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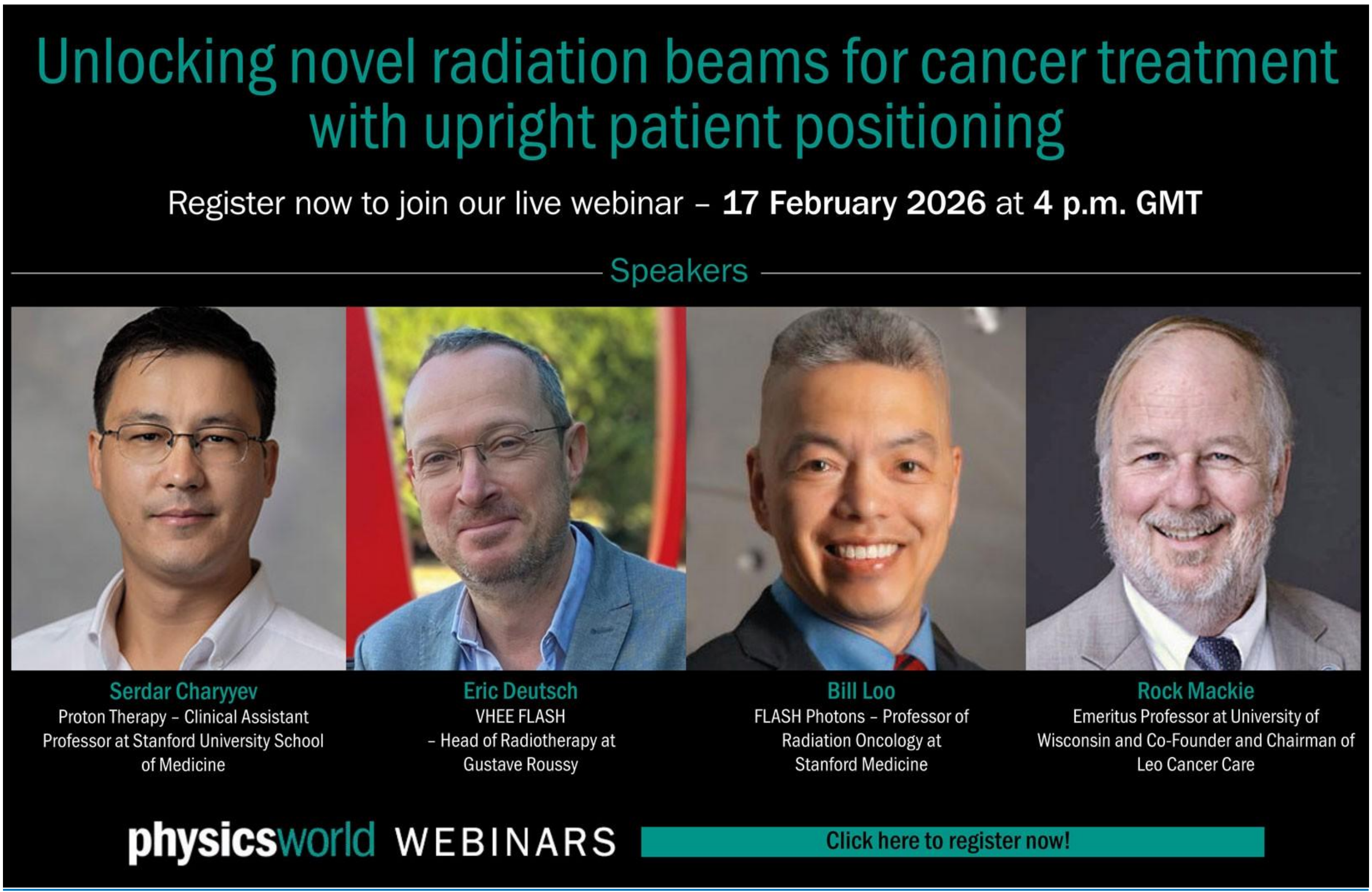

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Reducing false arrhythmia alarms in the ICU using multimodal signals and robust QRS detection

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Abstract

This study developed algorithms to decrease the arrhythmia false alarms in the ICU by processing multimodal signals of photoplethysmography (PPG), arterial blood pressure (ABP), and two ECG signals. The goal was to detect the five critical arrhythmias comprising asystole (ASY), extreme bradycardia (EBR), extreme tachycardia (ETC), ventricular tachycardia (VTA), and ventricular flutter or fibrillation (VFB). The different characteristics of the arrhythmias suggested the application of individual signal processing for each alarm and the combination of the algorithms to enhance false alarm detection. Thus, different features and signal processing techniques were used for each arrhythmia type. The ECG signals were first processed to reduce the signal interference. Then, a Hilbert-transform based QRS detector algorithm was utilized to identify the QRS complexes, which were then processed to determine the instantaneous heart rate. The pulsatile signals (PPG and ABP) were processed to discover the pulse onset of beats which were then employed to measure the heart rate. The signal quality index (SQI) of the signals was implemented to verify the integrity of the heart rate information. The overall score obtained by our algorithms in the 2015 Computing in Cardiology Challenge was a score of 84.03% for retrospective and 79.92% for real-time analysis.

Keywords: intensive care unit, photoplethysmography, arterial blood pressure, electrocardiogram, asystole, arrhythmia false alarm, signal quality index

(Some figures may appear in colour only in the online journal)

1. Introduction

An intensive care unit (ICU) involves a large number of medical devices, background noise and alerting signals of the devices with a number of attending medical staff (Donchin and Seagull 2002). An ICU aims to monitor the biological signals of patients in critical conditions. The monitoring systems often incorporate alarms to attract staff attention (Donchin and Seagull 2002). The alarms from the physiological monitors can be classified into technically correct or false groups (Lawless 1994). False alarms are alerting signals of monitoring equipment with no associated clinical cause (Chambrin *et al* 1999) or relation with life-threatening conditions of the patient (Donchin and Seagull 2002). Studies show that over 85% of the ICU alarms are false (Lawless 1994, Chambrin 2001, Sendelbach and Funk 2012) and that they have a number of negative effects. The extra noise generated by the false alarms negatively impacts the patient's sleep and increases the stressors in ICU which can reduce the recovery rate (Novaes *et al* 1997). The uwanted alarms can also lead to vital monitoring equipment being switched off (Lawless 1994). Also, the medical staff lose sensitivity to frequent false alarms which in turn increases the likelihood of missing true alarms (Clifford *et al* 2006). Alarm fatigue is a destructive outcome of the large number of false alarms in ICU in which the clinical staff ignore the alerting signals or change the settings to a level of deactivation which has been identified as a critical health and safety problem (Sendelbach and Funk 2012).

The disruptive consequences of false alarms can be alleviated in two ways. The first solution is automatic detection of false alarms and the source of the alarm. Secondly, medical staff can help solve the issue by persistent observation of the systems and signals and diagnosing the false alarms (Imhoff and Kuhls 2006).

In this paper, we developed a signal processing system for automatic detection of the following arrhythmias: ventricular tachycardia (VTA), ventricular fibrillation or flutter (VFB), extreme tachycardia (ETC), extreme bradycardia (EBR) and asystole (ASY) by processing one or more of the following signals: the photoplethysmography (PPG), the arterial blood pressure (ABP), and two electrocardiogram (ECG) signals. To train and test our system, we have used the signals of the *2015 Computing in Cardiology Challenge Dataset*. The detections are then used to assess the validity of alarms generated by ICU equipment with goal of identifying false alarms. The signal processing algorithms we describe here are the basis of our entry in the *PhysioNet/Computing in Cardiology Challenge 2015*. An early description of these algorithms were published in *Computing in Cardiology Challenge 2015* (Sadr *et al* 2015).

2. Input data

The input dataset was provided by the *PhysioNet/Computing in Cardiology Challenge 2015* (Clifford *et al* 2015). The dataset incorporates 1250 arrhythmia alarms which were selected randomly from four hospitals in US and Europe. Less than three alarms from the five arrhythmia types were selected from an individual patient and they are often more than five minutes apart. The dataset was divided into 750 open-access recordings used as a learning set and 500 recordings for test set which were hidden. Train and test set were comprised of signals recorded from different patients. Five hundred and ninety recordings in the training data included four signals comprising of two ECG signals and two pulsatile signals (the photoplethysmogram (PPG) and arterial blood pressure (ABP)). While the first ECG signal was mostly lead II and the second ECG signal was mostly lead aVr, there were a number of recordings where different leads were recorded. One hundred and sixty recordings in the training data

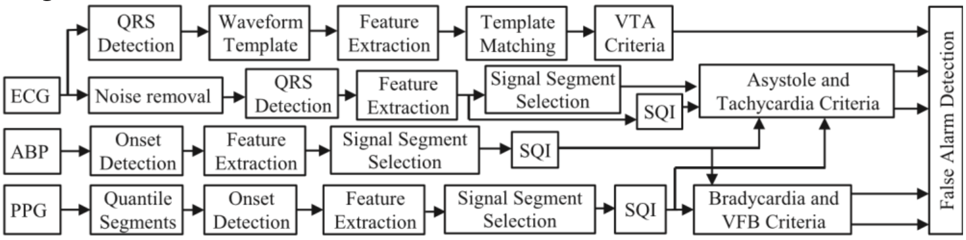

Figure 1. Block diagram of the proposed system for arrhythmia false alarm detection in the ICU. Abbreviations: arterial blood pressure (ABP), electrocardiogram (ECG), signal quality index (SQI), ventricular flutter or fibrillation (VFB), ventricular tachycardia (VTA).

comprised of three of the four signals listed above (i.e. two ECG and one pulsatile or one ECG and two pulsatile signals). Each patient had a maximum of two recordings of separate alarms in the dataset. The chosen recordings had been annotated by three or more experts and the alarm outcome was determined by agreement of at least two-thirds of the experts. Recordings that did not have a two-thirds agreement were excluded. Each alarm was annotated as 'true', 'false', or 'impossible to tell'. Each record includes an alarm at the fifth minute from the start of the record and the corresponding arrhythmia event happens within ten seconds of the alarm. If further arrhythmias occurred before the fifth minute of a record, they were not annotated. The repeated alarms and information from alarms prior to the annotated one are not employed to reduce the probability of transferring errors from one alarm to the next one. Resampling was applied to the four sensor signals at the rate of 250 Hz, 16 bit. Band pass filtering in the range of 0.05–40 Hz was implemented with an FIR filter. Also, common notch filters were utilized for noise removal of powerline noise. Pacemaker and other noise artefacts still existed in the ECG signals. In some cases, movement artefacts, failure in sensor connection, line flush, coagulation and other interferences also influenced the pulsatile signals.

3. Signal analysis

The block diagram of the proposed system for false arrhythmia alarm detection is shown in figure 1. A high level description of system is provided here and more detail is given in sections 3.1–3.3. The top-down order of the signal blocks represents the priority for signal selection in the analysis process.

VTA detection relied solely on features extracted from the ECG signals which were processed without noise removal and using template matching. QRS detection was applied to the ECG for identification of QRS complexes. A reference waveform template was generated from the first QRS and subsequent QRSs were compared to the reference to determine if they were irregular beats. If five or more beats were deemed irregular in the alarm segment then the VTA alarm confirmation was set to true, otherwise it was set to false.

The alarm confirmation procedure of asystole and tachycardia were similar. First, signal interference was removed from the ECG signals. QRS beats were detected from the clean ECG signals and discriminating features were extracted. A segment of the ECG signal containing the alarm was identified and SQI measurements determined. A similar process was applied to the ABP and PPG signals resulting in SQI and feature values. Finally, for the alarm segment, the features of the ECG signals, the ECG SQI measures, the features and SQI measures of the available pulsatile signals served as inputs to assess the validity of the tachycardia alarms. Processing for the asystole alarm evaluation was similar except that we did not use the SQI measures of the ECG signals.

The process of detecting bradycardia and VFB false alarms were identical. The pulsatile signals were employed to diagnose these two arrhythmias. After distinguishing the onset beats of ABP signals, features were measured and the segment of the alarm was identified for criteria assessment and SQI evaluation. The available pulsatile signals, ABP and PPG, were processed similarly, with the exception of the PPG processing which included a quantile segmentation step prior to onset detection. This was followed by feature extraction and identifying the alarm segment and the features in that segment. Finally, the SQI of the alarm segment was measured and the features from available ABP and PPG with their SQI measures were used to confirm the bradycardia or VFB alarm status.

In the following sections, we first describe the signal processing methods for interference removal, heartbeat identification, SQI measurement and feature extraction for the ECG, PPG and ABP signals. We then describe our hierarchical processing of the ECG and pulsatile signals to determine the final alarm status.

3.1. ECG signals

In order to diagnose the high risk arrhythmias, the ECG signals are functional and informative. The recordings in the Challenge dataset are comprised of lead II and/or lead aVr and/or other leads. The block diagram of the proposed system to detect false arrhythmia alarms in the ICU containing the ECG signal processing algorithm is shown in figure 1. The ECG signals are mostly corrupted by movement artefact, pacemaker, and fibrillator signals. A first step was to detect and remove these artefacts. Filtration, described below, was applied to the raw ECG signals to remove the unwanted interference. The filtered signals were then processed to find the QRS complexes. After calculation of RR-intervals from the QRS detection points and applying the above signal processing steps, there were still QRS complexes in some recordings that were not detected successfully. To attempt to recover these missed signal beats, we detected heart beats in the other sensor channels and then used the beat detections across all channels to obtain an enhanced recognition. The final step was feature extraction for arrhythmia detection.

3.1.1. Interference removal. The ECG signals of the challenge database were distorted by motion artefact, powerline interference, baseline drift, displacement of sensors and instrumentation noise produced by pacemakers. Baseline drifts lead to deformation of the ST segment which plays an important role in arrhythmia detection, results in failure in false alarm recognition. Thus, elimination of baseline wander is an essential part of interference removal for detecting arrhythmias and false alarms.

Interference removal was performed by applying filters for noise reduction. The ECG signals of the database were distorted by baseline wander noise which originated from movement, respiration and perspiration affecting the electrode impedance (Tinati and Mozaffary 2006). Baseline wander noise affects the low frequency component of the ECG signals (Jain and Shakya 2014) and can influence the clinical interpretation of ECG signal. In this study, baseline wander noise was removed by two median filters (de Chazal *et al* 2003). The first median filter with 200 ms width is applied to remove the QRS complexes and P waves. Then, the resulting PQRS-free signal is used to apply the second median filter. The width of the second median filter was 600 ms to eliminate T waves. Thus, the output of the second median filter did not include the information from the ECG waves and contained only the baseline wander. By subtracting the output of the second median filter from the raw input ECG signals, the resulting signal contained the P-QRS-T complexes minus baseline wander. This method

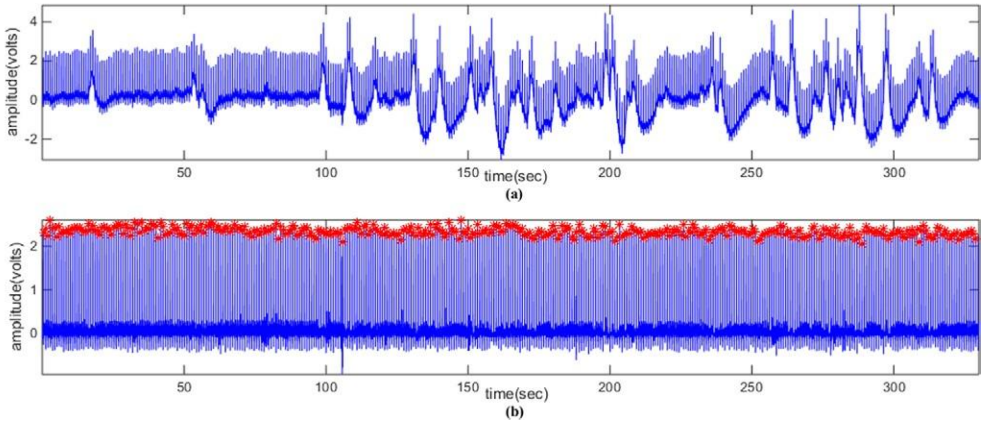

Figure 2. Sample result of applying interference removal to ECG signal (a64) and noise removal. (a) Raw ECG lead II with Asystole as a false alarm. (b) The result of applying interference removal on the input ECG. Stars are the R peaks detected by Hilbert QRS algorithm.

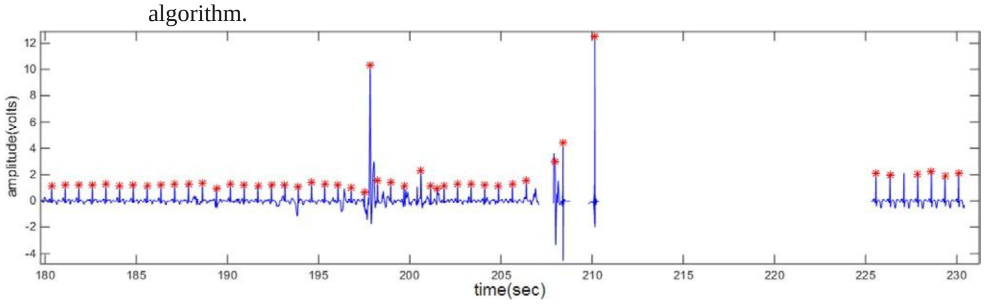

Figure 3. Result of the application of Hilbert QRS detector on ECG II signal after interference removal.

was applied to both available ECG signals of each recording. The result of implementing this algorithm on an ECG signal of the Challenge training set is shown in figure 2, where baseline wander noise is easily seen in figure 2(a) of the ECG recording (a64). The resulting signal after this interference removal is shown in figure 2(b) which reveals that interferences including the baseline wander were appropriately eliminated. Subsequent to interference removal and denoising the ECG signals, QRS detection was applied to the signals. Reliable identification of QRS complexes is difficult due to the changing nature of their morphology and the influence of unwanted interference on the ECG signal (Thakor *et al* 1984). By removing the unwanted interference from the ECG signals, we can improve the likelihood of successful arrhythmia detection. The other important factor is the changing morphology of the QRS complexes which were taken into account in the utilized QRS detection algorithm explained in the following section.

3.1.2. RR interval and signal segment selection. The first step toward feature extraction for arrhythmia recognition by ECG signal is QRS detection. There are various QRS detection algorithms but selecting a reliable method is highly significant for false arrhythmia alarm recognition. In this work, the QRS complexes were identified by a Hilbert transform based algorithm (Benitez *et al* 2001). The result of applying Hilbert QRS detector on an ECG signal of the Challenge training set which contains missing values is shown in figure 3. The Hilbert QRS detector employed in this study (Shouldice *et al* 2004, Redmond and Heneghan 2006) was tested on various ECG signals and leads. It was reported to reliably detect QRS complexes of all common leads with a satisfactory noise tolerance (Shouldice *et al* 2004). The algorithm used in this paper was previously tested on the MIT-BIH Arrhythmia database and obtained 98.4% positive predictive accuracy and sensitivity of 98.5% (Hickey *et al* 2004).

Finally, the QRS detections were used for feature extraction. The RR-intervals were determined by calculating the time difference between two adjacent QRS detections. Then, the information closer to the alarm is utilized for false alarm identification. Thus, the segment comprising the alarm is selected for arrhythmia recognition. In this study, the alarm segment begins 16 s prior to the alarm and is ended by the alarm which occurs at the fifth minute of the signal.

3.1.3. ECG SQI. Visual observation of QRS detection points and corresponding RR intervals revealed that some of the heart beats were missed or falsely detected. Missing value intervals and noisy alarm segments can produce issues in signal processing and suspect QRS detection points. Also, ECG artefact was reported as a reason for false arrhythmia alarms (Aboukhalil *et al* 2008). Therefore, before further processing, the quality of the ECG signal was assessed.

In order to assess the quality of the ECG signal, signal quality index (SQI) was exploited to determine if it possessed reliable information for false alarm detection. The signal evaluation index has been widely studied (Silva *et al* 2011, Clifford and Moody 2012).

In this paper, four tests were applied to determine the ECG SQI. If the alarm segment satisfied the tests, it was allowed to proceed for further processing. The first test determined if the segment was empty. No heart beat in the segment indicated a failure of the heart beat identification algorithms and was indicative of the presence of significant signal interference. In the second test, the number of the detected QRS detection complexes or the available beats of each ECG signal was measured in the segment. This test allowed recognition of the signals with a high proportion of missing heart beats and the inspection of the proportion of motion artefact, failure in sensor attachment and other noises in the segment. The minimum number of beats was set to ten beats. If an ECG signal segment contained less than this minimum, it was not considered further in arrhythmia detection. The third test was the maximum RR-interval or minimum heart rate. This test examines the physiological reliability of the heart rate and indicates the noisy alarm segments and missed QRS complexes. The maximum measure of the third test was set to six seconds. If all RR-interval in a segment were less than six seconds, the test was passed. The fourth ECG SQI test was the standard deviation of the ECG in the segment containing the alarm. This test helps identify the segments with a high percentage of noise and artefact. The optimum standard deviation was adopted as 0.05 over the whole segment. These tests address most of the observed corruptions on the ECG signals comprising the level of noise and the percentage of missed or spurious QRS detections in the segment. The output of the ECG SQI algorithm determines whether the ECG signal is satisfactory for next processing.

It should also be noted that not all steps of the ECG SQI were evaluated for all of the arrhythmia detections. Studies identified that SQI evaluation diminished the accuracy of arrhythmia diagnosis due to their noisy manifestation (Behar *et al* 2013). Since the behaviour of some of the arrhythmias such as VTA is homogenous to noise structure, ECG SQI reduced the performance and was removed from the false alarm detection of those arrhythmias. Further details will be described in section 3.3.

3.2. Pulsatile signals

It is reported that implementation of pulsatile signals which contain cardiac cycles improves the diagnosis of false arrhythmia alarms when combined with cardiac cycle information from ECG signals (Aboukhalil *et al* 2008). In the *PhysioNet/CinC Challenge 2015* dataset, one or both arterial blood pressure (ABP) and photoplethysmogram (PPG) signals were available and we utilized them to reduce the false alarm rate. The signal processing algorithms of the sample submission provided by the *PhysioNet/CinC Challenge 2015* were utilized for determining the beat onset points from the pulsatile signals and arrhythmia identification in this study. We provide a short description of these algorithms in the next sections.

3.2.1. ABP signal. Arterial blood pressure (ABP) was another signal used to verify the false arrhythmia alarms. As it is recorded separately to the ECG leads, it rarely contains identical interference to the ECG signal (Aboukhalil *et al* 2008). Also, ABP is regarded as the pressure signal with the least noise and artefact (Clifford *et al* 2006).

There were three PhysioNet open-source algorithms employed to process the ABP. In order to find the onset of the ABP pulses, the 'wabp' algorithm was executed on ABP signal (Goldberger *et al* 2000). The Length transform is exploited in this technique (Zong *et al* 2003) and noise removal and feature enhancement was applied through the algorithm. Following this, ABP features were calculated with the 'abpfeature' algorithm. The features include systolic pressure, diastolic pressure, systolic area, and mean pressure on the onset beats of the ABP pulses. Next, ABP quality index (SQI) was estimated by the 'jSQI' algorithm at each ABP detected beats (Sun *et al* 2004). The ABP SQI algorithm explores if the features are physiologically plausible. The features that were not clinically reliable were eliminated. Lastly, the time between the pulse onsets in the ABP signal was measured to generate pulse intervals of ABP signal to be used for further signal processing.

3.2.2. PPG signal. The other pulsatile signal used for false alarm detection was the photoplethysmogram (PPG) which was available in many of the recordings in the learning set of PhysioNet/CinC Challenge 2015. The open-source PhysioNet algorithms were employed to process the PPG signal. Firstly, the signal was divided into three partitions by the open-source 'quantile' algorithm. The three quantiles used were 5%, 50% and 95%. Next, the subtraction of third quantile and first quantile was measured and employed to detect pulse onsets. The onset beats of the PPG waveform was verified with 'wabp' algorithm (Goldberger *et al* 2000). Then, the pulse intervals were measured by the difference of the adjacent onset beats and used to calculate the heart rate. Finally, the PPG signal quality was evaluated with 'ppgSQI' algorithm through a beat template correlation technique.

3.3. Alarm detection

The segment containing the alarm from the available signals of each recording was selected from the 16 s prior to the alarm ending. The heart rates and intervals corresponding to the alarm segment were used for further signal processing. This study aimed to recognize the false arrhythmia alarms in real-time and avoid using the data following the alarm occurrence. Our proposed algorithm can also be implemented in a retrospective manner which uses the information after the alarm. In the *PhysioNet/CinC Challenge 2015* dataset, the alarms were set to appear at five minutes after the beginning of the signal. To guarantee alarm inclusion in the segment, the segment started 16 s before the alarm time. Next, the beats in the alarm segment were identified for the available signals of each recording and the corresponding RR-intervals, pulse intervals and heart beats were chosen. Finally, the features were calculated from the heart rates, RR-intervals or pulse intervals of the pulsatile waveforms. It should be noted that signal processing for each arrhythmia alarm condition were separately executed with different models and features (Behar *et al* 2013).

3.3.1. Multimodal signal. Interference in the ECG signal could be a source of the false arrhythmia alarms. Using other leads of the ECG signal simultaneously with other signals to combine the information could improve the diagnosis (Aboukhalil *et al* 2008). Thus, exploiting information from multimodal signals enhances the arrhythmia detection. It was reported that false arrhythmia alarms were better recognized by multimodal signal fusion which was widely discussed in the PhysioNet/Computing in Cardiology Challenge 2014 (Moody *et al* 2014). Various algorithms studied robust detection of the heart beats for multimodal recordings and signal fusion purposes (Silva *et al* 2015).

The highest score of the challenge was achieved by a SQI based method (Johnson *et al* 2015). They noted that the onset of the ABP pulses appear with a delay after the heart pumps blood out of left ventricle. The delay between detected onset beats of the blood pressure waveform and R peaks of the ECG signals were collected and the R peaks were matched according to the delay (Silva *et al* 2015). Then, the SQI measures of the signals were used to identify the high quality signal (ECG or ABP) which was then used for heart beat detection (Johnson *et al* 2015). A major focus was on employing different peak detectors for blood pressure and ECG signal to compare and evaluate their detection outcome.

In our study, the Hilbert QRS detector identified the QRS complexes with a decent accuracy (Hickey *et al* 2004, Shouldice *et al* 2004). So the QRS detections of the ECG signals were reliable measures with which to proceed the signal processing and advance to the pulse onsets of pulsatile signals provided by 'wabp' algorithm. Also the accuracy of the Hilbert QRS detector implied that application and comparison of other peak detectors for ECG signals is not essential.

Considering the available signals in the majority of the training set, the signals were prioritized from ECG signals to the pulsatile signals for feature extraction. However, unwanted interferences can corrupt the signal properties which are significant measures for arrhythmia detection. As previously mentioned, the noisy signals are known as a major source of false arrhythmia alarms (Aboukhalil *et al* 2008). Thus, the SQI of the signals were evaluated to identify noisy signals. If the signal passed the SQI tests, then features of the signal were extracted. The signal SQI measures were processed in the following order of first available ECG, second ECG, ABP and PPG. The SQI of the ECG signals was evaluated as explained in section 3.1.3. For all alarms with the exception of bradycardia and VFB, the result was decided based on the highest priority signal with the best quality of those considered and the alarm suppression or trigger was determined by that signal. For bradycardia and VFB, all considered signals satisfying the quality criteria were used in the decision-making process. The algorithm has been shown in the block diagram of the system in figure 1.

Combining the features and information of multimodal signals and evaluating the signal quality addressed the intervals with missing values or noises such as failure in sensor attachment and motion artefact as an observed issue in the challenge training set. This approach with multimodal signals benefits false arrhythmia alarm assessment in dealing with signals recorded in a real environment. This paper analyzed each arrhythmia through a different approach which will be explained in the following section. The contribution of each signal of training data in arrhythmia alarm detection is shown in table 1. It was identified after implementing and running the algorithm with the training set. It could be seen that multimodal signals benefit the arrhythmia recognition differently with various usage distributions. For

Table 1. The use of each signal in the decision criteria for each arrhythmia in the training set.

Signals	Asystole (%)	Bradycardia	Tachycardia	VFB	VTA
First ECG	75.4	Not used	100%	Not used	88.6%
Second ECG	1.6	Not used	Not used	Not used	3.2%
ABP	3.4	10.1%	Not used	22.4%	Not used
PPG	13.9	13.5%	Not used	8.6%	Not used
Not suppressed[a]	5.7	76.4%	0%	69.0%	8.2%

[a] Algorithm was not able to suppress the alarm using any of the four input signals.

instance, the table demonstrates that 75.4% of the asystole alarms were detected by the first ECG signals and 13.9% of the asystole alarms were detected by PPG signals. Only 5.7% of the asystole alarms could not be suppressed using any of the four input signals.

3.3.2. Asystole detection. Asystole (ASY) was defined as an absence of a heart beat for at least four seconds (Clifford *et al* 2015). Thus, the minimum threshold for asystole detection was set to four seconds with a tolerance of 0.5 s. The priorities of signals used for asystole detection were defined as the first ECG, followed by the second ECG followed by the available pulsatile signals. The criteria for using the ECG signals encompassed successful beat detection, a maximum RR-interval of less than the defined threshold for signal quality and a standard deviation (SD) within the defined threshold. This was less restrictive for use of the lower priority pulsatile signals where an availability of detected beats was sufficient. As is shown in the block diagram of the system in figure 1, the ECG SQI measures were not employed in asystole detection. This algorithm design decision was made as we found that implementing SQI measures tended to knock out heart beats, which increased the likelihood of false asystole alarm detections. The first signal to satisfy the aforementioned selection criteria was then used to determine the alarm result. The feature used for asystole was the maximum RR-interval of the segment which, if above the specified threshold and tolerance, triggered an alarm and otherwise, suppressed it. An alarm on the selected sensor resulted in the final decision being set to true alarm.

3.3.3. Extreme bradycardia detection. Extreme bradycardia (EBR) was defined as five continuous beat intervals greater than 1.5 s (Clifford *et al* 2015). We detected extreme bradycardia by processing the estimated minimum heart beats and identifying five or more consecutive beats with intervals exceeding 1.5 s. The pulsatile signals were exploited for EBR alarm recognition and the minimum heart rate of the available ABP and PPG signals were measured. Five or more consecutive beats with intervals exceeding 1.5 s were identified. The average heart rate of the beats were calculated and the minimum of these average heart rates in the alarm segment was recognized as the features called ‘Low HR’. Firstly, the SQI of the pulsatile signal was assessed. The SQI threshold for pulsatile signals set to 0.9. If the SQI of the signal satisfied the threshold, then the alarm segment was checked if it contained beats meeting the above criteria. If the feature was over the threshold with the tolerance for either pulsatile signals of ABP or PPG, the alarm was set to true. Otherwise, the alarm was assigned to false.

3.3.4. Extreme tachycardia detection. Extreme tachycardia (ETC) was defined as a heart rate elevation of more than 140 beats per minute for 17 consecutive beats (Clifford *et al* 2015). The algorithm begins with processing the first ECG signal, followed by the second ECG and the pulsatile signals, in the same order as that for asystole detection. The last feature of the

ECG SQI which was the standard deviation of the segment was omitted in the SQI evaluation for tachycardia alarm detection. Instead, a minimum number of beats defined for tachycardia served as an additional criterion for signal selection. This threshold was set to 11, which was chosen based on an iterative process, varying the threshold and adjusting according to the tachycardia detection performance on the training set. If ECG SQI reported a high quality signal and there was a sufficient number of beats detected in the segment, the signal was utilized for the next phase of tachycardia detection. Tachycardia minimum threshold was set to 110 bpm with a tolerance of 10 bpm. For the ABP signal, the SQI was compared to the threshold of 0.9 and the number of identified beats in the alarm segment was compared to the minimum acceptable beats for tachycardia detection. The heart rates from the selected signal were then able to trigger an alarm in two ways; the first was if the number of beats exceeded 30 for the acquired segment or secondly, if the number of beats above the tachycardia threshold and tolerance exceeded the minimum acceptable beats. If neither of these criteria were fulfilled, the alarm was suppressed.

3.3.5. Ventricular tachycardia detection. Ventricular tachycardia (VTA) was defined as five or more ventricular beats with heart rate higher than 100 beats per minute (Clifford *et al* 2015). Diagnosis of VTA was obtained by a template subtraction process using the raw ECG signals only. We did not use the pulsatile signals for VTA. Also, by removing the ECG SQI measures used in the other alarms from the process, the performance of false alarm detection was enhanced as VTA signals generally had poor SQI.

The first QRS complex in the series was taken as the reference template against which the subsequent waveforms were compared. A beat-to-beat sliding window was applied to the alarm segment to detect each QRS complex. The standard deviation (SD) and mean value of each QRS waveform were subsequently calculated and compared with the peak of the waveform. The complexes with peaks that did not lie within 1 SD of the mean were chosen for evaluation. Then, the mean value of each complex as well as the mean of the template waveform was removed. The waveforms with a SD that did not lie within 0.6 of the overall SD of the segment were labeled as 'irregular' waveforms. This feature was called 'filter vector'. If there were four or more irregular waveforms in the alarm segment, that is, the minimum threshold of 5 beats for VTA with a tolerance of 1 beat, the VTA alarm was set to true. Otherwise, it was labeled as a false alarm.

3.3.6. Ventricular flutter or fibrillation detection. Ventricular flutter or fibrillation (VFB) was assumed to be fibrillatory, flutter, or oscillatory waveform for at least 4 s (Clifford *et al* 2015). It is recognized as a difficult condition to detect using ECG signal (Clayton *et al* 1993, Jekova 2000). Different methods were applied in the studies such as threshold crossing intervals (TCIs) (Thakor *et al* 1990), autocorrelation function (ACF) (Chen *et al* 1987), and complexity measure (Zhang *et al* 1999) which the results were compared in studies (Clayton *et al* 1993, Jekova 2000). The comparisons showed the importance of threshold tuning and choosing the appropriate criteria.

To detect VFB in this study, the ABP SQI was evaluated and compared to the threshold of 0.9. If SQI was above threshold, then the maximum heart rate in the alarm segment was compared to the VF threshold. The VFB threshold was set to 250 bpm with a tolerance of 10 bpm. If the maximum heart rate of alarm segment was greater than the VFB threshold with the tolerance, the VFB alarm was set to true. A similar algorithm was repeated for PPG signal. Either of the pulsatile signals satisfying the criteria resulted in an alarm being triggered.

4. Results and discussion

The results of train and test set are shown in tables 2 and 3 respectively. The best alarm detection was achieved for the bradycardia alarm which obtained a score of 96% for train and 99% for test set. The average score of train set was 79%. While for the test set, the real-time score

Table 2. The results of true positive rates, true negative rates, and scores of training set.

	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
VFB	0.103	0.19	0	0.707	100	78.82	81.0
VTA	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

Table 3. 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
VFB	100	59	65.52
VTA	91	55	58.07
Real-time	95	65	69.92
Retrospective	98	66	74.03

achieved 69.9% and retrospective score reached 74% which was placed among the top ten scores of the *PhysioNet/Computing in Cardiology Challenge 2015*.

While ECG signals assisted in arrhythmia detection, the noisy characteristics of ECG signals were found to trigger false alarms. Hence, multiple steps were taken to minimize the corruption and negative effect of artefact. Interference removal of ECG signal, signal quality index, and utilizing information from multimodal signals was investigated to differentiate the inferences and improve false alarm detection. On the other hand, in some arrhythmias, interference removal, noise reduction and examining the signal quality did not help in false alarm reduction. We did not apply interference removal to ECG for the VTA arrhythmias. This was because the VTA signals exhibited behavior similar to the noise which our noise removal algorithms were designed to remove. For further improvement, a redesign of our noise removal algorithms so they did not knock out the VTA signal could enhance the results. The VTA alarm identification was reported as the most difficult alarm for detection among the entries of the *PhysioNet/Computing in Cardiology Challenge 2015* (Clifford *et al* 2015). An analysis of algorithms of the top scored entries revealed that better VTA and VFB alarm detection was achieved through algorithms that included descriptive statistics and QRS detection by amplitude envelopes using Fourier and Hilbert transform (Plesinger *et al* 2015), statistical analysis and hand-selected transform (Plesinger *et al* 2015), phase wrapping and machine learning (Ansari *et al* 2015) and adaptive frequency tracking and adaptive mathematical morph ology approach (Fallet *et al* 2015). The top entries utilized all of the signals comprising the ECG signals for VFB detection. In our approach, ECG signals were not utilized in the VFB and extreme bradycardia detection algorithms, and hence incorporating ECG information may improve the false alarm detection of these arrhythmias.

Table 4. The features that were selected in the evaluation process for each alarm type.

Features[a]	Asystole	Bradycardia	Tachycardia	VFB	VTA
Number of first ECG beats	√		√		√
Max RR of first ECG	√		√		
First ECG SD	√				
Number of second ECG beats	√		√		√
Max RR of second ECG	√		√		
Second ECG SD	√				
Number of ABP beats	√	√	√		
Max pulse intervals of ABP	√				
ABP SQI		√	√	√	
Low HR of ABP		√			
Max HR of ABP				√	
Number of PPG beats	√	√	√		
Max of RR PPG	√				
PPG SQI		√	√	√	
Low HR of PPG		√			
Max HR of PPG				√	
Length of filter vector					√
Number over threshold			√		

[a] The features were measured over the alarm segment and the detected beats and peaks in the segment.

Table 4 shows a list of the features that were incorporated and contributed in each arrhythmia alarm detection. It demonstrates which features were responsible in making the decision of each arrhythmia alarm identification. The last feature of the table, ‘Number over threshold’, refers to the number of beats above the tachycardia threshold and tolerance which exceeded the minimum acceptable beats. The results of arrhythmia detection and their employed features of table 4 suggest that the drawback of the proposed algorithm is the variety of features used. The more features employed, the better detection is achieved. We obtained our best result with extreme tachycardia alarm detection which the results of this exploration at table 4 showed to have the largest variety of features.

The various characteristics of the arrhythmias led to different implementation processes for individual arrhythmia alarm detection. This meant that some required noise reduction, while others needed the application of raw data with minimal noise removal. SQI evaluation improved the processing performance in some of the arrhythmia detection. Thus, a fixed method of signal quality evaluation is not suitable for analysis of a variety of arrhythmias with different properties. The evaluation techniques should be adapted to each arrhythmia.

The proportion of each arrhythmia alarm detected by each signal of training set is shown in table 1. Since we had the hierarchical or priority-based approach to selecting the signals to use (i.e. ECG was used firstly, then ABP followed by PPG), we did not necessarily use all of the signals to make the final decision. The results are comparable with the obtained scores from train and test set. It can be observed that asystole alarm identification was mainly detected by the first ECG signal and the distributions match the order of selection criteria. For instance, the ECG signals were firstly investigated for asystole detection and then the algorithm progressed to pulsatile signals for processing. The results from investigating the usage of the signals (see table 1) validated our assumption of giving the highest priority to ECG signals for asystole detection. It revealed that only 5.7% of the asystole alarms were not suppressed. In contrast, 76.4% of the bradycardia alarms and 69.0% of the VFB alarms were not suppressed by input signals. As we did not utilise ECG signals for detection of either of these alarms, the results suggest that utilising the ECG signals may improve suppression of these false alarms. The VTA alarm detection algorithm relied heavily on the first ECG signal for heart beat detection. A small number of cases (3.2%) were detected with second ECG signal and 8.2% were not successfully suppressed.

We found that varying the threshold setting significantly affected false alarm detection. Thus, implementation of parameter optimization methods such as SVM (support vector machine) as a threshold tuning and model selection algorithm could enhance the scores.

As a final comment, we describe one signal processing step we trialed and abandoned as it did not result in improvement in the scores of either the train or test set. The signal processing step attempted to boost the heart rate identification by multimodal signal integration. The algorithm examined the detected beats of the ECG signals. In case of low quality ECG signals or missing beats, it switched to pulsatile signals. In order to match the R peaks of ECG with pulse onsets of pulsatile signals, the delay between R peaks of ECG signals and pulse onset of pulsatile signals was measured. We adapted a fusion method proposed in the *PhysioNet/Computing in Cardiology Challenge 2014* by Johnson *et al* (2015). The peaks of the available ECG signals and pulsatile signals in the alarm segment were checked. In the case that more than 90% of the R peaks were followed by the pulse onsets of the pulsatile signal, the delays between the peaks were measured. The average of the delays in the alarm segment was set to the delay for the whole segment containing the alarm. A default delay value of 200 ms was used for the segments which did not satisfy the criteria. Then, the R peaks and the corresp onding pulse onset beats of the pulsatile signal were compared in a one second window through the whole alarm segment. The percentage of the R peaks matching the pulsatile onset beats in an interval of the corresponding delay between them was calculated. If the matching rate was above 90% then the signal quality was deemed acceptable. As our algorithm was not successful, further work is needed to improve the integration technique. Finding an optimum matching rate and adjusting the delay for the available signals could enhance the performance of the algorithm.

5. Conclusion

Our result placed us among the top ten scores of the *PhysioNet/Computing in Cardiology Challenge 2015*. Our proposed system achieved the highest score in detecting tachycardia false alarms. Our best performing algorithm used multimodal signals, combined the information from ECG and pulsatile signals, extracted and evaluated a number of features of the signals for alarm identification. Modification of the signal quality measures for different arrhythmias rather than employing a fixed SQI for every arrhythmia, setting the threshold in an iterative performance evaluation, and considering various possible effects of each arrhythmia on the features of the signals enhanced the arrhythmia identification performance. For future alarm management systems, a modified noise removal algorithm, adaptive SQI measurements for each arrhythmia, multimodal signal integration with optimum matching rate and adjusted delay could improve the performance.

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