Reduction of False Critical ECG Alarms using Waveform Features of Arterial Blood Pressure and/or Photoplethysmogram Signals

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Abstract

To address the Physionet/Computing in Cardiology (CinC) Challenge 2015 [1], this article presents practical algorithm to reduce false critical ECG alarms using waveform features of arterial blood pressure (ABP) and/or photo-plethysmogram (PPG). The ABP/PPG pulse features are extracted on a beat-by-beat basis in real-time manner. For each detected pulse (or forced detection), 5 event feature indicators (EFIs), which correspond to the 5 critical ECG arrhythmia alarms, are generated from a group of pulses prior to the current pulse. At the time of a critical arrhythmia alarm, the corresponding EFI values of those ABP/PPG pulses prior to or around the alarm time are checked for adjudicating (accept/reject) this alarm. As an extension or option, available electrocardiogram (ECG) signals are included in a way similar to ABP/PPG processing. Quantitative results on the Challenge training and test datasets are presented. The algorithm is practical owing to its real-time processing mechanism and computational efficiency.

1.   Introduction

False alarms of medical devices have been ranked number 1 in the top 10 lists of health technology hazards every year, since 2012, by the ECRI Institute, a non-profit research and consulting organization that specializes in medical devices [2]. False critical alarms, including false critical arrhythmia alarms, are most annoying and disturbing to clinicians and patients, from which the "crying-wolf" effect may be resulted and patient safety may be jeopardized.

To tackle the false alarm problem, efforts in two aspects may be made: a) clinical usage aspect; b) technology aspect. In the clinical usage aspect, the efforts include more appropriate training for nurses, better preparation of the electrodes/sensors, more appropriate parameter limit settings, improved hospital policies, etc. The efforts in the technology aspect involve artefacts identification and signal quality assessment, integration of event features from correlated multiple sources (data fusion), trending of parameters from good signals, etc.

The Physionet/CinC Challenge 2015 [1] presents an opportunity for researchers to tackle the problem of reducing critical arrhythmia alarms in the technology aspect.

To address this challenge, this paper presents an algorithm to reduce false critical ECG alarms using waveform features from ABP and or PPG signals. In an extension of the base algorithm, ECG features from all available ECG leads are further utilized to see what improvements would be achieved. The algorithm is implemented in C language; for its real-time processing mechanism and computational efficiency, the algorithm is practical and may be easily incorporated into a patient monitor host device.

2.   Materials and Methods

2.1.   Data sets

The PhysioNet/CinC Challenge 2015 provides the training and test sets of reference alarm data with total of 1250 ICU patient waveform records [1]. Each record contains one of the 5 categories of critical ECG arrhythmia alarms, namely asystole (ASY), ventricular fibrillation/flutter (VFB), extreme bradycardia (EBR), extreme tachycardia (ETC), and ventricular tachycardia (VTA), which was detected by a commercial patient monitor device and then annotated by experts (as true or false). Each record has 300 seconds (5:00) of up to 4 channels of waveform (2 ECGs, ABP and/or PPG, etc.) data before the alarm. Half of the records have additional 30s waveform data after the alarm, making their duration to 5:30 (long records); the other half have just the 5:00 data before the alarm (short records). The short records are for evaluating real-time algorithms which can only use the data prior to the alarm time. The long records are for evaluating algorithms that are allowed to use not only the data prior the alarm but also the data extended up to 30s after the existing alarms.

The training dataset consists of 750 records, of which 375 are short records and the other 375 are long records. The test set has 250 short records and 250 long records. Detailed description of the reference alarm data is seen in PhysioNet/CinC Challenge 2015 introduction paper [1].

2.2. Methodology overview

As shown in Figure 1, the algorithm takes available ABP and/or PPG signals and the critical ECG arrhythmia alarms as input. The ABP and/or PPG signals are processed in real-time on a beat-by-beat basis. Features of each ABP and/or PPG pulse, such as signal quality, pulse features (time, amplitude, slope, etc.), and pulse rhythms, are detected and analyzed to form five event-feature indicators (EFIs) for ABP/PPG, corresponding to the five types of critical arrhythmia alarms.
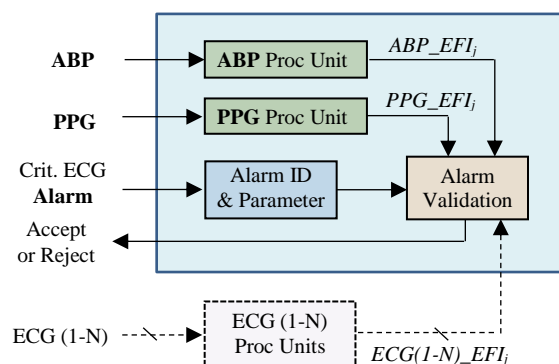

Figure 1. Overview of the algorithm

The PPG Proc Unit, in Figure 1, processes PPG signal and generates five PPG-derived event feature indicators, PPG_EFI_j (j = 1, 2, …, 5), corresponding to the five critical ECG alarms. Similarly, the ABP Proc Unit processes ABP signal and generates five ABP-derived EFIs, ABP_EFI_j (j = 1, 2, …, 5). The critical ECG alarms, produced by the existing ECG arrhythmia detector(s), are fed into the algorithm with their alarm type, time, and alarm limit (if applicable). At the time of an alarm (e.g. $ALARM_x$), the algorithm activates the alarm validation process, which checks the corresponding PPG_EFI_x and/or ABP_EFI_x of those pulses prior to or around the alarm time. If there is strong evidence from PPG_EFI_x and/or ABP_EFI_x that the ECG alarm cannot be true, the alarm is judged as false and is rejected; otherwise the alarm is considered as true and is accepted.

As an extension or option of the algorithm, ECG lead-base processing units may be included. Each ECG Proc Unit generates ECG lead-specific event feature indicators, $ECG(1-N)\_EFI_j$ (j = 1, 2, …, 5), which may be utilized in the alarm validation process.

2.3. PPG and ABP processing units

The PPG and ABP processing units are similar to each other. The unit consists of 4 components as shown in Figure 2: Low-pass (LP) filter, pulse detection, feature extraction (FE) including signal quality assessment (SQA), and event feature indicator (EFI) calculation.
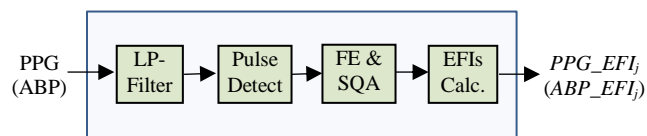

Figure 2. Diagram of the PPG/ABP processing unit

The LP-filter and pulse detection are an adapted (real-time) version of wabp algorithm [3]. The FE and SQA are based on the previous study for reduction of false ABP alarms [4]. The directly extracted pulse features include: detection type (normal pulse detection or forced detection (FD)), time of the pulse or FD, pulse-to-pulse interval (PPI), pulse peak and valley values, positive and negative pulse slopes, etc. An FD is made if there is no pulse detected for 2 seconds from the previous pulse or FD. The derived features include short-term averaged values of some directly extracted features (e.g. PPI_ave, etc.). The signal quality index is derived from the extracted pulse features via SQA process [4].

For each of the signal (ABP and PPG), the EFI Calculation component generates 5 EFIs (EFI_j, j = 1, 2, …, 5), which contain the events signatures for the corresponding 5 critical ECG arrhythmia alarms. The core definitions of the EFIs are as below: The EFI for ASY alarm, *efi_asystole*, is assigned value 0 (none-ASY), if for the most recent 5 pulse detections, the pulse rhythm is regular (PRIR); otherwise, is assigned value 1 (ASY possible). For a pulse to qualify PRIR in the region, the averaged PPIs must be in the reasonable range (e.g. 300ms ~ 1800ms) and the variation (standard deviation) of PPIs and pulse amplitudes must be small enough.

The EFI for VFB alarm, *efi_vfb*, takes value 0 (none VFB), if in the most recent 7 pulse detections, there is no forced detection, are less than 4 abnormal pulses, and averaged pulse rate is less than 120 bpm; otherwise, the *efi_vfb* is assigned value 1 (VFB possible). The abnormal pulse is determined by the variation of the PPI and pulse amplitudes of the current pulse to previous and averaged pulses [5].

The EFI for EBR alarm, *efi_brady*, gets value 0 (none-EBR) if in the past 10 pulses detections, the signal quality is good (SQI > 0.5) for the 3 pulses with the longest PPIs and the average pulse rate calculated from the 3 longest PPIs is greater than 40 bpm; otherwise, is assigned value 1 (EBR-possible).

The EFI for ETC alarm, *efi_tachy*, takes value 0 (none-ETC), if in the most recent 6 pulse detections, the number of abnormal pulses is less than 4 and the averaged pulse rate is greater than 140 bpm; otherwise, is assigned value 1 (ETC possible).

The EFI for VTA alarm, *efi_vta*, gets value 0 (none VTA), if for the recent 6 pulse detections, there is no forced detection and number of abnormal pulses is less

than 2 and the averaged pulse rate is less than 100 bpm; otherwise, *efi_vta* is assigned 1 (VTA possible).

2.4.   (Optional) ECG processing units

The additional ECG processing units are an extension or option to the algorithm. The structure is similar to that described in Figure 2: instead of the pulse detection, the QRS detection is in place. A real-time QRS detection algorithm, adapted from wqrs algorithm [6], is employed. Similar EFI rules used for the ABP/PPG signals are applied to the ECGs - by substituting the pulse features (e.g. pulse intervals, amplitudes, etc.) with the QRS features (e.g. R-R intervals, QRS amplitudes, etc.). Each ECG lead (ECG(i), $i = 1,2, ..., N$) is processed separately, and the five ECG lead-specific EFIs, $ECG(i)\_EFI_j$, $j = 1, 2, ..., 5,$ are generated.

2.5.   Alarm validation

At the time when a critical ECG alarm, $ALARM_x$, is received, the alarm validation process is activated, which checks the corresponding ABP_EFI_x and/or PPG_EFI_x values on those pulse detections within a predefined validation window. The validation window includes a look-back window and a look-forward window to the alarm time. The look-back and look-forward windows are initially set to 4s and 3s, respectively and slightly adjusted for the individual alarm type using the training dataset.

In the real-time case (Event 1), in which only the waveform data prior to the alarm (short records) are available, the look-forward window is set to 0 (not used); and in the retrospective case (Event 2), both look-back and look-forward window are used.

If any either ABP_EFI_x or PPG_EFI_x have value 0 in the validation window, which means that there is at least one source provides evidence that this alarm is not true, this alarm is considered false and is rejected; otherwise, the alarm is accepted as true.

In the case the ECG signals are included in the algorithm, the same validation windows are applied to the ECG lead-based alarm validation process, and if any of the $ECG(1\text{-}N)\_EFI_x$ have value 0 in the validation window, the alarm is considered false.

3.   Results

The algorithm has been implemented in C-Language in a way that mimics real-time dynamic processing: The ABP and/or PPG (as well as ECGs if they are optioned in) waveform data are read in a small block (e.g. 128ms) at a time and get processed dynamically. A alarm file for each Challenge data record is created, which contains the corresponding alarm message in terms of alarm time

(5:00), alarm type, and alarm limit (if applicable, e.g. 40 bpm for Bradycardia). The algorithm reads the alarm file and, according to the alarm time and parameter (type and limit), activates the alarm validation process to adjudicate the alarm using the EFIs from multiple sources (ABP, PPG, and/or ECGs) in the validation window. The final validation result for each record is saved the Challenge format for statistics.

3.1.   Results on the training set

Table 1 shows the performance of the algorithm, when it uses ABP and/or PPG only, on the training set for the real-time (Event 1, short records) and retrospective (Event 2, long records) cases.

Table 1. Performance of the algorithm, using ABP/PPG only, on the training dataset:

	Event 1 (Real-time)			Event 2 (Retrospective)		
	TPR	TNR	*Score	TPR	TNR	*Score
Asystole	100%	68%	74.57	100%	77%	80.00
Bradycardia	96%	84%	83.75	100%	71%	84.10
Tachycardia	100%	75%	98.60	100%	40%	95.60
VFB	100%	61%	63.34	100%	33%	42.90
VTA	93%	45%	54.10	100%	29%	47.10
Average	98%	63%	74.73	100%	51%	70.10
Gross	97%	56%	69.73	100%	45%	65.60

TPR: True Positive Rate, indicating how many (percent of) true alarms are retained;

TNR: True Negative Rate, indicating how many (percent of) false alarms are removed;

*Score = $100 \times (TP + TN) / (TP + TN + FP + 5 \times FN)$, which is defined by the Challenge [1].

It is notable that, for the retrospective case, all the true alarms are retained (TPR = 100%) and the false alarm reduction rates are 77%, 71%, 40%, 33%, and 29% for Asystole, Bradycardia, Tachycardia, VFB, and VTA, respectively; the overall false alarm rates are 51% and 45% in Average and Gross statistics, respectively.

When the ECG components are optioned in, the overall performance of the algorithm improves in general, in terms of the Score, in a way of gaining significantly on the TNR and sacrificing slightly on the TPR. Table 2 shows the performance detail of the algorithm using additional 2 channels of ECG processing components for the real-time (Event 1, short records) and retrospective (Event 2, long records) cases.

Table 2. Performance of the algorithm, using ABP/PPG and ECGs, on the training dataset:

	Event 1 (Real-time)			Event 2 (Retrospective)		
	TPR	TNR	*Score	TPR	TNR	*Score
Asystole	92%	83%	79.32	100%	83%	85.70
Bradycardia	96%	95%	87.87	100%	83%	90.91
Tachycardia	100%	75%	98.60	100%	40%	95.60
VFB	100%	79%	80.00	100%	42%	50.00
VTA	82%	54%	51.81	93%	39%	49.58
Average	96%	76%	78.73	99%	60%	74.18
Gross	93%	67%	70.22	98%	54%	68.22

3.2.   Results on the test set

The algorithm was submitted to PhysioNet/CinC Challenge 2015 web server as Close Source entries.

Table 3 shows the algorithm's entry results on the (hidden) test set. In the real-time case, when the algorithm uses only the ABP/PPG signals, its overall TPR and TNR are 92% and 58%, respectively, scoring 62.96; and when the algorithm uses the ABP/PPG and 2 channels of ECGs, it has an increased TNR (70%) but a slightly decreased TPN (90%), with an increased Score of 68.21.

In the retrospective case, using only the ABP/PPG, the algorithm has overall TPR and TNR of 95% and 51%, respectively, scoring 61.65; and while the algorithm uses additional ECG signals, its overall TNR increases to 64%, TPR slightly decreases to 94%, and Score increases to 68.52.

Table 3. Performance of the algorithm on the test set, using ABP/PPG and using ABP/PPG plus 2-channels of ECGs.

	Using ABP/PPG			Using ABP/PPG + ECGs		
	TPR	TNR	*Score	TPR	TNR	*Score
Asystole	89%	63%	62.58	83%	84%	77.84
Bradycardia	100%	78%	86.60	100%	78%	86.60
Tachycardia	98%	80%	90.76	98%	80%	90.76
VFB	89%	78%	74.19	78%	88%	75.76
VTA	84%	43%	45.31	81%	54%	51.18
Real-time	92%	58%	62.96	90%	70%	68.21
Retrospective	95%	51%	61.65	94%	64%	68.52

With regard to the computational load, the algorithm's average and maximum running times (on the test set) are 0.103% and 0.193% of quota, respectively, when the algorithm uses ABP/PPG signals only; and are 0.213% and 0.310% of quota, respectively, when the algorithm uses ABP/PPG and 2 channels of ECG signals.

4.   Discussion

The algorithm is developed with emphasis on retaining true alarms while rejecting false alarms, especially in the case of using ABP/PPG only; this is reflected in the results of Table 1 Event 2, in which all TPRs are 100%. With patient safety concerns, we think that rejecting a true alarm is more severe than 5 times letting go a false positive alarm.

The look-forward window (in the retrospective case) of the algorithm is set to about 3s, so only the first 3s of the 30s data after the alarm were utilized. In this way, the total alarm announcing time, including this extra 3s delay caused by the alarm validation process, would still be within (or very close to) the 10s time requirement as set by the AAMI standard [7].

The performance of the algorithm is reasonably good, especially in retaining true alarms while rejecting false ones; there are still rooms to improve the results. The algorithm's computational load appears being very low.

In conclusion, we have presented an effective algorithm to reduce false critical arrhythmia alarms using waveform features of ABP and/or PPG signals. The algorithm is practical on account of its real-time dynamic processing mechanism and computational efficiency. Adding additional features extracted from all available ECG leads to the algorithm would further enhance the algorithm's overall performance, given that the existing ECG arrhythmia detectors do not usually analyze all available leads of ECG signals.

Acknowledgement

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