Reduction of False Blood Pressure Alarms by use of Electrocardiogram Blood Pressure Relationships

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Abstract

This paper presents an algorithm for reducing false alarms related to changes in arterial blood pressure (ABP) in intensive care unit (ICU) monitoring. The algorithm assesses the ABP signal quality, analyzes the ECG-ABP relationships using a fuzzy logic approach, and post-processes (accepts or rejects) ABP alarms produced by a commercial monitor. The algorithm was developed and evaluated using disjoint sets of data from the MIMIC database. By rejecting 96.8% of the false ABP alarms (182 of 188) produced by the monitor using the test set of data, the algorithm was able to reduce the false alarm rate from 34.9% to 1.7% of ABP alarms, while accepting 99.4% of true ABP alarms (346 of 348). The results show that the algorithm is both effective and practical, and feasible for use in future monitoring systems.

1. Introduction

In intensive care unit monitoring, there is a high incidence of false alarms, which becomes a distracting and annoying problem[1, 2]. Sometimes alarms may be disabled by medical staff because of the false alarm problem. It is desirable to reduce the incidence of distracting false alarms without causing true alarm events to be missed. ICU monitors most often produce false alarms when a physiologic signal is corrupted by artifacts, which may cause certain measurements to cross thresholds. Although most such false alarms can be easily identified by looking at the signal quality and by reference to other related signals, ICU monitors do not typically have sophisticated signal quality analysis, and they generally do not take advantage of the relationships among signals of different types in order to assess the reliability of their inputs or the plausibility of potential alarms.

Fig. 1 shows some examples of ABP artifacts found in the MIMIC Database. It should be noted that some artifacts (such as that in Fig. 1d) are very similar in appearance to real physiologic changes.

Previous efforts have been made to reduce ICU false alarms based on analysis of multi-channel measurements available from commercial monitors [3,4]. Although these studies did not directly address the quality of the signals from which the measurements were derived, their results encourage further research.

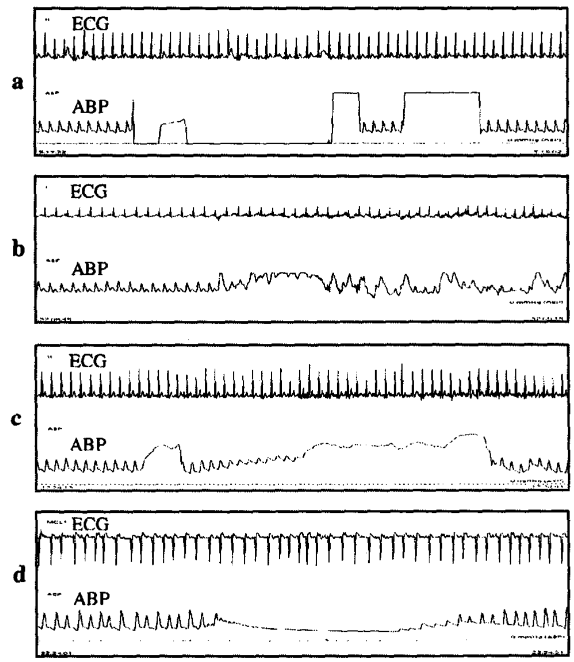

Fig. 1. Examples of artifacts in ABP signals (a: transducer flushing, b: motion, c: catheter obstruction, d: proximal BP cuff inflation; 30 seconds per trace).

This study presents an algorithm for reducing false ABP alarms by assessing the signal quality of the ABP waveform, and fusing information from simultaneous ECG and ABP signals. A fuzzy logic analysis approach was employed in the process. We used separate records from the MIMIC Database [5] for development and for evaluation. Our results show that this algorithm is both effective and practical, and shows promise for use in future monitoring systems.

2. Materials and methods

We used 53 MIMIC Database records containing both ABP and ECG signals for development and evaluation. The first 25 records were used for algorithm development, and the remaining 28 were reserved as a test set. Once the algorithm had been developed, it was used to process the test data set without any further adjusting.

The MIMIC Database includes an annotation for each alarm produced by the patient monitors from which the records were acquired. The monitors produce these alarms at intervals of 1.024 seconds, from the time when the alarm condition (a measurement crossing a threshold) is first detected until either the measurement returns to the acceptable range, or the ICU staff silence the alarm by pressing a button on the monitor. In this study, repeated alarms referring to the same alarm condition and separated by 15 seconds or less were treated as a single alarm event. We visually judged each alarm to be either true or false by reviewing all data available to the monitors.

Our algorithm is based on beat by beat ABP signal quality analysis with incorporation of ECG-BP relationships. The structure of the algorithm is shown in Fig.2.

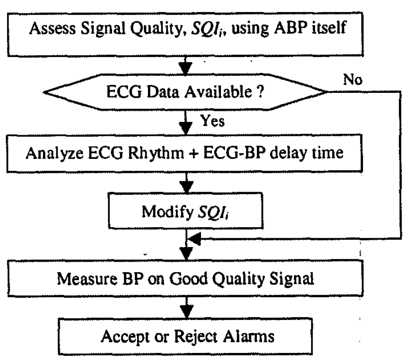

Fig. 2 Overview of the algorithm.

First, ABP signal quality is assessed on a beat-by-beat basis using the ABP itself, yielding a signal quality index (SQI_i), which has a value between 0 and 1. SQI_i is derived from and is attached to each beat. If QRS information from ECG data is available, SQI_i may be modified, based on analysis of the ECG rhythm and ECG-BP delay time (the time delay between the QRS and following ABP pulse). The BP measurements (systolic, diastolic and mean blood pressure) are derived only from good quality signals (those signals with high SQI_i). Acceptance or rejection of alarms is based on the BP measurements and recent SQI_i values.

2.1. ABP signal quality assessment

Signal quality assessment of the ABP itself is performed through beat-by-beat signal feature fuzzy testing. Fig. 3 shows a flow chart of the process.

First, a two-second detection/measurement time window is defined. If an ABP pulse is detected within the window, the end of the window is reset to the time of the onset of the next detected pulse. Features of the waveform within the window, such as amplitude and slope, etc., are extracted (whether a pulse was detected or not). The *base feature set*, established during an initial learning period, evolves using weighted averaging as the ABP waveforms change. The waveform features are then described by linguistic (fuzzy) variables. The signal quality index, SQI_i, is obtained via fuzzy reasoning [6] on these linguistic variables.

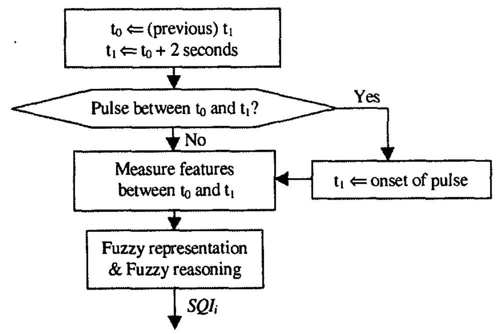

Fig. 3. Assessing signal quality using the ABP itself.

The linguistic variables for describing local waveform characteristics, such as *'ABP_amplitude_too_high' (ATH)*, *'ABP_slope_normal' (SN)*, etc., are defined with the S and Z functions [7,6]. For example, the certainty degree of *ATH* is determined by the S function (see Fig. 4) as:

$$\mu_{ATH} = S(x\,;\,a,\,b) \qquad (1)$$

where x is the ratio of current BP amplitude to the averaged systolic BP kept in the base feature set; a and b are bounds, between which S varies from 0 to 1 (here we choose a=1.0, b=1.8).

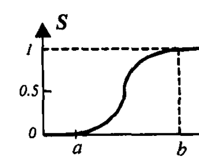

Fig. 4 The S function

A fuzzy variable, *'Signal_quality_good' (SQG)*, is used to describe the signal quality. *SQG* is derived from the linguistic variables that describe the signal features, in part as follows:

IF [**not** *'ABP_amplitude_too_high' (ATH)*] **and**
[**not** *'ABP_keeps_rising_too_long' (KRTL)*] **and**
'ABP_slope_normal' (SN) **and**
. . .
THEN *'Signal_quality_good' (SQG)*

The signal quality index (SQI_i) is assigned as the certainty degree of *SQG*, i.e.,

$$SQI_i = \mu_{SQG} = (1-\mu_{ATH}) \wedge (1-\mu_{KRTL}) \wedge \mu_{SN} \wedge \ldots \qquad (2)$$

2.2. Use of ECG-ABP relationships

ECG and ABP are closely related in terms of rhythm and timing. When ECG data are available, the SQI_i as described above may be modified, based on an analysis of the ECG-ABP relationship. Figure 5 summarizes this procedure.

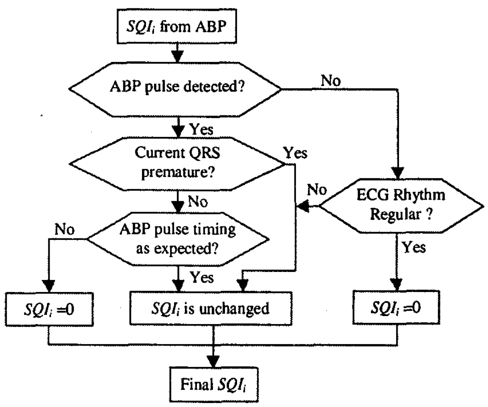

Fig. 5. Procedure for ABP SQI_i modification.

In this study, we employed a previously developed ECG beat detection algorithm, Aristotle [8], to obtain times of occurrence and types of QRS complexes.

The analysis of the ECG-ABP relationship begins by checking the ECG-BP delay time against a range of delay times established during the learning period. If an ABP pulse was detected, and the delay time falls within the expected range (indicating the BP pulse is associated with a real beat), or if the beat is premature (in which case the algorithm does not attempt to predict the timing of the BP pulse), then SQI_i is not modified; otherwise the pulse may be an artifact, and SQI_i is set to zero. If no ABP pulse was detected, SQI_i is set to zero unless the ECG rhythm is irregular. (If at least 8 of the last 15 QRS complexes are either on-time or of normal morphology, the ECG rhythm is considered regular for this purpose. SQI_i is accepted without modification in the context of an irregular rhythm, since such rhythms may be accompanied by loss of ABP pulses.)

Fig. 6 shows an example of the ABP signal quality index (SQI) derived by the algorithm from the ECG and ABP data (which are from record 254 in the MIMIC Database). Low values of SQI correspond to poor ABP signal quality (note that there is a one-beat delay from the ECG and ABP signals to the SQI signal).

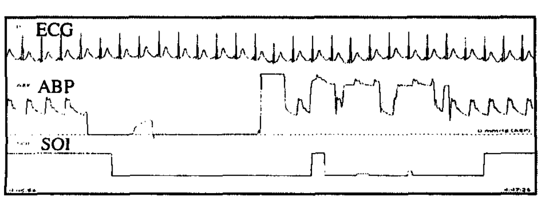

Fig. 6 Example of ABP Signal Quality Index (15 seconds).

2.3. BP measurements

In addition to the SQI_i, the algorithm produces ABP measurements (systolic, diastolic and mean). The algorithm obtains both instantaneous (beat-by-beat) measurements and short-term averaged measurements (derived from only those instantaneous measurements with $SQI_i > 0.5$). In other words, those values associated with poor signal quality are not counted in the averaged measurements used as a basis for our algorithm's decisions with respect to alarms.

When we compare the ABP measurements produced by the monitor and those derived from our algorithm (see the example in Fig. 7, with data from MIMIC record 212), we can see that most unexpected spikes in the monitor's measurements are removed by the algorithm.

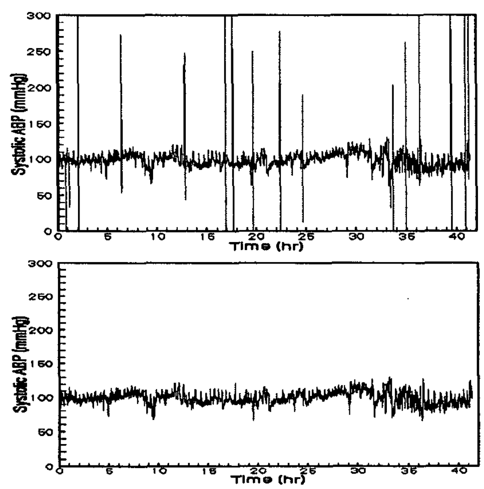

Fig. 7 Systolic blood pressure (SBP) vs time:
Upper: SBP measurements produced by the monitor
Lower: SBP measurements from our algorithm

2.4. Reduction of false ABP alarms

Our algorithm judges the alarms produced by the monitor, based on the SQI_i in the 15 seconds immediately prior to the onset of the alarm condition noted by the monitor. If all the SQI_i in this 15 second interval are good (≥ 0.5), the alarm will be judged as true. If there are 4 or more bad SQI_i (< 0.5) in this interval, this alarm is judged as false. If there are 1, 2, or 3 bad SQI_i, then the systolic ABP measurement from the monitor (at the onset of the alarm, as recorded in the MIMIC Database) and the averaged systolic ABP measurements from our algorithm (during the 15 seconds prior to the alarm onset) are compared. If at least three of our algorithm's measurements are within 15 mmHg of the monitor's measurement, then the alarm is judged as true, otherwise, false.

3. Results

The development data set contains 25 records averaging 33 hours in length (ranging between 8.4 and 62.7 hours; in all, 825 hours). The monitors produced 637 ABP alarms, of which 140 (22%) were false alarms based on visual review. When we compared the judgements by our algorithm with human judgements, we found that our algorithm rejected all 140 false alarms (100%) and only 2 true alarms, as shown in table 1. Thus our algorithm reduced the false alarm rate in the development data set from 22% to zero at a cost of rejecting 0.4% of true alarms.

		ALGORITHM		
		True	False	Total
TRUTH	True	495	2	497
	False	0	140	140

Sensitivity: 99.6%
Positive predictivity: 100 %

Table 1. Algorithm performance on the development data.

We repeated this experiment using the test set (28 records averaging 38 hours in length, with a range of 10.6 to 58.5 hours; 1065 hours in all). Table 2 shows the evaluation results on the test data. The monitors produced 536 ABP alarms, of which 188 (35%) were false alarms based on visual review. The algorithm rejected 182 (97%) of these false alarms, reducing the false alarm rate from 35% to 1.7%, while rejecting only 2 (0.6%) of the 348 true alarms.

		ALGORITHM		
		True	False	Total
TRUTH	True	346	2	348
	False	6	182	188

Sensitivity: 99.4%
Positive predictivity: 98.3 %

Table 2. Algorithm performance on the test data.

4. Discussion and conclusion

Artifact is a major factor responsible for false alarms. It is very necessary to have signal quality control for reducing false alarms. Sometimes artifacts appear very similar to real physiologic changes; thus additional information from other related signals is crucial in such cases.

This paper presents an approach to reducing false ABP alarms based on both the analysis of ABP signal quality and the use of ECG-ABP relationships. The use of fuzzy feature representation and fuzzy reasoning provides a comprehensive and effective way to assess signal quality for each ABP episode. Data suspected of being artifact-corrupted are marked but not canceled. ABP measurements from those data with good SQI appear more reliable than those without adequate signal quality control. By use of this approach, false ABP alarms were very significantly reduced with only a very small number of rejected true alarms. (Note that the number of alarm events missed by the monitors themselves was not determined in this study.)

Our extensive evaluation results indicate that this approach appears to be both effective and practical, and should be considered for use in future monitoring systems.

References

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