An Applicability Recognition Method for Multi-parameter Analysis

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Abstract

Alarm fatigue has always been a clinical problem. Multi-parameter Analysis (MPA) is a popular technology to solve this. However, there are some inapplicable cases in practice, such as in severe peripheral circulation disorder, CPR etc or even vital signs collecting from different subjects. In these cases, important alarms may be wrongly suppressed if MPA is applied, increasing clinical risk for subjects. This study focuses on recognizing the applicability for MPA with multi-parameter monitor.

Electrocardiograph (ECG) and pulse wave are normally synchronous. Based on this, our method evaluates the MPA applicability as below: first, multiple physiological signals are analyzed by highly reliable single-parameter analysis methods to obtain the parameters results and signal quality index; Then, signal features of different channels are grouped for each cardiac cycle. Finally, the group feature are derived and used with a simple decision tree for MPA applicability evaluation.

There database were used for algorithm testing. DB1 contains 200 clinical waveform records whose length is 1 hour and the heart rate range is 35 to 160. DB2 includes 100 clinical waveform records; DB3 contains 30 cases recorded in cardiopulmonary resuscitation, each case spanning 2 hour long. The true recognition rates on the three databases are all more than 90%. The applicability recognition method proposed can effectively decide whether physiological signals can be used for MPA.

1. Introduction

False alarm from monitors has been ranked as top patient safety hazard in intensive care unit[1]. In order to reduce the impact of alarm fatigue, multi-parameter analysis (MPA) has been widely adopted to reduce false alarms and alleviate alarm fatigue, Qiao L. et al[2] in 2012 used a machine learning algorithm to fuse the features of electrocardiogram (ECG), photoplethysmogram (PPG) and arterial blood pressure (IBP) and reduced more than 80 percent of the false alarms of asystole and severe bradycardia. Wei Z. et al[3] developed an event feature for malignant arrhythmia detection, based on the waveform features of ABP and PPG, and showed that it could reduce false alarm by 50 percent. Multi-parameter fusion technology, if used appropriately, can greatly improve alarm accuracy.

However, it should be noted that there are some clinical situations where the underlying assumption of MPA technology is not valid. For example, in severe peripheral circulation disorder and cardiopulmonary resuscitation (CPR), subject's cardiac rhythm often differs dramatically from the pulsatile rhythm; or in some situation, different patients may be connected to the same monitor. Although the latter scenario is not commonly seen, we found, in the post market clinical follow-ups that it's not rare in some region when short of monitors. Only when solving these problems properly can we use MPA technology without adding new risks.

This article introduces a method to address the problems described above. . This method can be used as a preceding module of a MPA method to ensure the safety and effectiveness of sensor fusion.

2. Methods

A typical example of multi-parameter analysis(MPA) technology is the joint analysis of ECG, PPG and IBP. Normally, in one cardiac cycle, ECG records heart's electrical activity, whereas the synchronized PPG and IBP record the pulsatile variation in the arterial blood resulted from the corresponding heart contraction – we refer to situations like this as MPA applicable situations in this paper[4]. As shown in Fig.1, in MPA applicable situations, the temporal relationships between the metaphoric characteristics of these recordings are usually regular and consistent. On the contrary, when these signals are not synchronized, collected from different person or from a person suffering circulatory collapse, the relationship will vary dramatically. We propose an algorithm to recognize the MPA applicable situations.

The applicability recognition technology of MPA mainly includes two parts, as shown in Fig. 2: Part I: multiple physiological signals are analyzed by highly

reliable single-parameter analysis methods to obtain the characteristics and parameters results (including heart rate, arrhythmia, severe ventricular fibrillation, asystole…) and signal quality index (SQI); Part II: signal features of different channels are synchronized and grouped for each cardiac cycle. After that, the group feature sequence is derived and used for situation recognition.

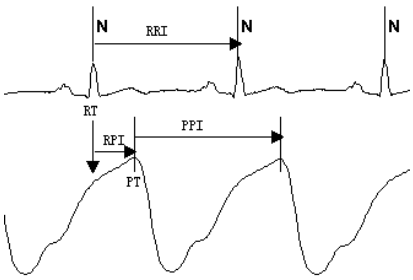

Figure 1. Features used in MPA applicability recognition method. RRI: R-R interval, RT: R wave peak time, PPI: Pulse peak interval, PT: Peak time of pulse wave, RPI: R wave-pulse wave interval.

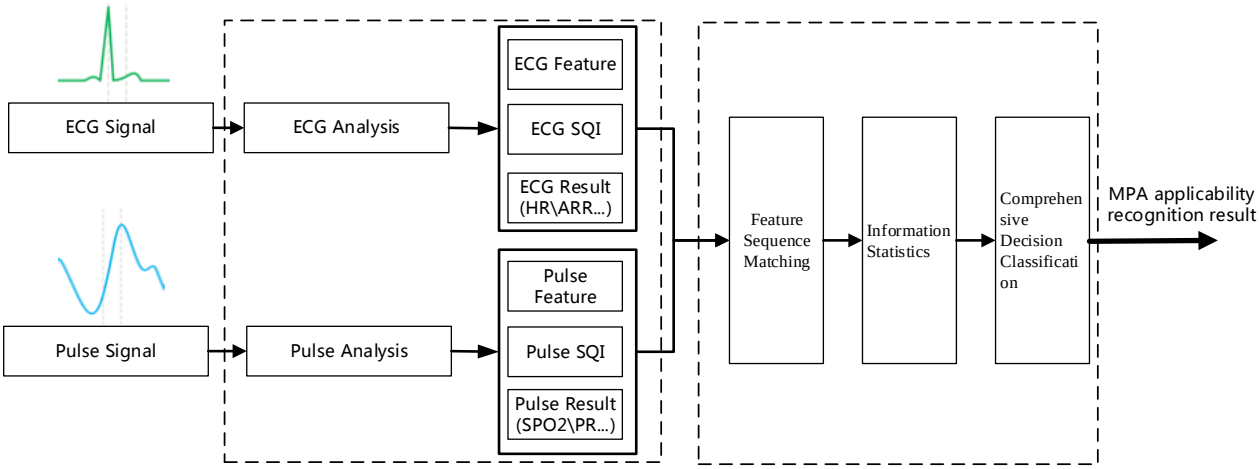

Figure 2. The applicability recognition method for Multi-parameter Analysis

2.1. Single-parameter Signal Analysis

After resampling and filtering , the multi-channel ECG signals are processed by *Mindray ECG Algorithm* [5,6] to accurately locate the QRS complexes and get heart rate, arrhythmias and signal quality index (SQI). PPG is also processed by our high performance algorithm to get SPO2, PPG SQI and to locate the pulse peaks [7,8,9].

The results of single parameter analysis are used as inputs to MPA, and after information fusion, MPA will further improve the accuracy of ECG and PPG parameters results.

2.2. MPA Applicability Recognition

2.2.1. Feature Sequence Matching

The purpose of this module is to group ECG features and PPG features resulting from the same cardiac cycle by matching the ECG R peaks and PPG pulse peaks. It consists of two parts:

The first part is to exclude abnormal feature sequences. If there is a high-risk ECG alarm such as ventricular fibrillation and asystole or a high-risk blood oxygen alarm such as extremely low oxygen, or extremely low SQI caused by severe interference, or other situations like sensor drop. The current feature sequence won't be used for further feature matching.

The second part is feature sequence matching. In MPA applicable situations, the number of peaks in ECG signal is same with that of pulse signal. In other situations, such as invalid heart ejection or severe signal interference, the number of R peaks in ECG can be different with that of pulse wave peaks, or the offset between the locations of these peaks varies dramatically, making it difficult to identify the adaptability. Therefore, it is very important to align the ECG signal features with the pulse signal features in order to form a feature group sequence.

ECG and PPG are aligned as in below:

A pulse peak is always later than the corresponding ECG R peak. The time delay between a pulse peak and the corresponding R peak is called R-peak Pulse-peak Interval (RPI). A window of delay is therefore used whenever an R peak is detected in ECG, to check if a pulse peak will be detected shortly after. The length of delay is set to 100ms to 200ms before a new R peak is detected – we refer to the delay times in this paper[10].

If only one pulse peaks in PPG is detected in the window of delay, the pulse peak and the R peak will be grouped; if more than one pulse peak is detected as in figure 7 – it could occur when signal amplitude is unusually low and interference is severe – a pulse peak will be selected based on the historical trend of RPI.

There are three types of matching between QRS wave

and pulse wave:

1) 1 QRS - corresponds to1 pulse wave, as shown in Figure 3, when the signal quality of both ECG and PPG is good.

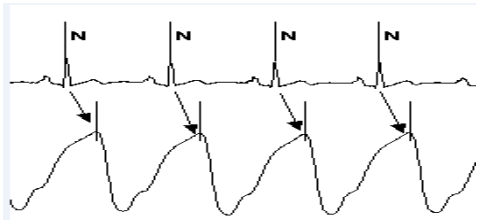

Figure 3. 1 QRS wave - 1 pulse wave

2) 1 QRS corresponds to 0 pulse wave, as shown in Figure 4. Invalid ejection results in no wave in the pulse signal, so that QRS complex has no corresponding pulse wave in the same time window.

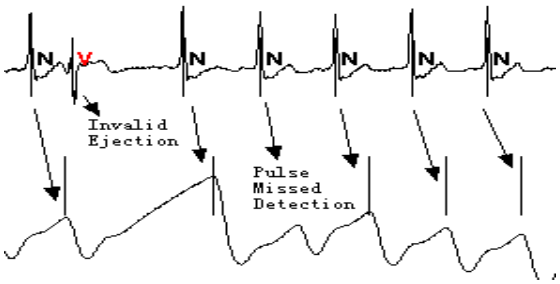

Figure 4. 1 QRS - 0 pulse waves

3) 1 QRS wave corresponds to N pulse waves (N > 1), as shown in Figure 5. Low amplitude and interference lead to missed QRS detection, which makes one QRS wave correspond to multiple pulse waves in the same time window; False detection of pulse waves may also cause this situation.

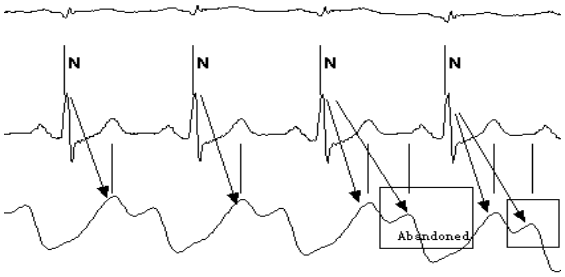

Figure 5. 1 QRS wave - N pulse waves (N > 1)

2.2.2. Information Statistics

The R-peak Pulse-peak Interval (RPI), R-peak Pulse-valley Interval (RVI) and their means and variances are calculated based on the grouped R peak and Pulse wave.

R-R intervals (RRI) are calculated for ECG. Peak-peak interval (PPI) and Valley-Valley Interval (VVI) are calculated for PPG.

2.2.3. Comprehensive Decision Classification

The MPA applicability is classified into *surely applicable*, *applicable*, *not applicable and surely not applicable*, following a simple decision tree.

1) First, we compare the RRI of ECG and the PPI and VVI of PPG. If they vary greatly and the trends agree as in Fig. 6, MPA is *surely applicable*. Otherwise,

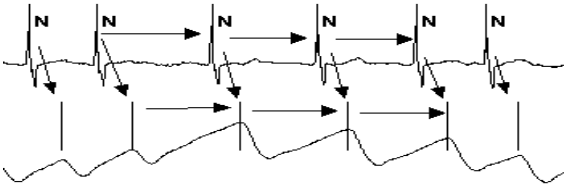

Figure 6. Joint feature type I

2) When premature ventricular contraction (PVC) is detected in ECG, and the R-R intervals of the normal heart beats right before and after the PVC are close to the corresponding interval of the pulse wave, as shown in Fig. 7, MPA is also *surely applicable*. Otherwise,

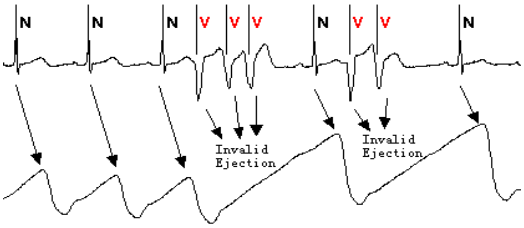

Figure 7. Joint feature type II

3) MPA applicability is decided according to the rules below:

- If the consistency ratio of RPI to RVI exceeds 80%, MPA is *applicable*;
- If the number of effective RPI is less than 5, the previous judgment result is maintained.
- If the consistency ratio of RPI or RVI is less than 20%, MPA is *not applicable*.
- If variances of RRI, PPI and VVI are all very small, but values have big difference, MPA is *surely not applicable.*

3. Results

3.1. Database Description

We used three databases to evaluate the proposed method as shown in Table1. DB1 contains 200 clinical recordings，each spanning 1 hour long and heart rate ranging from 35 to 160. DB2 were created using signals in DB1 to simulate the MPA inapplicable situations. It contains 100 cases, with the ECG signals taken from the first 100 cases in DB1, paired with the PPG signals taken

from the remaining 100 cases. DB3 contains 30 recordings collected in cardiopulmonary resuscitation, each spanning 2 hour long.

3.2. Method Evaluation

We run the algorithm on all the cases in DB1, DB2 and DB3. The algorithm makes an evaluation of the signals for MPA applicability every 15 seconds until a decision of *surely applicable* or *surely not applicable* is made; and the evaluation process is only restarted when sensor dropping is detected (the sensors later could possibly be placed on a different subject). Following this strategy, a total of 1444, 775, and 569 detections are made for DB1, DB2 and DB3 respectively. All the detections were reviewed retrospectively and marked as correct detections or false detections.

The results are listed in Table 1. DB1 is used to evaluate the recognition performance on *applicable* cases. DB2 is employed to evaluate the recognition performance on the *not applicable* (*N/A*) signals. Clinical cardiopulmonary resuscitation data in DB3 are mixed, with a majority being *not applicable* signals.

Table1. Algorithm results

database	total	Evaluation results	
		applicable Total (%)	*N/A* Total (%)
DB 1-*applicable*	1444	1351 (93.5)	93(* %)
DB 2-*N/A*	775	43(* %)	732(94.4)
DB 3-mixed	569	62 (* %)	507(89.1)

4. Discussion

There are 93 "*MPA not applicable*" detections in DB1 whereas the truth is that all the cases in DB1 are MAP applicable. There are 3 possible reasons for the false detection like this. Firstly, the pulse peaks are not precisely located. Secondly, missed or falsely detected peaks appear in a sequence so long that it meets the decision condition for *MPA not applicable*. At last, the distributions of the group features have overlaps for *applicable* and *not applicable* situations. To alleviate false detection in those situations, we need to adopt more signal features and group features in the decision process. In practice, false *MPA not applicable* detections introduce no clinical risk.

There are 43 *MPA not applicable* signal segments were decided as *MPA applicable* in DB2. The main reason is that heart rate and pulse rate are close to each other, and meanwhile the difference of intervals varies very slowly. Fortunately, these false *MPA applicable* detections only sustained for a short while, and introduced little clinical risk.

DB3 contains CPR induced pulse waves intermitted with spontaneous circulations. The 62 *MPA applicable* detections are all spontaneous heart beats, and therefore are all true detections.

5. Conclusions

From the results above, it is effective to utilize the consistency of the grouped metaphoric features to decide whether physiological signal can be used for MPA.

ECG and PPG fusion are used in this paper as an example for MPA applicability recognition. Other vital signs such as fingertip PPG and invasive blood pressure can also be analysed together to evaluate the MPA applicability of pulse waves. Generally, all the signals with high correlation can be considered for MPA applicability recognition before using multi-parameter fusion technology.

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