Reliability of Clinical Alarm Detection in Intensive Care Units

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Abstract

In hospital environments advanced medical devices are vital for both monitoring and therapy. Many have alarms, especially in intensive care areas. To ensure that important and unwanted clinical events are not missed, there is a tendency for devices to react to noise and artefact in the physiological waveforms, with many resulting false alarms.

PhysioNet along with Computing in Cardiology have made available clinical alarm data, to allow improved algorithms for alarm detection to be developed. We present our results.

Our analysis steps included: high pass filtering to remove baseline instability, scaling to normalise waveform amplitudes, detection of noisy and flat waveforms, differentiation to accentuate sharp waveform edges, beat detection, timing between beats preceding alarm onset, and detection of alarm conditions. When the waveforms were assessed as noisy they were labelled as false alarms. When noise-free and alarm conditions were met they were labelled as true alarms.

The original PhysioNet analysis algorithm analysed arterial blood pressure (ABP) and photoplethysmograph (PPG) waveform data, resulting in true alarm detection sensitivity of 89% and 88%, and specificity of 38% and 38%, for the training and test data sets respectively, indicating a similar range of data in both sets.

We investigated the use of ECG data alone with the training data, and this resulted in overall gross sensitivity and specificity for the first ECG channel of 89% and 68%, and for the second 87% and 68% respectively, indicating similarity in the two ECG channels. When BP and PPG were analysed following detection of noise in the ECG the results were 92% and 56%, and 90% and 54% respectively.

We have shown that analysis of the ECG alone can obtain average sensitivity of 88%, with little difference in results between two simultaneous ECG channels. When the arterial blood pressure and peripheral pulse were also analysed this additional physiological data improved sensitivity by 3% points, but decreased specificity by 13% points in the training set, and 4% and 9% respectively in the test set.

1. Introduction

Patient monitoring has continued to develop in hospitals from early monitoring systems [1]. To enable medical and nursing staff to attend quickly to changes in patient conditions, medical monitoring devices have been developed to detect unwanted clinical conditions and hence initiate alarms. Although these alarms often work well, even a small percentage of false alarms can lead to significant frustration with increased workload in already busy medical units, such as surgical theatres or intensive care units [2-4].

Although the quality of physiological data has been studied in ambulatory monitoring [5] and in Intensive Care [6], there is as yet no adequate compromise between reliable detection of genuine alarms and the elimination of false alarms.

The PhysioNet/CinC Challenge was introduced to aid the development of improved alarm monitoring.

2. Methods

2.1. Alarm conditions

Programs to identify alarm conditions were written in Matlab. They were developed using the training database provided by PhysioNet. Five alarm conditions had to be identified:

Asystole
Bradycardia
Tachycardia
Ventricular flutter/fibrillation
Ventricular tachycardia

2.2. Alarm data

The physiological data were from recordings that could include two ECG channels, one peripheral pulse channel and one arterial blood pressure waveform channel. Data were made available by PhysioNet:

http://www.physionet.org/challenge/2015/

True alarm conditions were provided for the training data set of 750 recordings.

The test data set of 500 recordings were retained by PhysioNet, and overall test results were provided for programs to detect alarm conditions, sent in Matlab code. Results for individual patients were not provided.

2.3. Algorithm development

The beat detection algorithm (Figure 1) included the following signal processing stages that were applied to either of the two ECG channels, followed by the additional analysis of the arterial blood pressure (ABP) and photoplethysmography (PPG) pulse signals.

The recorded signals were band pass filtered using a finite impulse response (FIR) filter designed with lower and upper cut-off frequencies of 5 and 30 Hz respectively, and with a Hamming window approach. This was followed by scaling to make signals have approximately the same amplitude. The output was then differentiated using a 2-point first-order digital differentiator, followed by the application of a sample-by-sample non-linear squaring operation, which was then low pass filtered. The differentiation operation was equivalent to high pass filtering that attenuated the P and T waves, while amplifying higher frequencies. The low pass filter was implemented using a 7th order time averaging FIR filter.

The output of the low pass filter was then presented to the timing extraction stage that computed the heart rate and decided on the presence of the various arrhythmia alarm conditions (Figures 2 and 3).

Prior to the timing extraction stage the signal was analysed for non physiological conditions, such as unusually flat baseline signals, non-numerical signal values and extremely noisy signals resulting from poor electrode contact. If any such condition was identified, ECG detection was disabled without further analysis and a false alarm flagged.

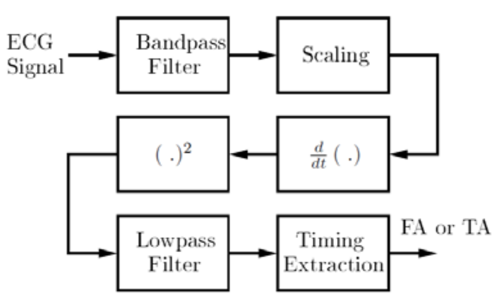

Figure 1. Stages in physiological signal processing.
FA False alarm, TA True alarm

2.4. Evaluation

Our Matlab programs were used to determine alarm conditions, and hence assess sensitivity and specificity of alarm detection.

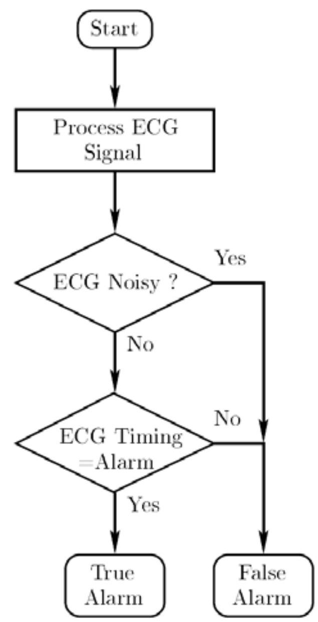

Figure 2. Decision algorithm for analysis using ECG data only.

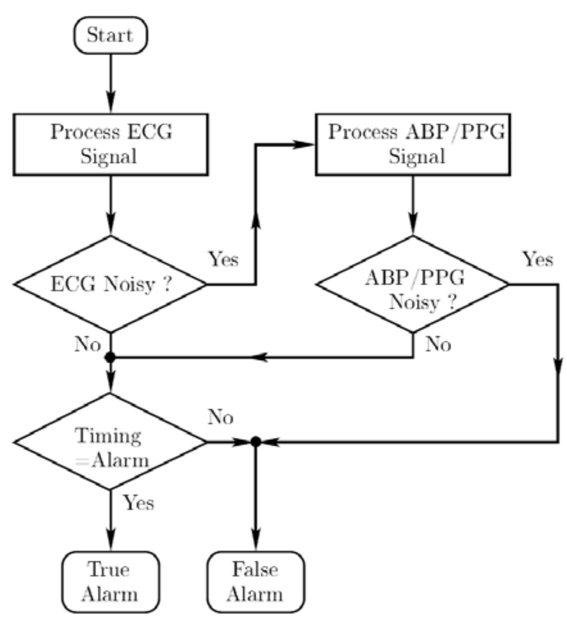

Figure 3. Decision algorithm for analysis using ECG, arterial blood pressure and photoplethysmograph data.

3. Results

3.1. PhysioNet algorithm results

The results for detection of the 5 clinical conditions, for both the training and test data sets are given in Table 1. It can be noted that the results for the two data sets are similar, indicating similar conditions in both sets.

Training data analysis

Alarm condition	Sens	Spec
Asystole	82%	51%
Bradycardia	98%	58%
Tachycardia	87%	56%
Ventricular flutter/fibrillation	83%	48%
Ventricular tachycardia	90%	26%
All alarm conditions	89%	38%

Test data analysis

Alarm condition	Sens	Spec
Asystole	75%	44%
Bradycardia	92%	63%
Tachycardia	87%	60%
Ventricular flutter/fibrillation	83%	68%
Ventricular tachycardia	84%	23%
All alarm conditions	88%	38%

Table 1. Results for the algorithm provided by PhysioNet. Sens = Sensitivity; Spec = Specificity.

3.2. Newcastle algorithm results

Results for the training set are given in Table 2 firstly for the use of only the ECG channels, where the two channels are treated separately. The table also gives the results for the analysis of the ECG channels along with the arterial blood pressure and pulse channels. The results for all alarm conditions were similar with the use of either of the two ECG channels, indicating similar difficulty in identifying alarms in both ECG channels.

Results for the test data set are given in Table 3. In comparison with the training data, the sensitivity was lower and the specificity higher. Across all data, sensitivity increased by 3% points for the training and 4% points for test data (average 3.5% points), compared with a fall in specificity by 13% points for the training and 9% points for test data (average 11% points).

Training data analysis

ECG 1 only

Alarm condition	Sens	Spec
Asystole	96%	95%
Bradycardia	98%	77%
Tachycardia	95%	67%
Ventricular flutter/fibrillation	100%	90%
Ventricular tachycardia	72%	51%
All alarm conditions	89%	68%

ECG 2 only

Alarm condition	Sens	Spec
Asystole	77%	94%
Bradycardia	94%	79%
Tachycardia	95%	56%
Ventricular flutter/fibrillation	100%	98%
Ventricular tachycardia	73%	51%
All alarm conditions	87%	68%

ECG 1 + ABP + PPG

Alarm condition	Sens	Spec
Asystole	100%	80%
Bradycardia	98%	70%
Tachycardia	98%	67%
Ventricular flutter/fibrillation	100%	87%
Ventricular tachycardia	80%	31%
All alarm conditions	92%	56%

ECG 2 + ABP + PPG

Alarm condition	Sens	Spec
Asystole	100%	80%
Bradycardia	94%	70%
Tachycardia	96%	56%
Ventricular flutter/fibrillation:	100%	94%
Ventricular tachycardia	76%	33%
All alarm conditions	90%	54%

Table 2. Results for the training data set.
ABP Arterial Blood Pressure
PPG Photoplethysmography
Sens = Sensitivity; Spec = Specificity.

Test data analysis

ECG 1 only

Alarm condition	Sens	Spec
Asystole	83%	91%
Bradycardia	44%	84%
Tachycardia	96%	80%
Ventricular flutter/fibrillation	33%	92%
Ventricular tachycardia	69%	53%
All alarm conditions	79%	70%

ECG 2 only

Alarm condition	Sens	Spec
Asystole	67%	85%
Bradycardia	62%	83%
Tachycardia	98%	80%
Ventricular flutter/fibrillation	78%	84%
Ventricular tachycardia	88%	52%
All alarm conditions	87%	66%

ECG 1 + ABP + PPG

Alarm condition	Sens	Spec
Asystole	83%	79%
Bradycardia	64%	78%
Tachycardia	96%	80%
Ventricular flutter/fibrillation	33%	92%
Ventricular tachycardia	76%	42%
All alarm conditions	84%	61%

ECG 2 + ABP + PPG

Alarm condition	Sens	Spec
Asystole	83%	78%
Bradycardia	67%	78%
Tachycardia	98%	80%
Ventricular flutter/fibrillation	78%	84%
Ventricular tachycardia	93%	36%
All alarm conditions	90%	57%

Table 3. Results for the test data set.
ABP Arterial Blood Pressure
PPG Photoplethysmography
Sens = Sensitivity; Spec = Specificity.

4. Discussion and conclusions

The reduced sensitivity with the test set indicates that the analysis was slightly tuned to the training set, rather than being generalized. This is a typical problem with developing any analysis system. When the sensitivity was improved by including arterial blood pressure and pulse data, this improvement was offset by a reduction in specificity. In other words, the improved detection of clinical conditions was offset by an increased number of false alarms. The percentage point decrease in specificity (increasing false alarm rate) was greater than the percentage point increase in detection of true clinical alarm conditions. Across all data, sensitivity increased by an average of 3.5% points, compared with a fall in specificity by an average of 11% points. There is a need for an analysis technique that would improve both the sensitivity and specificity.

References

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