Reducing ECG Alarm Fatigue Based on SQI Analysis

Zehui Sun, Jianwei Su, Chaocheng Xie, Jiao Yu, Wenyu Ye, Shen Luo

Mindray, Shenzhen, China

Abstract

Alarm fatigue can cause many negative results. Regarding ECG signals, an algorithm to reduce alarm fatigue is described, regardless of whether or not VPBs are involved in the false alarms. ECG signals are divided into five signal quality index levels (SQI): 0~4, where level 0 represents a noise free signal and level 4 indicates the worst signal quality. The key of the method is to judge the noise level by recognizing P, QRS, and T waves effectively. If the SQI value is found to be high, some strategies can be implemented to reduce alarm fatigue, including improvement of the classification of VPB-like QRS complexes, correction of some false ARR alarms, and freeze of the HR value for a few seconds. The AHA and MIT-BIH database as well as the Mindray database were used to evaluate the performance of the SQI analysis. Compared with the new method, QRS and VPB detection accuracies are almost the same based on DB1, and both incorrect HR values and false ARR alarms can reduced more than 40% based on DB2, DB3, and DB4.

1. Introduction

Computer-based patient monitoring systems perform feature estimations of the signals acquired from patients. As with electrocardiogram (ECG) signals, these features include heart rate (HR) and arrhythmia (ARR). However, when ECG signals are contaminated by noise, HR and ARR results may be incorrect. A monitoring device is expected to warn clinicians of the patients' serious conditions in a reliable manner, but contaminated ECG signals may bring about an excessive number of false monitor alarms. High false alarm (FA) rates in care areas, including ICUs, are a major concern as clinicians tend to get desensitized to alarms – alarm fatigue [1] – which brings about many negative impacts, such as delayed response times, missed true events, decreased patient care quality, increased length of patient stay, and increased hospital costs. According to a very recent national survey, 19 out of 20 US hospitals surveyed rank alarm fatigue as a top patient safety concern [2]. Reducing nuisance alarms and alarm fatigue has become a hot topic in the patient safety world [3] [4]. Some researches aim to enhance the accuracy of the HR value and reduce the false ARR alarms related to HR (e.g. tachycardia, bradycardia, asystole, etc). However, in practice this approach cannot reliably reduce common false alarms if ventricular premature beats (VPBs) are involved.

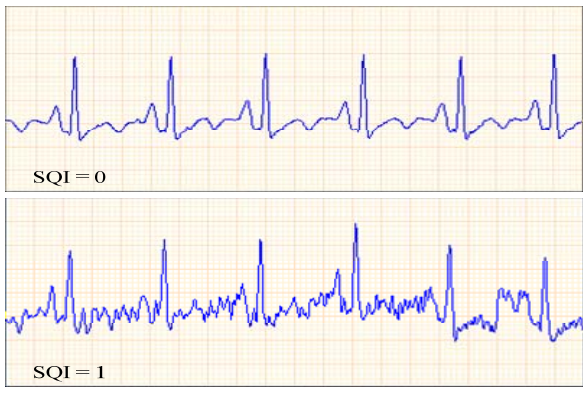
This study is intended to provide real-time signal quality information which will be fused with the ECG conventional analysis results to decide whether or not to trigger the alarm, with subsequent improved outcomes especially for false alarms related to VPBs.

2. Methods

Mindray has previously developed an ARR algorithm (called the MECG algorithm) to detect and classify QRS complexes, calculate HR value and trigger ARR alarms. In this article, based on the MECG algorithm, a new signal quality index (SQI) method is introduced to judge the noise level of ECG signals, with a series of criteria to improve QRS classification, enhance HR value robustness and suppress false alarms.

2.1. The definition of the SQI level

ECG signals are divided into five SQI level groups: 0~4, where level 0 represents a noise free signal and level 4 indicates the worst signal quality (Figure 1).



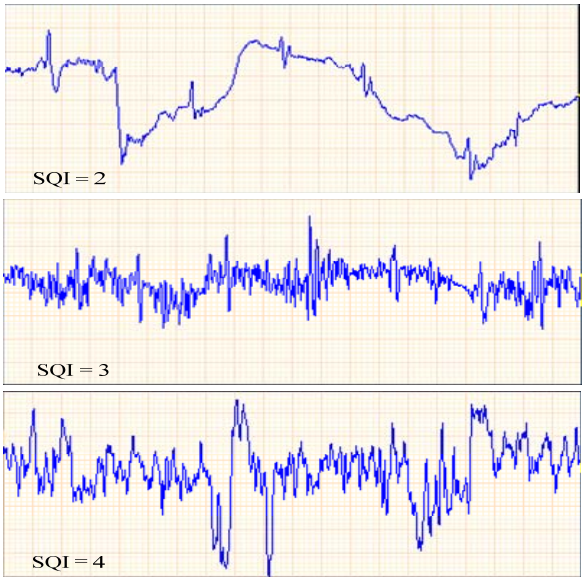


Figure 1. Examples of SQI levels 0~4. According to the signal and analysis results of QRS complexes, level 0 affects neither QRS detections nor classifications; level 1 represents an ECG signal with low noise without having an effect on QRS detection and classification performance; level 2 represents a medium noise level that does not affect QRS detections, but might affect QRS classifications; level 3 represents a high noise level that affects both QRS detections and classifications, while the QRS complexes can be recognized with visual inspection; level 4 represents a full noise level where the signals are severely contaminated by noise and the QRS complexes cannot be recognized even with visual inspection.

2.2. The SQI method

The ECG signals are divided into effective and noisy segments, where P, QRS, and T waves are considered as effective segments and the remaining signals are considered as noise. The SQI method includes the following steps:

(1) Data preprocessing

The MECG algorithm can use at most 2 channels to analyze ECG features. Each channel of ECG is resampled to 250Hz when necessary. For synchronous analysis, the SQI analysis and the MECG analysis use the same time window (for example, one second). After proper trap filtering reduces the line frequency noise in each time window, saturation sample points are counted. If the points counted are greater than half the window size, the SQI level of this window is level 4.

(2) QRS metric calculation

The MECG algorithm detects and classifies QRS complexes from each channel. For every QRS complex some basic metrics are calculated, including the location, QRS type, amplitude, width, interval, onset, offset, polarity, uniformity, wide-or-narrow state, etc.

(3) Peak and valley detection and classification

Local peak and valley (PV) features directly describe the changes of ECG signals and indirectly represent the contamination level. For distinguishing the effective and noisy segments of ECG signals, PV features are introduced.

First, all PVs are identified by using a threshold process, and PV metrics are also calculated, such as the location, amplitude, interval, onset, offset, polarity, etc. Second, based on PV sequences and all of the QRS complex metrics in the time window, every PV is classified as an effective or noisy type. There is an established principle that corresponding PV parts of QRS complexes are considered effective types. Also, based on the location of each QRS complex, the probable P wave and T wave are searched and verified by using basic morphologic judgment and statistical history information. If the P wave or T wave is valid, the corresponding PV part should be classified as effective. Finally, remaining PV parts are considered noisy types.

(4) Data blank-filtering

The effective segments obtained are flattened by using a blank-filtering method. The key of the method is to determine a blank value which is the onset amplitude value of corresponding QRS complexes. After the blank-filtering, effective segments are smoothed to flat segments, and then the remaining pieces consist of baseline wander, noisy PVs or other noisy signals (Figure 2).

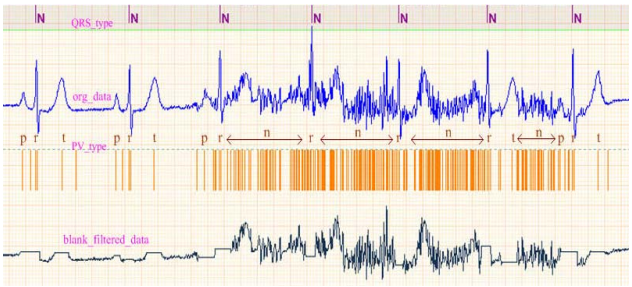


Figure 2. An example of data after the PV classification and blank-filtering process. PVs are classified into four types: n (noise), p (P wave), r (QRS-complex), and t (T wave). The n's represent noisy segments, and the others are the effective segments.

(5) SNR evaluation for each QRS

The signal to noise ratio (SNR) of each QRS complex is calculated by using the ratio of the amplitude of QRS complexes to the nearby disturbance amplitude which can be obtained using the blank-filtered data. The SNR ratio is quantified into 3 levels for simplification: 0~2, where level 0 represents the highest and level 2 the lowest.

(6) SQI assessment

The SQI is synthesized and quantified based on the following factors: a) the SNR levels of all the QRS complexes, b) PV features, c) the sum of saturation data

points, and d) some special signal status, such as flat-line segment or ventricular fibrillation incident (from the MECG algorithm).

When another synchronous ECG channel is available, a combined SQI score is calculated. If one channel is very noisy and another channel is noise free, the combined SQI score should represent good signal quality.

2.3. SQI and MECG algorithm fusion

Faulty QRS detection and classification caused by noise might lead to incorrect HR and false alarm results. The fusion process aims to use the SQI score to improve the classification of VPB-like QRS complexes, enhance HR value robustness, and suppress false alarms.

(1) Improvement of QRS classification

The corresponding combined SQI score should be used to correct the QRS classification results. For each channel, the channel's SQI level is used to determine if modification of the corresponding ventricular type is needed. If the SQI level is larger than 2, ventricular type can be changed from VPB to normal directly. If the SQI level is 2 and the SNR level of the related QRS complex is 1 or 2, then the corresponding ventricular type can be changed also.

(2) Enhancement of HR value

The instantaneous HR value is updated beat by beat and is easily affected by faulty beat detection due to noise. If the SQI level is larger than 2, the corresponding beat detected is considered invalid, and the RR interval should not be updated. Therefore, the HR output becomes more robust.

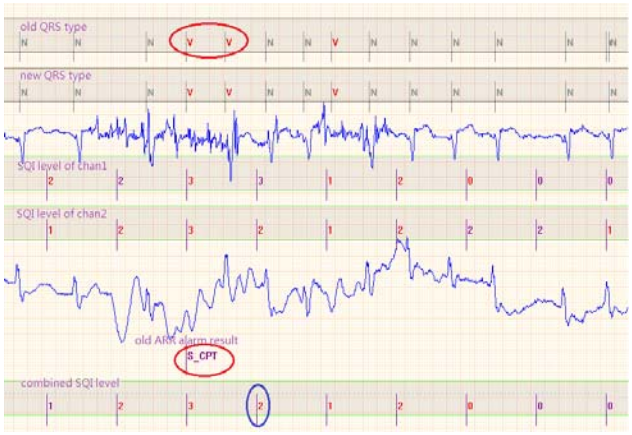


Figure 3. An example of false ARR alarm suppression. Without fusion of the SQI level, the two consecutive VPBs will trigger the CPT alarm (see "old ARR alarm result"), where "S_" indicates the starting position of the alarm occurrence. With the new algorithm, since the combined SQI level of the starting position of the CPT alarm is 2, the false alarm is suppressed.

(3) Suppression of false alarms

ARR alarms related to HR and VPBs are checked for their reliability by using the SQI level. A check range is formed by referring to the occurrence conditions of each alarm. If more than 50% of the SQI levels in the range are larger than level 1, the alarm is suspicious and should be suppressed. An example can be seen in Figure 3.

However, there is no effect or suppression for some lethal ARR types (such as Vent.Fib/Vtac, Vent.Tachy, Vent.Brady, Vent.Rhythm).

3. Results

3.1. Database description

Table 1 shows the databases used in the study. DB1 contains the standard AHA Database with 78 records and MIT-BIH Arrhythmia Database with 44 records. DB2, DB3, DB4 were collected by using Mindray's patient monitors from 4 hospitals; mostly in ICUs, CCUs, PICUs and NICUs.

Table 1. Summary of training and test database

Dataset	DB1	DB2	DB3	DB4
Use	Training	Training	Test	Test
Cases	122	985	119	192
Hours	67	53	119	192
Patients	A	A	A/P/N /Paced	A/P/N /Paced
Data quality	Mixed	Mixed but without ARR	More noisy	Relatively clean

Acronyms: A: Adult, P: Pediatric, N: Neonatal

3.2. Evaluation methods

The MECG algorithm (old) and the MECG algorithm with SQI (new) are compared to consider performance.

The performance of QRS detection and classification is evaluated by using the beat-by-beat comparison method from ANSI/AAMI EC57: 2012 [5].

The HR enhancement performance is evaluated by comparing HR values of the two algorithms. If the difference of HR values in the same time exceeds 10 beats per minute or 10% of the reference value (the old algorithm used as the reference), an unmatched status will be marked and a review process will be performed to calculate the false HR values.

The performance of FA suppression is evaluated by confirming ARR alarms from the two algorithms. As a training set, DB2 contains no true ARR alarms. As a test set, DB3 is very noisy, and all ARR events of the two algorithms should be confirmed so that the false and missed alarms can be counted completely; DB4 is relatively clean, and mostly the ARR alarms are true, thus only unmatched ARR alarms are confirmed.

3.3. QRS performance

The beat-by-beat comparison results of DB1 are presented in Table 2, which shows the QRS detection and classification performance is almost the same for the two algorithms.

Table 2. QRS Performances of two algorithms

Database	AHA		MIT-BIH	
Algorithm	old	new	old	new
QRS Se (%)	99.89	99.88	99.89	99.89
QRS +P (%)	99.95	99.95	99.85	99.85
PVC Se (%)	94.86	94.76	94.51	94.43
PVC +P (%)	98.67	98.68	97.00	97.03
PVC FPR (%)	0.130	0.129	0.222	0.219

3.4. HR enhancement performance

Table 3 lists the HR Performance. The results show the number of incorrect HR values reduces significantly.

Table 3. HR Performance of two algorithms

Database	DB3		DB4		Total	
Algorithm	old	new	old	new	old	new
Total unmatched	1087	1087	345	345	1432	1432
False	546	51	105	13	651	64
Reduction ratio (%)	45.54		26.66		40.99	

3.5. FA suppression performance

Table 4 and Table 5 summarize the FA suppression performance results, which show that false alarms are effectively suppressed by using the new algorithm. The suppression ratio also in some way reflects the reduction ratio of average false alarm times per hour.

Table 4. ARR Alarm Performance for Training Dataset

Database	DB2	
Algorithm	old	new
True ARR	0	0
False ARR	411	290
FA suppression ratio (%)	29.44	

Table 5. ARR Alarm Performance for Test Dataset

Database	DB3		DB4	
Algorithm	old	new	old	new
True ARR	1784	1833	565	668
False ARR	832	398	180	99
Missed ARR	3	11	24	10
False/(True + False) (%)	31.8	17.84	24.16	12.91
FA suppression ratio (%)	52.16		47.34	

4. Discussion and conclusions

DB3 is noisy and close to the monitoring circumstances in CCU, where most patients are conscious and may move frequently. DB4 is relatively clean and it can reflect the typical circumstances in ICU, where most patients are unconscious and ECG signals are relatively clean. Based on the fusion of SQI analysis and the MECG algorithm, without increasing the risk of missed alarms, false HR and ARR alarms can be effectively suppressed.

Table 5 shows some missed alarms for both algorithms. For the new algorithm, every missed alarm was manually checked. A missed alarm is considered nontrivial if it lasts over 5 seconds or involves at least 3 VPBs. After review, however, no nontrivial cases occurred.

From what has been discussed above, the new technology highly depends on the accuracy of QRS detection and SQI metrics. To minimize the dependency, future work will be based on the homology of ECG, invasive blood pressure, pulse oximetry signals and/or other homodynamic parameters to improve the performance for reducing and/or eliminate false and non-actionable alarms and providing a safer health care environment.

References

[1] Kowalczyk L. Patient alarms often unheard, unheeded. 2011.

[2] Society for Technology in Anesthesia. Alarm fatigue. Society for Technology in Anesthesia Annual Meeting, Orlando 2014.

[3] Behar J, Oster J, Li Q, Clifford GD. ECG signal quality during arrhythmia and its application to false alarm reduction. IEEE Trans Biomed Eng 2013; BME-60: 1660-1666.

[4] GE Marquette Medical Systems, Inc. System and method for selecting physiological data from a plurality of physiological data sources. US 2003/0009106 A1, 2003.

[5] American National Standard ANSI/AAMI EC57:2012. Testing and reporting performance results of cardiac rhythm and ST segment measurement algorithms. Arlington, Virginia: Association for the Advancement of Medical Instrumentation (AAMI), 2012.

Address for correspondence:

Zehui Sun
Mindray Building
Keji 12th Road South, High-Tech Industrial Park,
Nanshan, Shenzhen, China
sunzehui@mindray.com