Identification of ECG Signal Pattern Changes to Reduce the Incidence of Ventricular Tachycardia False Alarms

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Abstract

The paper focuses on the reduction of the false alarms in the Intensive Care Units (ICU). Five alarm types were analyzed in this study: Asystole, Extreme Bradycardia, Extreme Tachycardia, Ventricular Tachycardia and Ventricular Flutter/Fibrillation. Most of the analyzed alarm types rely on the quality of the heart rate estimation. The false alarm reduction algorithms analyzed in this paper use the quality estimate of the arterial blood pressure signal from which the heart rate is estimated and additionally the results of heart beat detection in two ECG signals are analyzed before making the final decision about the true or false alarm type.

The most attention in this paper is focused on the correct detection of Ventricular Tachycardia alarms. The decision about the true or false alarm is made according to RR interval variation and changes of QRS complex shape features.

A subset of sample entries data of the Physionet/CinC Challenge 2015 is used to test the proposed algorithm modifications. The false alarm detection according to the RR interval variation gave 49% TPR, 49% TNR (score 34.82) for the Phase I Entries data set and 46% TPR, 51% TNR (score 34.59) for the Phase II Entries data set. The VT alarm detection algorithm based on the features related to the the ECG waveform shape has increased the VT score for Phase I Entries data set to 41.98.

1. Introduction

The paper focuses on the reduction of the false alarms in the Intensive Care Units (ICU). Many research works has shown the impact of the false alarms in the ICU to the quality of care [1, 2], stress for the patients and staff [3–6], the interior sleep structure [7, 8] and sleep deprivation [9–11] to name a few.

Five alarm types we analyze in this study: Asystole, Extreme Bradycardia, Extreme Tachycardia, Ventricular Tachycardia and Ventricular Flutter/Fibrillation. The data for the experimental research and algorithm validation is taken from the sample entries, prepared for the 2015 PhysioNet/CinC Challenge [12]. One of the most problematic alarm type is the Ventricular Tachycardia. Aboukhalil et al. has noted, that the algorithm proposed in their paper reduces the number of false alarm incidents up to 22.7% for the all analyzed alarm types except Ventricular Tachycardia (VT) [13]. The reduction of false alarm incidents for the all alarm types including VT is received not less than 42.7%. Aboukhalil et al. have performed their tests on the PhysioNets MIMIC II waveform database [14, 15]. The received false alarm reduction rate is equal to 33.0% and received true alarm recognition error reduction rate is equal to 9.4% [13].

The aim of our study is to propose an algorithm for real-time analysis of two simultaneously recorded ECG signals in order to identify the VT incidence and reduce the true alarm recognition error to the minimum. The VT alarms are usually initiated by the five or more ventricular beats observed with heart rate higher than 100 bpm. Visual analysis of the ECG signal shape recorded during true VT incident lead to the hypothesis that these incidents are followed by the noticeable changes of the QRS complex shape and evenly spaced heart beat annotations. Additionally the modification of the test entry code, given in 2015 PhysioNet/CinC Challenge, is performed in order to reduce the number of false alarm incidents for the rest four alarm types, annotated in challenge data set.

In this paper we propose an algorithm, which was tested on the 341 VT related records (89 records with true VT alarm incidents and 252 with false alarm incidents) taken from the 2015 PhysioNet/CinC Challenge sample entries data set. At minimum the 4 true alarms (4%) were not recognized in this data set by the proposed algorithm with false alarm rate equal to 74%.

2. Methods

In our study we analyzed the Ventricular Tachycardia related records by excluding the arterial blood pressure signal. We used the heart beat annotations detected by applying the Pan-Tompkins algorithm [16] MATLAB implementation, prepared by Hooman Sedghamiz.

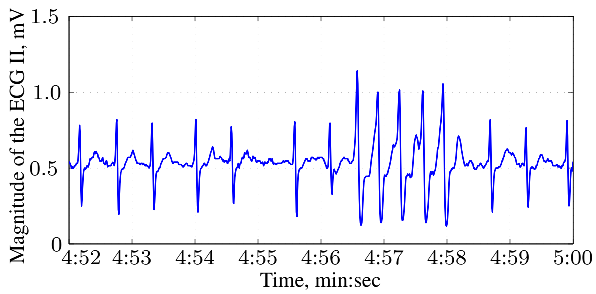

Figure 1. Illustration of the ECG II with VT true alarm

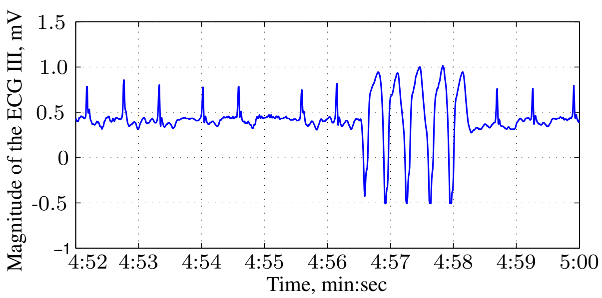

Figure 2. Illustration of the ECG III with VT true alarm

Five different hypothesis were tested in our study presented in this paper. The first hypothesis states that the RR intervals in the measured ECG II signal during VT incident become evenly distributed (see Fig. 1) while the patient's RR intervals tends to vary. The second hypothesis states that the peaks in heart rate during the VT incident appears at the same time as the peaks of RR interval standard deviation, estimated for the each five successive heart beats in the ECG II signal analysis frame.

The conjunction of the two first hypothesis into the signal analysis algorithm gave 22% of VT true alarm detection error and 58% of VT false alarm detection error. In order to reduce the VT true alarm detection error, three additional hypothesis were tested on the signal waveform data set.

The third hypothesis states that the shape of the QRS complex in the ECG waveform becomes wider (see Fig. 2) during the VT incident. In order to estimate the signal feature related to the QRS complex width, the signal was analyzed by centering the analysis frame on the peak of each QRS complex. To simplify the analysis algorithm, the width of the signal analysis frame was selected equal to the mean of the RR interval estimated for the last five successive heart beats. This also included a part of P wave and T wave into the same analysis frame. A standard deviation of the waveform magnitude was estimated for each analysis frame. This feature was used for classification accordingly to the manually set decision threshold.

The experimental tests of the third hypothesis gave promising results: the 96% of all true alarms were detected by the algorithm. However the amount of false alarm incidents remained high and have reached the 74% of all false alarms in the sample entries data set.

Two additional hypothesis were tested in order to reduce the false alarm incident rate: the hypothesis which states that the low level of coherence between the ECG II and V waveform signals may indicate that the ECG II waveform is too distorted and should be not used for alarm incident analysis; the hypothesis which states that if the signal power spectrum standard deviation higher than the manually set threshold, it indicates the bad quality of ECG II signal and the incident should be treated as a false alarm.

The fourth and the fifth hypothesis were experimentally tested on the test dataset, however we were able to reduce the number of false alarm incidents only when the number of true alarm incidents were higher than 4%.

Asystole, Extreme Bradycardia, Extreme Tachycardia and Ventricular Flutter/Fibrillation related false alarms were reduced by analysis of arterial blood pressure (ABP) signal. The ABP quality index [17] is estimated for each analyzed record. Additionally the quality index of the photoplethysmogram (PPG) [18] is estimated and compared to the threshold. The threshold is selected individually for each alarm type.

The ABP signal quality index for Asystole alarm type was selected equal to 0.7. The lower signal quality requirements were selected for Asystole alarm type because the alarm had to be initiated when no QRS were detected during four seconds and the quality of estimated heart rate was not so important.

The ABP signal quality indexes for Extreme Braycardia, Extreme Tachycardia and Ventricular Flutter/Fibrillation were experimentally estimated to get the individual values for each alarm type. If the ABP signal quality have met the requirements set by the threshold the QRS annotations in two ECG signals were additionally analyzed in each case in order to verify the heart rate calculated from the ABP signal.

The decision for the Extreme Braycardia and the Extreme Tachycardia alarm types in the algorithm were made in similar manner. In Extreme Braycardia case the minimum of the heart rate was estimated in the analysis frame. In the Extreme Tachycardia case the maximum of the heart rate was estimated in the analysis frame. In both cases the two thresholds of the acceptable heart rate were used: the strict and the soft one. When the estimated heart rate have reached the alarm level only for the one signal the strict threshold was used to make the final decision. If the heart rate estimated from two signals have reached the alarm level, the soft threshold was used.

3. Results

The experimental investigation was performed mainly on the 2015 PhysioNet/CinC Challenge Phase I Entries data set. The first attempts to increase the efficiency of the false alarm incident reduction using the analysis RR interval changes for Ventricular Tachycardia alarms were tested both on Phase I and Phase II Entries data set. However the final solution test on the hidden data set failed because of entry reading error.

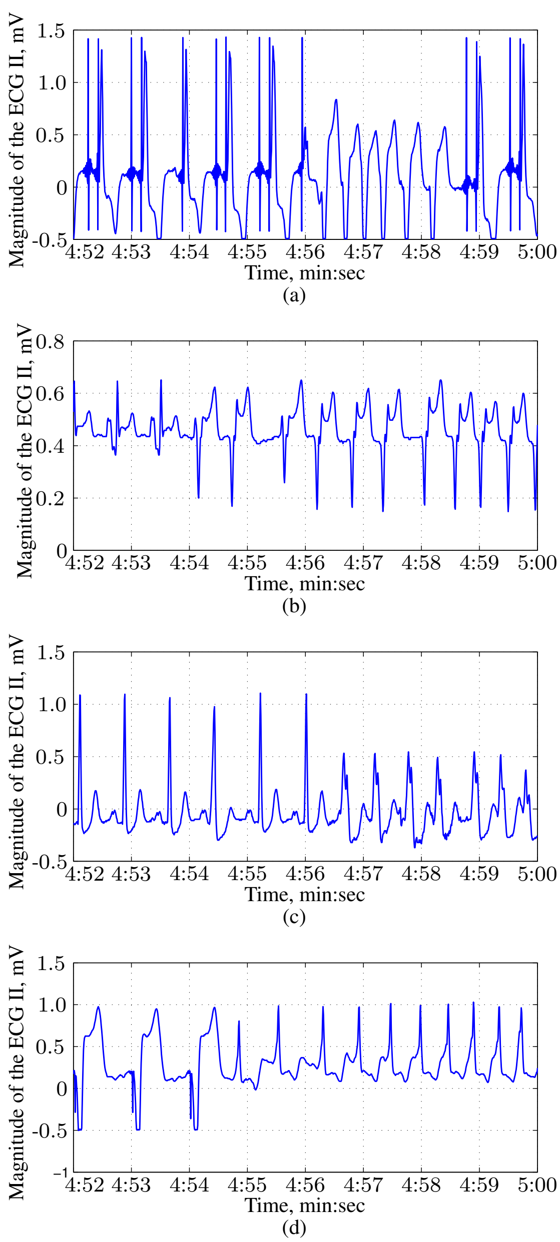

Figure 3. Illustration of the ECG II with VT true alarm for records: a – v329l; b – v348s; c – v733l and d – v844s

There were 750 recordings of different alarm types available in sample entries dataset. Our proposed false alarm incident reduction algorithm used different threshold values for the arterial blood pressure signal quality estimate, according to the analyzed alarm type. The true positive (TP), false positive (FP), false negative (FN) and true negative (TN) rates are given in table 1.

Table 1. Results received on the test dataset

Alarm Type	TP, %	FP, %	FN, %	TN, %
Asystole (A)	14.8	4.9	3.3	77.0
Bradycardia (B)	48.3	3.4	3.4	44.9
Tachycardia (T)	90.0	1.4	3.6	5.0
Ventricular Fl. Fib. (VFF)	6.9	12.1	3.4	77.6
Ventricular Tach. (VT)	24.9	54.8	1.2	19.1
Average	37.0	15.3	3.0	44.7
Gross	36.8	27.3	2.4	33.5

The generalized score received for each alarm type was calculated according to the following formula:

$$Score = \frac{TN + TP}{TP + TN + FP + 5 \cdot FN}. \quad (1)$$

The score values and the optimal threshold values received for each alarm type are given in table 2.

Table 2. Summary of the selected threshold values and received score

Alarm Type	jSQI	ppgSQI	thd., s	tol., bpm	Score
A	0.7	0.7	4	0.5	81.10
B	0.92	0.92	40	10	82.04
T	0.94	0.94	140	7	83.04
VFF	0.8	0.8	250	5	74.38
VT	–	–	–	–	41.98

Since the Ventricular Tachycardia alarms were analyzed excluding the arterial blood pressure signal analysis the jSQI, ppgSQI, etc. threshold values are missing in table 2. However the algorithm used additional threshold for the QRS complex shape feature, based on standard deviation. If the maximum difference between the normalized ECG II signal waveform standard deviation, estimated for the all QRS complexes in the last 20 second duration record was above 0.07, the VT alarm was set to be true. The received algorithm application on the sample entries data set results are given in table 1 and table 2.

4. Discussion

The quality of the recorded signals have a high influence to the algorithms that could be applied for arrhythmia alarm incident verification. The variety of noisy ECG II signal features requires several different signal features to be estimated and verified using complex set rules in order to recognize all the possible type of noise in ECG signal and distinguish it from the signal shape changes related to Ventricular Tachycardia incident.

The application of the band pass or median filter did not increase the VT true alarm recognition rate and did not decrease the false alarm rate for the ECG waveform signals in this research by the application of the algorithm proposed in this paper.

The score received by testing the VT incident detection algorithm on the sample waveform data set was 41.98. However the most important is that only 4 true alarms (from 89 true alarms in total) were not detected by the algorithm keeping the false alarm rate at 74% (187 from 252 false alarms were annotated as true alarms). Fig. (3) illustrates the ECG II waveforms of the records with true alarms that have not been detected by the algorithm. The main reason of detection error is the uneven distribution (below the threshold) of the heart beats during the VT incident. However the shape changes observed in these waveforms were significant. Therefore an additional modification of the ECG II signal analysis and classification algorithm is needed in order to completely solve this automatic VT alarm recognition task.

The analysis of the coherence between two ECG signal records made in parallel does not give an opportunity to distinguish between noisy ECG signal and waveform changes related to VT incident. The same situation was observed when the signal power spectrum distribution changes in time were analyzed. At least six signal waveforms with VT incident had the standard deviation of the power spectrum as high as the feature value estimated form the ECG waveform corrupted by noise.

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