A Multimodal Approach to Reduce False Arrhythmia Alarms in the Intensive Care Unit

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Abstract

As part of the 2015 PhysioNet/CinC Challenge, this work aims at lowering the number of false alarms, which are a persistent concern in the intensive care unit. The multimodal database consists of 1250 life-threatening alarm recordings, each categorized as a bradycardia, tachycardia, asystole, ventricular tachycardia or ventricular flutter/fibrillation arrhythmia. Based on the quality of available signals, heart rate was either estimated from pulsatile waveforms (photoplethysmogram and/or arterial blood pressure) using an adaptive frequency tracking algorithm or computed from ECGs using an adaptive mathematical morphology approach. Furthermore, we introduced a supplementary measure based on the spectral purity of the ECGs to determine if a ventricular tachycardia or flutter/fibrillation arrhythmia has taken place. Finally, alarm veracity was determined based on a set of decision rules on heart rate and spectral purity values. Our method achieved overall scores of 76.11 and 85.04 on the real-time and retrospective subsets, respectively.

1. Introduction

High false alarm (FA) rates are a persistent concern in the Intensive Care Unit (ICU) [1]. Limited performance of ICU monitoring devices results in the desensitization of the medical staff and longer response times, which can have severe repercussions. In addition, the noise disturbances that are induced may lead to sleep deprivation for the patients. Several studies have been conducted to reduce the number of FAs, which are mainly caused by artifacts and short fluctuations in the signals. For instance, in [2], a recursive two-stage median filter was used for the tracking of heart rate (HR) trends and the removal of artifacts. The resulting proportion of true alarms increased from 12% to 49% during postoperative haemodynamic monitoring of cardiac patients. Another possible course of action to facilitate the rejection of FAs is to analyze cardiovascular signals from independent sources. For example the arterial blood pressure (ABP) waveform was employed in [3] to suppress FAs for different types of arrhythmia. In their study, an overall FA suppression of 59.7% was achieved while preserving the true alarm rate, except in case of ventricular tachycardia. Since the quality of the waveforms is a major issue in most cases, the development of signal quality indexes (SQIs) can contribute to the improvement of the decision making process [4]. For instance, the validity of an alarm can be determined on the basis of the ABP waveform when its SQI exceeds a certain threshold [5]. Another important issue in this context is the processing of ventricular arrhythmia alarms. Previous studies have pointed out the challenges linked to the classification of ventricular tachycardia and ventricular fibrillation episodes [3, 6, 7]. In these cases, accurate HR values are not sufficient to suppress FAs and additional features are required. For example, an approach based on wavelet transform was investigated in [7] to reduce the number of false ventricular tachycardia alarms. An FA suppression of 21% on the PhysioNet MIMIC II dataset was achieved.

This study aims at reducing the incidence of FAs in the ICU. Our approach relies on robust adaptive signal processing techniques in order to extract accurate HR values from the ECG, photoplethysmogram (PPG) and ABP waveforms. Furthermore, in case of ventricular arrhythmia, we use a supplementary measure based on the spectral purity of ECGs in order to investigate the veracity of the alarm.

2. Methods

For this challenge, a multimodal database with various life-threatening events was used. More details about this database can be found in [1]. Based on the available channels, various features were extracted and employed to determine whether a true arrhythmia has taken place when the alarm was triggered. Figure 1 illustrates the block diagram of our method. The features of interest were obtained using the following techniques.

HR estimation using ECG: Observations of ECG channels in the training set indicated that the available ECG

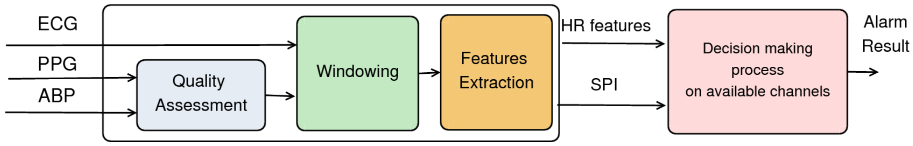

Figure 1. The general framework to determine the validity of an alarm.

waveforms present various perturbations such as clipping of the QRS complexes, large baseline drift modulation and high muscle activity noises. Therefore, a robust heartbeat detection algorithm is needed in order to have a reliable FA suppression. To this end we used a QRS complex extraction algorithm, called AMM, proposed in [8]. Authors propose a mathematical morphology approach with an adaptive structuring element. In this approach, the structuring element is continuously updated based on morphological features extracted from the detected QRS complexes. At the same time, AMM avoids excessive use of arbitrary thresholds, and is robust against baseline drift and other perturbations. Furthermore, it offers low computational cost in the order of $O(n)$. Figure 2, demonstrates the performance of AMM on a low quality signal from the training dataset.

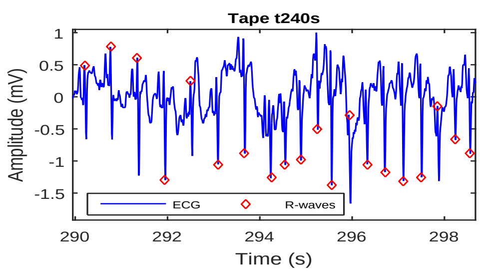

Figure 2. Performance of AMM on a tape from the training set.

ECG spectral purity index: Ventricular arrhythmia lead to morphological changes on QRS complexes. It can be observed that ECGs become closer to a sinusoid during these episodes, due to a widening of the QRS complexes. In order to quantify this behavior, the spectral purity index (SPI) [9] was used. It is defined as the running squared second-order spectral moment divided by the product of the running total power and fourth-order spectral moment. This measure, which ranges between zero and one, indicates how well the signal of interest can be described by a single frequency. In this study, the SPI of the available ECG channels was measured in case of ventricular tachycardia and ventricular flutter/fibrillation alarms. Higher SPIs were expected in case of true arrhythmia. ECG signals were first down-sampled to 35 Hz and smoothed using a 5-sample moving average filter. Then, a 2-second sliding window was used to estimate spectral moments in time domain, as proposed in [10]. Figure 3 illustrates an example of the SPI during a true ventricular tachycardia alarm.

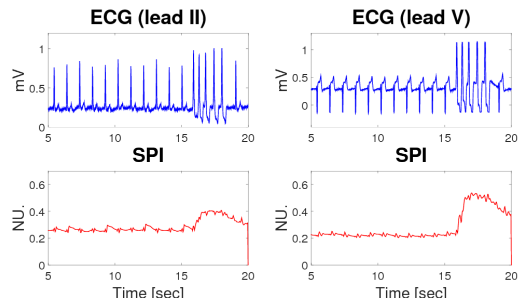

Figure 3. SPI during a true ventricular tachycardia episode.

PPG and ABP signal quality assessment: In order to assess the quality of the PPG and ABP signals, we used respectively the *ppgSQI* and the *jSQI* algorithms, provided for this challenge [1]. Based on the detected heartbeats, these algorithms compute the features needed to estimate signal quality. Heartbeats were detected using the algorithm described in [11]. The resulting signal quality indexes (SQIs), that ranged between zero and one, determined whether PPG/ABP waveforms should be analyzed.

HR estimation using PPG and ABP: This paper proposes an HR estimation method based on an adaptive frequency tracking algorithm. The basic algorithm, described in [12], is an oscillator based mean square error band-pass filter (OSC-ANF). In this algorithm, the central frequency of the filter is constantly updated to follow the instantaneous frequency of the signal. The underlying adaptive mechanism involves a cost function that is derived from the oscillator equation. This OSC-ANF algorithm was extended to multi-signal (OSC-ANF-W) [13], in order to track the common frequency component present in multiple input signals. More specifically, all signals are filtered by an adaptive band-pass filter in order to calculate individual frequency estimates. Then, a global frequency estimate is computed by weighting individual estimates. In addition, the OSC-ANF-W was further expanded to work in the complex domain (OSC-ANFc-W) [14], as it was empirically observed that using the complex domain approach improved the frequency tracking on some signals. In this study, an 8th-order Butterworth low-pass filter with a cutoff frequency of 5 Hz is first applied to the PPG signals. Then, the baseline of PPG and ABP signals is removed by subtracting the mean of the upper and lower envelopes that are estimated using maximum/minimum detection on a sliding window. Finally, in case the SQIs of the PPG/ABP signal reach a certain threshold, the OSC-ANF-W/OSC-ANFc-W algorithms are used to compute the instantaneous HR. To have a more robust estimation, smoothed versions of the input signals, by means of moving average of length l, are also fed to the algorithm. Furthermore, the parameters required for adaptive frequency tracking were selected in order to optimize HR estimation. These parameters are summarized in Table 1, where f_{re} indicates the re-sampling frequency, β is related to the bandwidth of the adaptive band-pass filter and δ is a forgetting factor.

Arrhythmia	Algorithm	f_{re} [Hz]	l [samples]	β	δ
Asystole	OSC-ANFc-W	15	3,5,7,11	0.8	0.8
Extreme Bradycardia	OSC-ANFc-W.	15	3	0.87	0.87
Extreme Tachycardia	OSC-ANF-W	35	5,7	0.89	0.9
Ventricular Tachycardia	OSC-ANF-W	35	7	0.89	0.9

Table 1. Algorithms and selected parameters for HR estimation using PPG and/or ABP waveforms.

Arrhythmia alarm processing: Each type of arrhythmia was processed separately and various features derived from HR and SPI values were extracted. Details about the waveforms, the extracted features, the windowing and the thresholds are provided in Table 2. PPG/ABP waveforms were processed when the corresponding SQI was above 0.6, except for extreme bradycardia alarms in which cases this threshold was set to 0.5.

3. Results

A hidden test set of 500 records (extended by 250 records for phase II) was used to assess the performance of the presented method. Details about the distribution of alarms and the scoring can be found in [1]. Tables 3 and 4 display the results obtained for the phases I and II of this challenge, respectively. Our method achieved an overall score of 72.95 in the first phase, with an overall true positive rate (TRP) of 94% and an overall true negative rate (TNR) of 71%. After some minor modifications, better scores were reached in the second phase. In this case, real-time and retrospective scores of 76.11 and 85.04 were reported, with TNRs of 77% and 80%.

4. Discussion

Accurate HR values were extracted from PPG and ABP signals using adaptive frequency tracking. Importantly, as the use of heartbeat detection techniques was avoided, our method allowed us to have a robust HR estimation for moderate quality signals, i.e. SQIs above 0.5 or 0.6. This makes our approach attractive because the existing methods involving ABP/PPG heartbeat detection require good quality waveforms, i.e. SQI around 0.9 [1, 5]. We decided to mostly rely on ECG analysis in case of ventricular arrhythmia because these arrhythmia display a more pronounced signature on ECG than on the pulsatile signals. Furthermore, spectral purity of the ECG seems to be a very promising candidate to characterize the morphological changes related to ventricular arrhythmia. To the best of our knowledge, SPI is used in this context for the first time. We decided to keep the decision-making process straightforward by setting physiologically interpretable thresholds on the extracted features. However, more elaborated approaches such as machine learning or fuzzy logic techniques could be employed to improve the performance. It must be noted that the heartbeat detection on ECG signals was helpful in the elimination of false asystole and bradycardia alarms. A limitation of this study lies in the absence of quality assessment for ECG signals which could help in improving the overall robustness of the proposed method. Finally, it should be mentioned that components of our approach can be implemented in real-time/online scenarios at a low computational cost. This makes our method suitable and efficient in the reduction of FAs, as confirmed by the overall TNRs of 77% and 80%.

Arrhythmia	TPR	TNR	Score
Asystole	92%	78%	76.42
Bradycardia	96%	66%	73.53
Tachycardia	96%	60%	80.00
Ventricular Flutter/Fibrillation	83%	88%	79.55
Ventricular Tachycardia	93%	65%	67.38
Real-time	**93%**	**65%**	**68.15**
Retrospective	**95%**	**77%**	**77.82**
Overall	**94%**	**71%**	**72.95**

Table 3. Results for phase I.

Arrhythmia	TPR	TNR	Score
Asystole	83%	88%	81.44
Bradycardia	100%	71%	82.47
Tachycardia	97%	60%	86.18
Ventricular Flutter/Fibrillation	89%	94%	87.10
Ventricular Tachycardia	94%	72%	72.75
Real-time	**94%**	**77%**	**76.11**
Retrospective	**99%**	**80%**	**85.04**

Table 4. Results for phase II.

Acknowledgements

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Table 2. Arrhythmia alarm processing.

Arrhythmia Type	Waveforms	Algorithms	Windowing	Extracted features	Conditions to suppress alarm
Asystole [1]	PPG/ABP	OSC-ANFc-W	5 sec. before alarm (+ 3 sec. after if retrospective)	mean(HR)	LDA [3]
			4 sec. before alarm (+ 2 sec. after if retrospective)	decrease of HR	
	ECG	AMM	consider 20 sec. before alarm	max(RR intervals)	<3.5 [s]
Extreme Bradycardia	PPG/ABP	OSC-ANFc-W	5 sec. before alarm	mean(HR) median(HR)	>54 [bpm] >54 [bpm] &
	ECG [2]	AMM	consider 16 sec. before alarm	min(HR 5 cons. beats)	>40 [bpm]
Extreme Tachycardia	PPG/ABP	OSC-ANF-W	4 sec. before alarm	mean(HR)	<90 [bpm]
Ventricular Tachycardia	PPG/ABP	OSC-ANF-W	consider 15 sec. before alarm	max(averaged HR) on 3 sec. sliding window	<90 [bpm] &
			consider 15 sec. before alarm	min(averaged HR) on 3 sec. sliding window	>60 [bpm]
	ECG	SPI measurement	consider 15 sec. before alarm	max(averaged SPI) on 3 sec. sliding window	<0.25/ 0.36 [4]
			consider 15 sec. before alarm	max(SPI increase)	<0.012/ 0.2 [4]
Ventricular Flutter/Fib	ECG	SPI measurement	consider 10 sec. before alarm	max(averaged SPI) on 3 sec. sliding window	<0.63

[1] A decision about alarm validity is made for each waveform, then a voting system is used to make the final decision.
[2] ECGs are used only when the SQIs of ABP and PPG are below 0.5.
[3] Linear Discriminant Analysis. False negative cost is considered as five times larger than that of false positive.
[4] The three independent conditions are: (max(SPI) <0.25), (max(SPI increase) <0.012) and (max(SPI) <0.36 & max(SPI increase) <0.2).

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