Towards enhancing the performance of multi-parameter patient monitors

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Multi-parameter patient monitors (MPMs) have become increasingly important in providing quality healthcare to patients. It is well known in the medical community that there exists an intrinsic relationship between different vital parameters in a healthy person, these include heart rate, blood pressure, respiration rate and oxygen saturation. For example, an increase in blood pressure would lead to a decrease in the heart rate, and vice versa. Although it is likely to improve the performance of MPM systems, this fact is not explored in engineering research. In this work, experiments show that deriving additional features to capture the intrinsic relationship between the vital parameters, the alarm accuracy (sensitivity), no-alarm accuracy (specificity) and the overall performance of MPMs can be improved. The geometric mean of the product of all the vital parameters taken in pairs of two was used to capture the intrinsic relationship between the different parameters. An improvement of 10.55% for sensitivity, 0.32% for specificity and an overall performance improvement of 1.03% was obtained, compared to the baseline system using classification and regression tree with the four vital parameters.

1. Introduction: Multi-parameter patient monitors (MPMs) [1] are widely used in intensive care units (ICUs) and general wards to continuously monitor patients' health based on the following human vital parameters: heart rate; blood pressure; respiration rate; and oxygen saturation (SPO2). MPMs in general require lower missing probability, probability for missing an alarm when an alarm is to be reported and false alarm probability, falsely reporting an alarm when there is no alarm to be reported. This means that the alarm accuracy, sensitivity and the no-alarm accuracy and specificity should be as high as possible.

Studies on physiological parameters [2] show that there is a well-established intrinsic relationship between vital parameters in healthy people. For example, when a heart rate is on the higher side, arterial blood pressure is expected to be on the lower side, and vice versa, otherwise the health condition is said to be abnormal. However, to the best of our knowledge, MPMs do not take advantage of this relationship.

In this Letter, we capture the correlation (positive/negative) between human vital parameters, which include heart rate, arterial blood pressure, respiration rate and SPO2 [2–4], to capture the intrinsic relationship between them and achieve higher sensitivity, specificity and overall classification accuracy. We use correlation features and geometric mean of the different vital parameters taken in pairs of two, in addition to the four vital parameters in the proposed system.

We use a classification and regression tree (CART) [5], the decision tree learning algorithm using Gini-impurity index as the parameter for constructing the tree, to verify the effectiveness of the proposed approach in enhancing the performance of the MPMs [6]. The system developed in the present work uses the MIMIC-II [7, 8] database to learn the trends in the vital signs.

2. Database used for the experiments: Experiments were performed with time series data such as heart rate, arterial blood pressure, respiration rate and SPO2, obtained from the MIMIC-II database [7, 8]. The MIMIC-II consists of two major components; namely clinical data and physiological waveforms. The physiological waveforms are collected from bedside patient monitors (Component Monitoring System Intellivue MP-70; Philips Healthcare) used in medical, surgical, coronal care and neonatal ICUs in a tertiary hospital. The waveform database includes high-resolution (125 Hz) waveforms (e.g. electrocardiograms), derived numeric time series such as heart rate, blood pressures and SPO2 [7]. The database also consists of monitor generated alarms along with the physician annotated files.

3. Decision tree algorithm for multi-parameter patient monitoring system: Decision tree learning [5] is one of the machine learning approaches used for classifying data based on certain attributes. In this Letter, we train the decision tree with a continuous record of vital signs denoting normal and abnormal conditions of the patient. We identify the vital signs in the normal condition with the 'no-alarm' label and those in the abnormal condition with an 'alarm' label. The classifier is ideally trained to make the mapping $x_i \rightarrow y_i$ in a way that lowers the number of errors in the classification, where x_i are the input data points and y_i are the output labels. Once the system is trained with all possible cases of normal and abnormal conditions, it can then classify the vital signs for an unlabelled data set, to indicate when the patient's condition is deteriorating.

The system developed in this work uses the CART [5] algorithm that learns the continuous multi-parameter patient data and the additional parameters to generate a tree model that makes decisions about the sample belonging to a normal or an abnormal patient condition. Decisions are made with the help of automatically generated rules. The CART algorithm is designed to produce a set of questions, the answers to which determine the next set of questions. The result of these questions is a tree structure, the ends of which are called terminal nodes, where the actual decisions are made. The algorithm makes use of the Gini-impurity index [4], a measure of node impurity; that is, it measures how often a randomly chosen element from the data set would be incorrectly classified if it were randomly labelled according to the distribution of the labels in the subset. Gini impurity can be computed by summing the probability of each item being chosen times the probability of a mistake in categorising that item [9]. It reaches its minimum, zero, when all cases in the node fall into a single target category . The decision tree algorithm always attempts to minimise the deviance or impurity indicated by Gini impurity index. The Gini index of a target node t may be defined as [5, 7, 9]:

$$I_G = 1 - \sum_{i=1}^{N} p(i/t)^2 \tag{1}$$

where N is the number of samples at the target node and $p(i/t)$ is the relative frequency of class i at node t.

4. Improving the performance of MPMs: Towards improving the performance of the MPM without any additional algorithmic complexity, we use geometric means of the vital parameters taken in pairs of two, in addition to the four vital parameters used in the baseline system. The expanded feature set contains additional information about the balance/imbalance in the patient's health status: for example, the relationship between the parameters exposes the risk factor for problems like cardiovascular abnormalities [3], hypoxia (low oxygen content in the blood), hyperoxia (high oxygen content in the blood) and so on. In this Letter, we gather this additional information by increasing the feature set to F, thereby improving the system performance. The improved feature set F is

$$F = \left[x_1, x_2, x_3, x_4, \sqrt{x_1x_2}, \sqrt{x_1x_3}, \sqrt{x_1x_4}, \sqrt{x_2x_3}, \sqrt{x_2x_4}, \sqrt{x_3x_4}\right] \tag{2}$$

where x_1, x_2, x_3 and x_4 are the vital parameters, i.e. heart rate, blood pressure, respiration rate and SPO2 values, respectively, and the remaining six correlation features help capture the instrinsic relatioship between the vital parameters.

5. Experiments and results: Experiments were performed using the MIMIC-II database. The database consists of vital parameters from 413 patients. We first split the data into training and test data; training data consisted of 300 patients and the test data consisted of the remaining 113 patients. No patient data was shared between the training and test data. Subsequently, for computational considerations, we randomly selected 20 patients from the training data for training the decision tree algorithm and 8 patients from the test data set for the testing the effectiveness of the approach. The trials were then repeated ten times, every time selecting a new set of patients for the trial, and the results averaged across the trials. The training data at every trial consisted of more than 50 000 samples, and the test data consisted of more than 19 000 samples, each sample having an instance of all the four vital parameters. More than 90% of the samples represented no-alarm condition, and the remaining alarms.

In this experiment, we did not use any windowing techniques to preprocess the physiological signals, and therefore each sample was taken as an example to train and test the condition of the patient. Table 1 compares the performance results of the baseline decision tree MPM system using four vital parameters: heart rate; blood pressure; respiration rate; and SPO2, and the system with additional six correlation features. The total number of features in the baseline system is four, and the proposed system is ten, with an additional six correlation features.

Table 1 Decision tree algorithm with vital parameters and correlation features

	Sensitivity, %	Specificity, %	Overall classification accuracies, %
baseline system	88.66	99.35	98.50
proposed system	99.21	99.67	99.53

Results conclude that the use of correlation features along with the four vital parameters helped enhance the MPM system performance by 10.55% in sensitivity, 0.32% in specificity and a 1.03% improvement in the overall classification accuracy, compared to the baseline decision tree system with the four vital parameters alone.

6. Conclusion: There exists an intrinsic relationship between the different human vital parameters, heart rate, blood pressure, respiration rate and SPO2. Our baseline decision tree system using CART algorithm uses these four vital parameters as its input features. In this Letter, we proposed a novel approach to improving the performance of the MPMs taking advantage of the intrinsic relationship between the different vital parameters, using additional six features that are the geometric mean of the vital parameters taken in pairs of two (correlation features), making the total number of features in the proposed system as ten.

We evaluated the baseline system and the proposed system using sensitivity, specificity and overall classification accuracy. Results show that the use of the correlation features, to capture the intrinsic relationship between the vital parameters, helped improve sensitivity by 10.55%, specificity by 0.32% and the overall classification accuracy by 1.03%.

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