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

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Abstract

The electrocardiogram (ECG) and arterial blood pressure (ABP) in the ICU are often severely contaminated by noise and artifact, producing large errors in the estimation of the characteristics of the signal 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 combining our proposed local-global ECG with existent ABP signal quality indexs (SQIs) to reveal the degree of signal quality. And then we use the previously existing SQI-weighted residual error of Kalman filters (KF) method developed by Li et al. to evaluate the heart rate (HR). Finally, the algorithm of arrhythmia false alarm reduction in ICU monitors was developed based on the method of combining SQIs and HR estimations and simple human-specified numerical rules. 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

The electrocardiogram (ECG) and arterial blood pressure (ABP) in the intensive care unit (ICU) are often severely contaminated by noise, artefact and missing data, resulting in large errors in the estimation of the heart rate (HR) and ABP [1,2]. Frequent false alarms caused by poor data quality may cause not only a serious waste of time, resources, but also sleep deprivation for patients and stress induction for patients and staff, which may cause insensitivity of clinical staffs to true alarms and decreases the quality of care [3]. Therefore, it is essential for developing automatic methods to reduce the false alarms and improve the quality of care in the ICU.

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 ECG de-nosing problem.

For quantifying signal quality index (SQI) of ECGs, we proposed a local-global ECG SQI calculation method based on the previously method proposed by Li et al. [6, 7]. After the ECG SQI calculation, the disturbance of high levels of noise and artefact in the ECG signal was greatly suppressed. Then, K-means algorithm [8] and improved Tompkins difference algorithm [9] were respectively applied to detect the QRS complex. In addition, apart from the ECG SQI, 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 [10] and heuristic constraints of each ABP pulse [11] to determine normality, following the previous study of Li et al. [6]. After that, we use the SQI-weighted residual error of Kalman filters (KF) proposed by Li et al. [6] to complete the date fusion for evaluating the HR. Finally, the simple human-specified numerical rules are used to determine the false alarms in order to reduce the complexity of the algorithm.

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 5 mins 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 and judgement of false alarms in sequence. Each major step was explained in more detail in the five upcoming subsections.

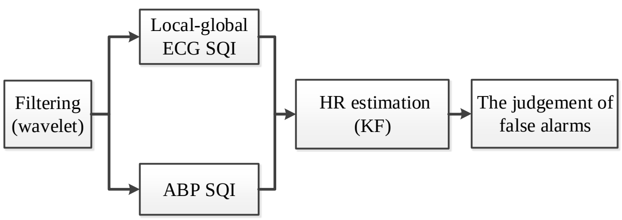

Figure 1. Flow chart of our approach.

3.1. Filtering

For signal denoising, each original ECG signal was decomposed by muti-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 [12], 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. Local-global ECG SQI calculation

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 [8] and improved Tompkins difference algorithm [9], respectively. Then, the number of QRS complex detected by each method was calculated by one lead. 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 (global 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:

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

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

$$SQI(Global, Local) = SQI_1 + SQI_2 \tag{3}$$

$$ECGSQI = SQI(Global) \cdot \eta_2 + SQI(Local) \cdot (1 - \eta_2) \tag{4}$$

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 improved Tompkins difference algorithm.

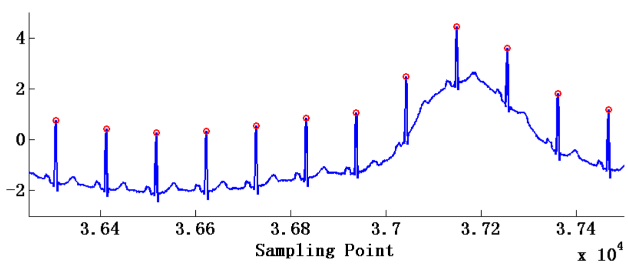

Figure 2. Detected QRS complex by the Tompkins difference algorithm.

3.3. ABP SQI calculation

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 [10] and heuristic thresholding of each ABP pulse [11] that are known as wSQI and jSQI respectively, following the same was as used in the previously study [6]. As described in their study [6], the wSQI algorithm applies an open-source ABP onset detection algorithm called wabp [13], with value ranging in (0, 1). In addition, the same beat detection algorithm was used for jSQI calculation and generated a binary value representing the feature of an ABP signal. The final ABP SQI was determined by combing wSQI and jSQI that has detailed description in the study [6]. In the Figure 3, we show an example of detected ABP onset that proves the effectiveness of the detected algorithm.

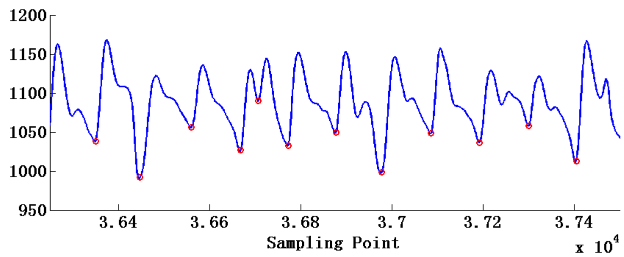

Figure 3. Detected ABP onset.

3.4. 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 Li et al. [6] by combining of KF with SQI calculation, was used for HR estimation. As being described in [6], the ECG and ABP signals were filtered by KF separately, and the SQI-weighted residual errors (r) derived from KF were proposed to calculate HR using modified Townsend and Tarassenko method [14-16]. Details of the calculation method can be found in the study of Li et al. [6].

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	Standards 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 and discussions

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 the described 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 the described 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

For the follow-up study, we should focus on the special categories such as ventricular tachycardia that obtains the lowest score. In the future, it is necessary to develop new algorithms for QRS detection to accurately identity QRS complex. In addition, more types of physiological signals can be used to extract more relevant information, and judge the false alarms with more robust machine learning algorithms.

5. Conclusion

In this work, we use the physiological signals such as ECG and ABP to tackle the problem of false arrhythmia alarms in the ICU. Based on the previous studies [6,7], we proposed here the calculation method of the local-global ECG SQI. After combining the calculation method of existing ABP SQI, we applied well-established SQI-weighted residual error of KF method to evaluate the HR, which can be used to reduce the false arrhythmia alarms with simple human-specified numerical rules. The experimental results demonstrated that the effectiveness of the described method in reducing the false alarms in the ICU. By mining multi-source datasets more effectively, the described method can be further improved to meet the needs for automatic clinical monitoring and serving for more patients in the future.

Acknowledgements

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