)max<0.12 and SQI=max(ECGSQI,ABPSQI)>0.5
Ventricular Flutter or Fibrillation	HRmax<150 and SQI=max(ECGSQI,ABPSQI)>0.5

4. Results

Based on the method described above, false alarms in test set of PhysioNet database were estimated. TPR, TNR and Score of five type arrhythmias in the Event-1 and Event-2 were listed in Table 2.

In this study, the TPRs of extreme bradycardia and extreme tachycardia were greater than or equal to 90 %, which indicated that our method has a good accuracy in true alarm judgement for these two diseases. The TNRs of asystole and ventricular flutter/fibrillation were greater than or equal to 90 %, which indicated that our method has a good accuracy in false alarm judgement for these two diseases. TPR represents the reduction rate of false alarms which is more important than TNR in this challenge. In general, the reduction rates of five diseases are greater than or equal to 60 %.

Table 2. Challenge scores for Event1 and Event2.

	TPR (%)	TNR (%)	Score
Asystole	33	96	67.98
Extreme Bradycardia	90	86	75.22
Extreme Tachycardia	92	60	68.03
Ventricular tachycardia	19	76	38.43
Ventricular Flutter/Fibrillation	56	90	66.22
Event1(Real-time)	65	82	53.19
Event2(Retrospective)	65	87	54.64

5. Discussion

After denoising，we applied a novel method of signal quality indices assessment to eliminate the effects of noise and artefact on HR estimation. It was found that an appropriate choice of signal quality threshold was important in producing a better HR estimation and reduced the occurrence of the false alarms. Data fusion of the ECG and the ABP significantly improved HR estimation when the ECG was completely corrupted by noise and artefact.

Two algorithms were applied to improve the precision of QRS detection and to assess signal quality. It is notable that thresholds for individual signal quality assessment were tightly correlated with the occurrence of the false alarms which needs more tests on different types of data. In future studies, this method can be further improved by introducing new algorithms for QRS detection and signal quality assessment.

It should also be noted that in our approach HR estimation used by KF was considered as the heart rate at each epoch is approximately the same as the next epoch. It is possible that more complicated conditions of the HR and ABP we may encounter which should use a variety of methods to estimate HR and ABP simultaneously. Also other parameters such as systolic blood pressure (SBP), mean blood pressure (MBP) and diastolic blood pressure (DBP) can be utilized to improve the estimation.

Acknowledgements

This study was supported in part by the National Natural Science Foundation of China (NSFC) under Grant No. 61571165 and No. 61572152.

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