Reducing False Arrhythmia Alarms in the ICU by Hilbert QRS Detection

Nadi Sadr, Jacqueline Huvanandana, Doan Trang Nguyen, Chandan Kalra, Alistair McEwan, Philip de Chazal

School of Electrical and Information Engineering, University of Sydney, Australia

Abstract

In this study, we develop algorithms that reduce the arrhythmia false alarms in the ICU by processing the four signals of Photoplethysmography (PPG), arterial blood pressure (ABP), ECG Lead II, and Augmented right arm ECG. Our algorithms detect five arrhythmias including asystole, extreme bradycardia, extreme tachycardia, ventricular tachycardia (VT), and ventricular flutter or fibrillation (VF). Real time algorithm is provided.

Our processing proceeded as follows. Firstly, preprocessing was applied to the ECG signals by two median filters in order to remove the baseline wander and high-frequency noise. Then a Hilbert-transform based QRS detector algorithm was used to detect R waves from the ECG signals. Following this, RR intervals were calculated from the available ECG signals. Pulse onset points of the pulsatile signals (PPG and ABP) were also detected and the signal quality index (SQI) of the four signals was measured. The ECG based RR intervals were combined with the pulsatile signal based RR intervals using the algorithms provided by the CinC2015 competition organizers. The combined RR intervals were thresholded at the clinically important values for the five arrhythmias. Template matching was used to detect ventricular tachycardia (VT) and power spectrum of ECG signals and identifying the VF frequency components employed to investigate ventricular fibrillation.

Our highest overall result was a 98% True Positive Rate (TPR), 66% True Negative Rate (TNR) with a score of 74.03% for the retrospective algorithm. For the real-time algorithm, we achieved a 98% TPR, 65% TNR and a score of 69.92%.

1. Introduction

False alarms in medical applications are warning alerts from monitoring systems which have not originated from clinical conditions [1] and they may result in disturbing the patients in an intensive care unit (ICU) setting and the attending clinical staff [2]. Alarms can be categorized into technically correct or false categories. As alarms could be technically correct but clinically irrelevant (such as improper threshold), they can be further categorised into clinically relevant and not relevant categories [3]. Over 80% of alarms in ICUs are false alarms [4]. These alarms were basically developed to detect the life-threatening conditions and save the patient's life. These false alarms would distort and interrupt treatments and care systems and may disrupt the monitoring in severe situations [3]. The most dangerous consequence of false alarms is the desensitisation of clinical staff to the alarms and their consequent ignoring or delayed reaction to true alarms [2]. This study aims to detect the severe alarm situations comprised of ventricular tachycardia (VT), ventricular fibrillation or flutter (VF), tachycardia, bradycardia and asystole. In this paper, we consider different signal processing methods to minimise the false alarms [5].

2. Input data

The dataset comprised of 750 recordings as training set and 500 hidden recordings as test set. There are four signals including two ECG leads II and aVr and one or both pulsatile waveforms of photoplethysmogram (PPG) and arterial blood pressure (ABP). There are 1250 arrhythmia alarms in the dataset randomly chosen from four hospitals in US and Europe. The experts labelled the alarms as "true", "false", or "impossible to tell" after reviewing the alarms. Those records with the labels agreed by the majority of annotators were chosen as the input data.

There is at least five minutes interval between alarms. The alarm for each record was at the fifth minute from the beginning of the record. The alarms originated from an arrhythmia event happening within ten seconds of the alarm. Each record has been labelled with one alarm and any other arrhythmia during the five minutes prior to the alarm was not annotated. In order to diminish transferring an error from one alarm to the next alarm, the repeated alarms and information from earlier alarms are not used. The signals were resampled to 250 Hz, 12 bit. Moreover, FIR band pass filter of 0.05 to 40 Hz and common notch filters were implemented to eliminate noise although pacemaker and other noise artefacts still are visible in ECG signals. The pulsatile signals also may have been damaged by movement artefacts, sensor disconnection, line flush, coagulation and other noises.

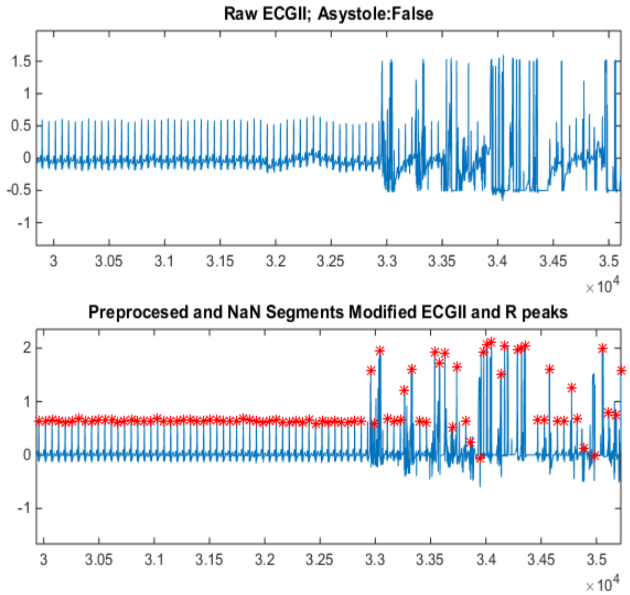

Figure 1. A sample ECG II signal and the result from applying preprocessing.

3. ECG signals

Each recording contains lead II and/or lead aVr. There are 33 recordings in the training set containing zero or missing values in the majority of the ECG signals.

Therefore, preprocessing was the first stage of signal processing before implementing ECG recordings. Signal noise was removed with filters. Next, QRS complexes were detected and then followed by QRS revision, RR-interval calculation, and feature extraction.

ECG signals are effective to detect life-threatening situations such as VT, VF, tachycardia, and bradycardia.

3.1. Signal preprocessing

Preprocessing has been applied to the ECG recordings as the first stage of data processing as shown in Fig. 1. This stage provides noise removal and filtering. Then, QRS detection, QRS revision and cleaning, and RR-interval computation were employed.

Baseline wander noise was removed by two median filters with 200-ms and 600-ms width and high frequency noise filtering was applied [6].

Then, the ECG signals with a large number of zeros and missing values were removed from the input signals. A number of features were used for signal quality investigation. The ECG signals with zero or missing values were detected and signal integration was used for the intervals with missing values.

3.2. QRS detection

After applying preprocessing to the ECG signals, QRS points were detected by a Hilbert transform based detection algorithm. A visual check of the resulting QRS detections revealed that the QRS detector identified almost all QRS detections except for the QRS points after missing values occurring in the ECG signals.

To solve this issue, the missing values were detected and replaced with zero values. With this step in place, the algorithm detected the QRS points after the missing values successfully. After collecting the QRS detection points, the replaced zeros were removed for those intervals. Finally, the RR-intervals were calculated by determining the time difference between adjacent QRS detections.

3.3. ECG SQI

Signal quality index (SQI) of the ECG was used to evaluate the quality of signal before utilizing the signal. Three ECG measures were checked for SQI. First, maximum RR-interval for each signal was calculated. The maximum RR-interval was compared to the threshold of six seconds. Thus, the ECG signal was used for false alarm detection, if the maximum RR-interval was between zero and six seconds. Second, the standard deviation of the ECG signal in the segment including the alarm was measured and compared to another threshold. The optimum threshold for standard deviation was chosen to be 0.05. Third, the ECG signal was implemented if the minimum available beats in the signal were 10 beats.

4. Pulsatile signals

One or both ABP and PPG signals were available for the recordings and were used to detect false alarms.

4.1. ABP signal

Three PhysioNet open-source algorithms were used to process the arterial blood pressure (ABP). The ‘wabp’ algorithm was applied to ABP signal to detect the onset points of the pulses in the signal [7]. This algorithm is based on the length transform [8]. The ‘abpfeature’ algorithm was then applied to extract features from ABP signal such as systolic and diastolic pressure, systolic area, and mean pressure at each detected pulse. The ‘jSQI’ algorithm was implemented to investigate the signal quality of each beat of ABP signal. It is based on removing the features and onset points that are not physiologically meaningful. Finally, the RR-intervals were calculated as the difference of the onset points of the pulses in the signal.

4.2. PPG signal

Three PhysioNet open-source algorithms were used to process the photoplethysmogram (PPG) signal. The ‘quantile’ algorithm was applied to partition the signal into three quantiles, (0.05, 0.5, 0.95). The ‘wabp’ was used for onset point detection and was applied to the subtraction of third quantile and first quantile. Then, the RR-intervals were calculated from the onset points. The ‘ppgSQI’ algorithm was used to estimate the signal quality index based on beat template correlation.

5. Decision making

The input data was segmented according to the alarm position. The aim was to detect the false alarms in a real-time manner and without any information after the alarm. The alarms occurred at the fifth minute from the start of the signal. To ensure that the data segment contained the alarm, the segment was assigned to 16 seconds before the alarm up to the alarm. Then, the beats of all of the available signals for each segment were found. Finally, the heart rate was measured from each available signal and the maximum RR-intervals were calculated.

5.1. Signal integration

When various physiological signals are used, integrating methods could enhance the performance. Signal fusion was the main aspect of the previous Computing in Cardiology Challenge in 2014 [9]. There were different methods employed including SQI based method [9] which was modified for this algorithm.

In this study, ECG signals were firstly employed as the most reliable signal. In fact, ECG signals were available for most of the recordings in train set and the Hilbert QRS detector resulted in reliable QRS complexes. The only issue was caused by the intervals with missing values.

In this approach, the mean value of RR intervals of each available signal was measured. The median of the RR-interval mean values was calculated and assigned as a robust RR-interval. Then, the algorithm started with analysing the ECG II signal. If an RR interval was greater than twice the robust RR-interval, the algorithm switched to the ECG aVr signal, if available. The same algorithm repeated for the second ECG signal. If it wasn’t available, the comparison takes place for the pulsatile signals. If the algorithm detected the same RR-interval for all of the signals, the RR-interval is accepted as a correct RR-interval. Otherwise, it was assigned as not physiologically plausible and was replaced by the minimum RR-interval derived from the other available signals.

5.2. Asystole

Asystole was defined as no heart beat for at least four seconds. Therefore, the minimum Asystole threshold was set to four seconds with a tolerance of 0.5. First, the algorithm checked if the ECG II was available and if the signal quality was adequate, the maximum RR-interval was compared to the asystole threshold. If it was greater, then the alarm was set to False. If the ECG II was not available or the signal quality was not in the proper range, then the algorithm checked the same for ECG aVr.

Then, the algorithm will go through ABP signal and then PPG signal to check the maximum RR-interval compared to the threshold.

5.3. Bradycardia

Bradycardia was defined by the heart rates of less than 40 bpm for five consecutive beats. Therefore, minimum heart rate for each five beats through the segment was measured and if it passed this threshold, the alarm was set to false. The SQI threshold for pulsatile signals set to 0.9.

5.4. Tachycardia

Tachycardia occurs when heart rate elevates to more than 140 bpm for 17 consecutive beats. The algorithm starts with ECG II. If the SQI of ECG signal was in the appropriate range, the heart rate values were set to the values of ECG heart rate. Then, the algorithm repeated the same approach for the other signals and thresholding was applied.

5.5. Ventricular tachycardia

Ventricular tachycardia (VT) defined as five or more ventricular beats with heart rate higher than 100 bpm. The approach for detecting Ventricular Tachycardia (VT) was based on a template subtraction process, adopting the first waveform in the series as the template against which subsequent waveforms would be compared. A presence of greater or equal to four 'irregular' waveforms that varied on average from the template by more than the standard deviation constituted the detection of VT.

5.6. Ventricular flutter or fibrillation

Ventricular Flutter (VF) was assumed to be fibrillatory, flutter, or oscillatory waveform for at least four seconds. To detect VF, firstly the SQI of the ECG signals and pulsatile signals were evaluated and the adequate beats are used for heart rate. Then, the spectrum of the heart rate was calculated using Discrete Fourier transform (DFT) and its amplitude was used to measure power of the signal. If the maximum heart rate is less than VF maximum threshold, the alarm is true. Otherwise, if it is greater than minimum VF threshold, the alarm set to false.

Table 1. Results of scores and true positive rates and true negative rate from training set.

Training set results from final submission

	TP	FP	FN	TN	TPR (%)	TNR(%)	Score(%)
Asystole:	0.164	0.057	0.016	0.762	91.11	93.04	87.11
Bradycardia:	0.517	0.247	0	0.236	100	48.86	75.3
Tachycardia:	0.936	0.043	0	0.021	100	32.81	95.7
VentFlutter:	0.103	0.19	0	0.707	100	78.82	81.0
VentTach:	0.246	0.361	0.015	0.378	94.25	51.15	58.87
Average:	0.393	0.18	0.006	0.421	98.50	70.05	79.49
Gross:	0.383	0.225	0.009	0.383	97.70	62.99	73.94

By observing the six positive VF classes in the training set with the energy in a frequency range of 10-20Hz which was lower in non-VF cases, power spectrum was chosen as a proper feature. If the power of the ECG spectrum was less than VF power threshold of 100, the alarm is labeled as true. If the heart rate was consistently less than 150 bpm, then it was "unlikely" to be irregular and wasn't detected as VF. Moreover, if heart rate was above 290 bpm, it was flagged as "irregular or VF". The VF maximum heart rate threshold was set to 150, minimum threshold assumed to be 300 and minimum VF beats needed for evaluation was considered to be 10.

6. Results and discussion

Our results from training set are shown in Table 1. The highest scores of train set obtained in tachycardia of about 97% and 87% for Asystole and 75% for bradycardia. The average score was 79%. The results for test set are shown in Table 2 with highest score of 99% for Tachycardia, 82% for Asystole, and 71% for bradycardia. The real-time score was 69.9% and retrospective score was 74%.

Our algorithm for detecting false alarms for tachycardia and asystole is working appropriately and it is working well for bradycardia and VF. Further work is required to improve the detection of VF and VT. Other signal fusion techniques including modification of delay between QRS points of ABP and ECG signals may enhance the results. Also the threshold based decision algorithms considered in this study could be replaced by machine learning algorithms (e.g support vector machines) and may improve the algorithm performance.

Table 2. Results of final submission from test set

	TPR	TNR	Score
Asystole	78%	93%	82.46%
Bradycardia	100%	52%	71.13%
Tachycardia	100%	80%	99.10%
VF	100%	59%	65.52%
VT	91%	55%	58.07%
Real-time	95%	65%	69.92%
Retrospective	98%	66%	74.03%

Acknowledgments

This research was supported by the Australian Research Council grant number FT110101098 and by the USyd scholarship support program.

References

[1] Chambrin MC, Ravaux P, Calvelo-Aros D, Jaborska A, Chopin C, Boniface B. , Multicentric study of monitoring alarms in the adult intensive care unit (ICU): a descriptive analysis, Intensive Care Med 1999; pp. 25(12):1360-6.

[2] G. D. Clifford, a. Aboukhalil, J. X. Sun, W. Zong, B. a. Janz, G. B. Moody, and R. G. Mark, "Using the blood pressure waveform to reduce critical false ECG alarms," 2006 Comput. Cardiol., pp. 829–832.

[3] S.T. Lawless, Crying wolf: false alarms in a pediatric intensive care unit, Crit Care Med 1994; 22(6), pp. 981-985.

[4] F. Schmid, M. S. Goepfert, and D. A. Reuter, "Patient monitoring alarms in the ICU and in the operating room," Crit. Care, 2013; vol. 17, no. 216, pp. 2–7.

[5] NV Thakor, YS Zhu, KY Pan, "Ventricular tachycardia and fibrillation detection by a sequential hypothesis testing algorithm," IEEE Trans. Biomed. Eng., 1990;37:837–843.

[6] P. de Chazal, C. Heneghan, E. Sheridan, R. Reilly, P. Nolan, and M. O'Malley, "Automated processing of the single-lead electrocardiogram for the detection of obstructive sleep apnoea.," IEEE Trans. Biomed. Eng 2003;50:686–96.

[7] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals," Circulation, 2000; vol. 13;101, no. 23, pp. E215–20.

[8] W. Zong, T. Heldt, G. B. Moody, and R. G. Mark, "An open-source algorithm to detect onset of arterial blood pressure pulses," Comput. Cardiol. 2003, pp. 259–262.

[9] AEW Johnson, J Behar, F Andreotti, GD Clifford, J Oster, "Multimodal heart beat detection using signal quality indices," Physiol. Meas., 2015;36:1665–1677.

Nadi Sadr nadi.sadr@sydney.edu.au

Electrical and Information Eng, University of Sydney, Australia