Reducing False Arrhythmia Alarms in the ICU

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Abstract

This study assessed the feasibility of using multimodal data, namely ECG, ABP and PLETH for reducing the incidence of false alarms in the Intensive Care Unit (ICU) for the PhysioNet/Computing in Cardiology 2015 Challenge. Our approach relies on the annotation of heartbeats using all available channels for each alarm recording. In addition, we also combine ECG and ABP/PLETH channels to create additional signals for analysis. The heartbeat annotations are performed using the gqrs and wabp routines in the WFDB toolbox as well as our in-house algorithm. For ventricular tachycardia alarms, the morphology of the ECG signals for a specified window centered on the annotated heartbeats are also analyzed. Subsequently, the intervals between heartbeats are computed for each channel and for the combined signals. A majority voting scheme with an alarm-specified threshold optimized to the training dataset is used to determine if the triggered alarm is a true or false alarm.

1. Introduction

Detection of false arrhythmia alarms in the Intensive Care Units (ICU) remains a challenging task as there could be multiple triggers of such false alarms such as (i) sporadic, accidental noises arising from motion artifacts, sweating and muscle contractions, or (ii) temporary machine malfunctions such as detachment of electrodes and sensors, that interfere with the heart beat detection. The incidence of such false alarms pose a huge problem in the ICU as it can lead to decrease quality of patient care [1, 2]. This decreased patient care results from clinical staffs exhibiting alarm desensitization and slower response to triggered alarms [3], as well as noise disturbance to both patients and clinical staffs, affecting their rest. In fact, false alarm rates as high as 86% have been reported in the ICU, reflecting the magnitude of this problem. Importantly, between 6% and 40% of ICU alarms have been shown to be true but are clinically insignificant, i.e., they do not require any immediate action [4]. The clinically significant true alarms that are important for patient management accounts for only 2% to 9% of all ICU alarms [5]. As such, the accurate detection and suppression of false alarms in the ICU is an important and on-going area of research.

The objective of this paper is to assess the feasibility of using multimodal data, namely ECG, ABP and PLETH readings from bedside monitors in the ICU for reducing the incidence of false alarms as part of the PhysioNet / Computing in Cardiology 2015 Challenge. For this challenge, the focus is on the accurate detection of life threatening arrhythmias, namely asystole, extreme bradycardia, extreme tachycardia, ventricular tachycardia, and ventricular flutter/fibrillation. If a given ICU alarm does not falls into one of the 5 alarm type specified above, the alarm will be classified as a false alarm. The detailed definitions of these 5 life threatening arrhythmias are found on the PhysioNet / Computing in Cardiology 2015 Challenge website.

The overarching principle of our approach relies on the detection of heartbeats using both the ECG and ABP/PLETH signals. The intervals between heartbeats are then used to determine if the triggered alarm is a true or false alarm. The detailed steps for this alarm classification will be described in the "Methods" section below. For detecting ventricular tachycardia, we modified our approach to include the analysis of the signal waveform centred on the location of the detected heartbeat. This additional analysis is required for detecting ventricular tachycardia as there must be a change in the morphological waveform of the ECG signal for the beat to be labelled as a ventricular beat. Without this additional analysis, the time intervals between heartbeats (heart rate higher than 100 beats per minutes) provide a very loose criterion for detecting ventricular tachycardia, resulting in a high percentage of false positives (false alarms being labelled as true alarms).

2. Methods

Our approach for detection of false alarms depends primarily on the intervals between heartbeats. These intervals are computed using all the available channels given for each record, namely 2 ECG channels, 1 ABP channel (if available) and 1 PLETH channel (if available).

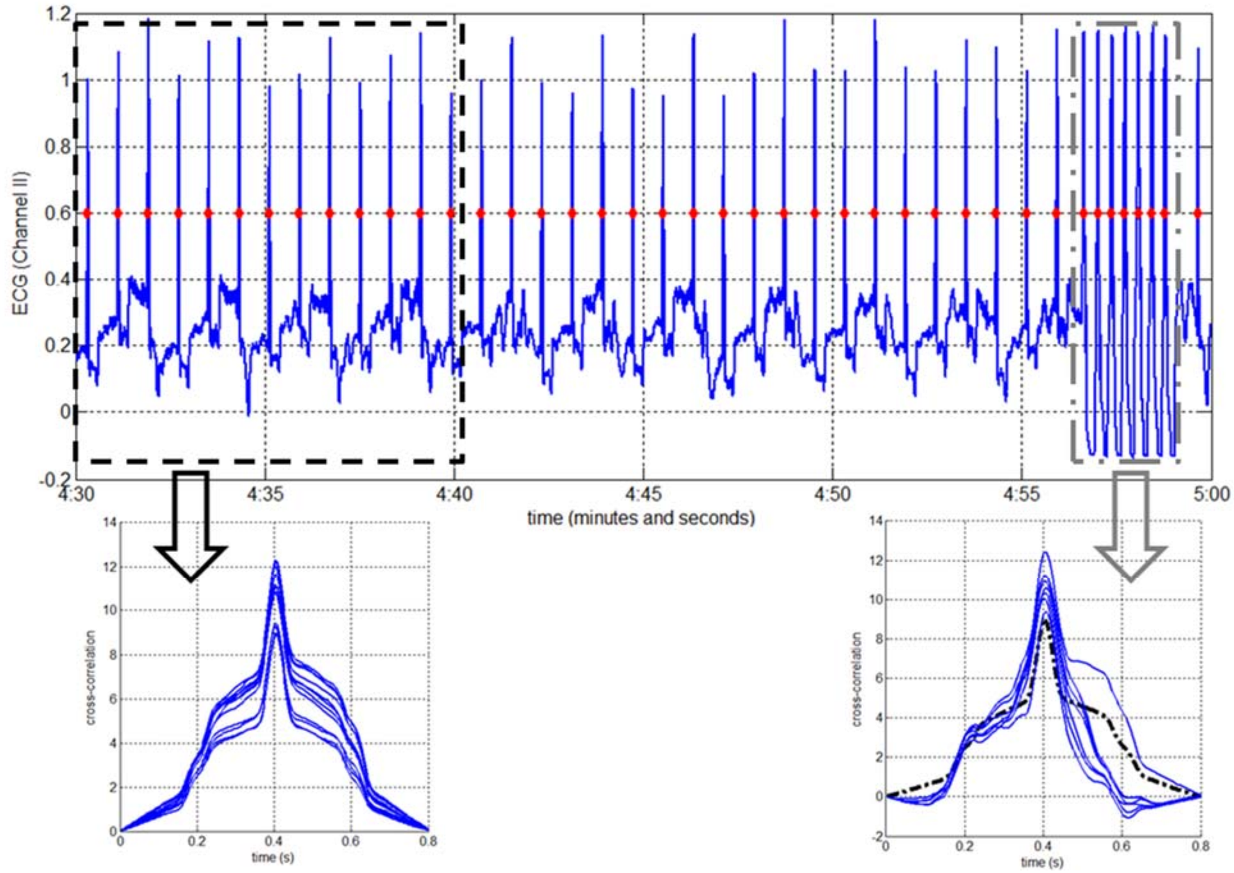

Figure 1. Top panel: ECG signal (channel II) for a typical true VT alarms from the time interval 4:30 to 5:00 with 7 consecutive ventricular beats appearing from 4:55 onwards (boxed out by grey dashed-dotted lines). The annotated heartbeats from the gqrs algorithm are denoted in red diamonds. Bottom panel (left): The cross-correlation profile between the reference ECG waveform and all subsequent ECG waveforms from 4:30 to 4:40 (boxed out by black dashed lines). The cross-correlation shows a symmetric profile; indicating similar ECG morphology. Bottom panel (right): The cross-correlation profile between the reference ECG waveform and the ECG waveforms of the ventricular beats. The cross-correlation shows a non-symmetric profile; indicating differences in ECG morphology. Black dashed-dotted line represents a symmetric profile expected if there were no changes in the ECG morphology.

The rationale for using a multimodal data analysis approach is that certain channels may be prone to noise and/or artifacts in certain alarm types whereas the other channels provide clean signals. Using all channels for decision making can potentially improve the signal-to-noise ratio in our analysis process. The overall workflow of our approach is as summarized below:

(i) Perform signal quality check for the time interval between 4:30 to 5:00 (this interval corresponds to the last 30 seconds for the "real-time" subset) for all available channels. This check is to eliminate signals that are flat (using standard deviation as indicator) or contain numerical artifacts (such as NaN entries). Detection of heartbeats will be performed using only signals that pass this quality check.

(ii) Heartbeat annotation on all available channels (ECG/ABP/PLETH) is performed using multiple annotation methods. List of target channels and annotation methods are as follows (maximum 8 sets of annotations are computed per record):

- ECG-1 (gqrs)
- ECG-2 (gqrs)
- ABP (wabp) - except for VT
- PLETH (wabp) - except for VT
- ECG-1 & ABP (in-house algorithm)
- ECG-1 & PLETH (in-house algorithm)
- ECG-2 & ABP (in-house algorithm)
- ECG-2 & PLETH (in-house algorithm)

(iii) The gqrs and wabp routines in the WFDB toolbox are used to annotate the heartbeats in the ECG signal and ABP/PLETH signals respectively [6, 7]. An in-house algorithm (adapted from last year's challenge) is used to annotate the heartbeats from combinations of ECG and ABP/PLETH signals [8].

(iv) For the in-house algorithm, the delay between the

ECG-annotated heartbeats and ABP/PLETH-annotated heartbeats are computed using a moving average approach and this delay is used to identify the ECG-annotated heartbeats when the ECG signal is noisy.

(v) If the ABP/PLETH signal is noisy, an error-correction is implemented in our in-house algorithm to check the computed delay. The error-correction ensures that within any sampled interval, if either the ECG or ABP/PLETH signal is NOT noisy, the locations of the heartbeat are uniquely identified.

(vi) For each set of annotation, the heartbeat intervals between successive heartbeats from the time interval 4:44 to 5:00 and the corresponding heartbeat per minutes (bpm) are computed. The bpm is then used as a criterion to determine if a triggered alarm is classified as a true or false alarm.

(vii) A majority voting system with an alarm-specified threshold (the values of these alarm-specified thresholds are determined by optimizing to the training datasets) is used to determine if the alarm is a true or false alarm.

The reason for eliminating signals that are flat or contain NaN entries is that such signals contain no useful information for the detection of heartbeats. These inadmissible signals are very likely due to anomalies in the sensor (i.e., drop of the sensor) and can cause false alarms. In addition, for detection of ventricular tachycardia (VT) alarms, heartbeat annotation computed solely using the ABP and/or PLETH signal(s) are discarded. This is because the decision making criteria for VT involves the analysis of the ECG signal morphology. The annotated heartbeats based on ABP / PLETH do not have an exact fit to the ECG morphology.

2.1. Analysis of ECG morphology for ventricular tachycardia alarms

For detection of VT alarms, we analyzed the morphology of the ECG signals to determine if ventricular beats are present in the time interval from 4:44 to 5:00 of the recording. The criteria for a true VT alarm are the presence of at least 5 ventricular beats and a heart rate higher than 100 bpm. Our approach for detection of such ventricular beats depends on the computation of the signal skewness and signal cross-correlation between a reference ECG waveform and all subsequent ECG waveforms. Briefly, our approach can be summarized as follows:

(i) Define a reference ECG waveform by specifying a time-window centered on the first annotated heartbeat after 4:30. The size of this time-window is kept constant in the following steps.

(ii) Compute the signal cross-correlation of all subsequent ECG waveforms with respect to the reference for the next 10 seconds. For ECG signals with similar morphology, the cross-correlation profile is expected to be symmetrical in shape (refer to Figure 1 bottom left panel).

(iii) Compute the mean and standard deviation of the skewness for the cross-correlation profiles in Step (ii).

(iv) Compute the individual signal cross-correlation of all ECG waveforms from 4:44 to 5:00 with respect to the reference waveform. Next, compute the skewness of each of these individual cross-correlation profiles. If this skewness differs from the mean skewness +/- 4 × standard deviation in Step (iii), this ECG waveform is labelled as morphologically different. The rationale for this criterion is based on our observation that morphologically different ECG waveforms results in non-symmetrical cross-correlation profile, thereby resulting in a skewness value that will be different from symmetrical profiles (refer to Figure 1 bottom right panel).

(v) Count the number of successive ECG waveform that is labelled as different from the reference. If there are at least 5 or more such successive waveforms and the heart rate is greater than 100 bpm, label this signal as a true alarm. Otherwise, the signal is a false alarm.

3. Results and discussion

The results from our approach for the training data-set and the testing data-set are as shown in Table 1 and Table 2, respectively. For the training data-set of 750 recordings (including both “real-time” and “retrospective” subsets), we achieved a final score of 64.3%, where the final score is computed as (**TP** + **TN**) / (**TP** + **TN** + **FP** + 5***FN**). Our approach correctly identified 249 out of 294 true alarms (**TP** = 249 and **FN** = 45) and 349 out of 456 false alarms (**TN** = 349 and **FN** = 107). For the testing data-set, our approach achieved a final score of 61.34% for the “real-time” data-set and 67.65% for the “retrospective” data-set.

3.1. Limitations

Our approach is highly dependent on the performance of the gqrs and wabp routines in the WFDB toolbox for heartbeat annotation. It is possible that the default parameters in these routines may not be optimized for certain alarm sub-types. Further optimization of the parameters used for both routines, especially the detection threshold used in the gqrs routine may potentially improve the accuracy of our approach.

Table 1. Results of our approach for the training data-set; final score for the training data-set is 64.3%. The **TP**, **FP**, **FN** and **TN** are reported as a ratio to the total number of recordings for each alarm type.

Alarm type	**TP**	**FP**	**FN**	**TN**
Asystole	0.164	0.057	0.016	0.762
Bradycardia	0.494	0.079	0.022	0.404
Tachycardia	0.914	0.043	0.021	0.021
Ventricular Flutter / Fibrillation	0.086	0.224	0.017	0.672
Ventricular Tachycardia	0.152	0.217	0.109	0.522
Average	0.362	0.124	0.037	0.477
Gross	0.332	0.143	0.060	0.465

True Positive (**TP**) are true alarms correctly identified by our approach as a true alarm; False Positive (**FP**) are false alarms wrongly identified by our approach as a true alarm; False Negative (**FN**) are true alarms wrongly identified by our approach as a false alarm; True Negative (**TN**) are false alarms correctly identified by our approach as a false alarm.

Table 2. Results of our approach for the testing data-set.

Alarm type	**TPR (%)**	**TNR (%)**	**Score**
Asystole	72	96	82.29
Bradycardia	90	64	63.72
Tachycardia	97	40	85.37
Ventricular Flutter / Fibrillation	44	82	56.41
Ventricular Tachycardia	51	77	51.41
Real-time	77	80	61.34
Retrospective	83	83	67.65

Also, we assumed that the first annotated heartbeat after 4:30 corresponds to a normal ECG waveform and used it as a reference for comparing against all subsequent waveform. This may not be valid for all cases of VT alarms. A more robust approach will be to construct the reference ECG waveform by averaging over all ECG waveforms from 4:30 to 4:40. Secondly, we defined a fixed threshold of mean +/- 4 × standard deviation as the skewness range for ECG waveforms to be labelled as morphologically similar. However, we have observed that baseline drift of the ECG signal can potentially affect the magnitude of the skewness computed, resulting in morphologically similar ECG waveforms having skewness values that differs greater than 4 × standard deviations. A more robust approach could be the use of an adaptive threshold that is dependent on the ratio between the standard deviation and the mean.

4. Conclusion

We have developed a multimodal approach utilizing ECG, ABP and PLETH readings from bedside monitors in the ICU for potentially reducing the incidence of false alarms. Our approach relies on the detection of heartbeats using (i) the individual ECG, ABP and PLETH signals, (ii) the combined ECG + ABP signals, and (iii) the combined ECG + PLETH signals. The intervals between heartbeats from these various signals are computed and a majority voting approach is used to determine if the triggered alarm is a true or false alarm.

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