Prediction of Acute Hypotension Episode

Hutashani B. Rayate, Vidya V. Deshmukh

Abstract*— *Acute hypotensive episodes (AHE) are serious clinical events in intensive care unit. It causes damage of irreversible organ and may lead to death. When occurrence of an Acute Hypotension Episode (AHE) is predicted in advance, an appropriate intervention can reduces the risk for patient. The prediction is to be made using two groups of ICU patient records from the MIMIC II Database from the Physionet. The physionet challenge is divided into two parts. The first part is to distinguish between patients who have experienced acute hypotension episodes and patients who do not. The second part of this challenge is to predict acute hypotension episodes. We here present an algorithm for prediction of AHE using mean arterial blood pressure (MAP). We then used information divergence (or Kullback-Liebler divergence) between two distributions to identify the most discriminative features. The objective of this work is to describe an automated statistical method that produces an automated method to predict AHE using the least data possible.

Index Terms---* *Hypotension Prediction, Information Diversion, K-L Diversion theorem, Mean Arterial Blood Pressure.

I. INTRODUCTION

The occurrence of Acute Hypotension Episodes is most critical event in ICU as it can cause multiple organ failure and result in death, so timely interventions can reduce the risk. We define an AHE is incidence in which one minute averages of MAP (mean arterial pressure) falling below 60 mmHg for at least 90% during any 30 minute period within interval. Prediction of AHE can provide medical experts enough time to prevent its occurrence through proper intervention. Physionet Challenge 2009 [1] was to forecast which subjects in the ICU would experience an AHE within a predefined forecast window of one hour using biomedical signals (ECG and ABP) data along with other physiologic information prior to the start of the forecast window (at time T0) as shown in fig. 1. The subjects are divided into two groups, H (patients with an AHE in the forecast window) and C (patients without an AHE in the forecast window).

In general, the development of automatic hypotensive predictive solutions explore the correlation of patient clinical information, such as arterial blood pressure (ABP), heart rate (HR) and oxygen saturation (SO2) with the onset of the hypotension episode. There are parametric and non-parametric methods to analyze and characterize ABP before hypotensive episodes.

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Hutashani B. Rayate, Amrapali Tower, Ashoka Marga, Near Fame Theather. Nashik Nashik Maharashtra,India

Vidya V. Deshmukh, Amrapali Tower, Ashoka Marga, Near Fame Theather. Nashik Nashik Maharashtra, India

In this paper, we have presented the solution of the prediction problem in challenge event 1, i.e. which of the patients would have AHE within forecast window [3].

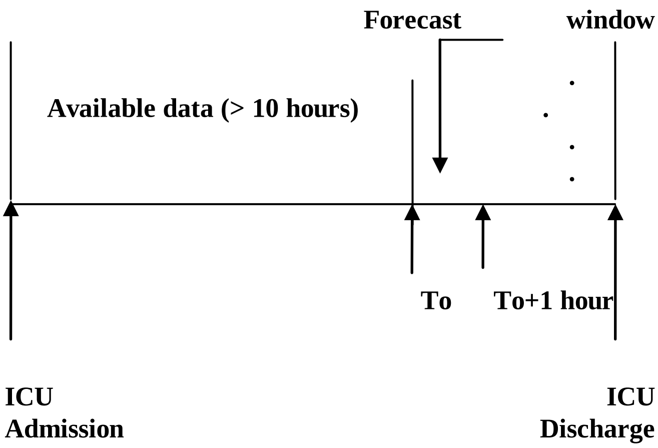

Fig.1. Forecast Window

II. DATASET

Patient data is collected from 2009 PhysioNet/Computers in Cardiology challenge and comprised training set and test sets. This data is a part of MIMIC II database. Training set consist of 10 minute data of each patient, which is sampled at 125 Hz. Test set again comprised with test set A and test set B with consist of 10 hour of data and sampled at 1 Hz [2].

The Multi-Intelligent Monitoring in Intensive Care (MIMIC) II patient records contain most of the information that would appear in a medical record (such as results of laboratory tests, medications, and hourly vital signs). The intent is that a MIMIC II record should be sufficiently detailed to allow its use in studies that would otherwise require access to an ICU, e.g., for basic research in intensive care medicine, or for development and evaluation of diagnostic and predictive algorithms for medical decision support [2].

III. MEAN ARTERIAL PRESSURE

The mean arterial blood pressure is combination of systolic blood pressure (SABP) and diastolic blood pressure (DABP). The systolic arterial blood pressure (SABP) is the maximum pressure when the heart contracts and blood begins to flow. The diastolic arterial blood pressure (DABP) is the minimum pressure occurring between heartbeats. The mean arterial blood pressure (MAP) can be calculated as [4],

$$DABP + \frac{SABP - DABP}{3}$$

From the database of mean arterial blood pressure, we extracted from the available signals statistical parameters, such as the mean, the standard deviation, the skewness and the kurtosis. We also computed robust statistics (median and median absolute deviation) in order to be less sensitive to outliers. The slope of the signals was computed using robust regression [6]. Those features were computed on signals of various lengths preceding the forecast window.

In this paper we describe an automated statistical method that produces an automated method to predict Acute Hypotensive Episode (AHE), using a minimal subset of the available data. Our automated statistical method uses information divergence to select relevant features.

IV. INFORMATION DIVERGENCE FOR DETECTION

Information divergence is a non-symmetric measure of the difference between two probability distributions P and Q. The Probability distribution of Mean arterial blood pressure (MAP) values of each patient is calculated. This algorithm was applied to training set with known results, and then development of template (class) of patient having AHE was carried out [5].

Kullback-Leibler (K-L) divergence is special case of divergences also called f- divergence. The Kullback-Leibler (KL) divergence is a fundamental equation of information theory that quantifies the proximity of two probability distributions. For probability distributions P and Q of a discrete random variable their K–L divergence is defined as in equation [6].

$$D_{KL}(P,Q) = \sum_i P(i) log(\frac{P(i)}{Q(i)}) + \sum_i Q(i) log(\frac{Q(i)}{P(i)})$$

This measure of information is used to identify the most discriminative features. To discretize the domain, 20 equal-sized bins divided from the minimum and maximum value of each feature dimension is used. In this work, we compared the relevance of taking more or less time before T_0 (the instantaneous time) in the training sets, in a single window or many consecutive windows [7]. Since we used the information divergence factor as the decision factor, we required a single value for each feature.

V. RESULTS

The hypotensive patients in the training set had significantly lower MAP than the non-hypotensive patients. In the non-hypotensive group the MAP is greater than 60 mmHg as shown in fig.3. On this basis we used MAP <60 mmHg as a predictor of AHE. In the hypotensive group the MAP is lower than 60 mmHg as shown in fig.4.

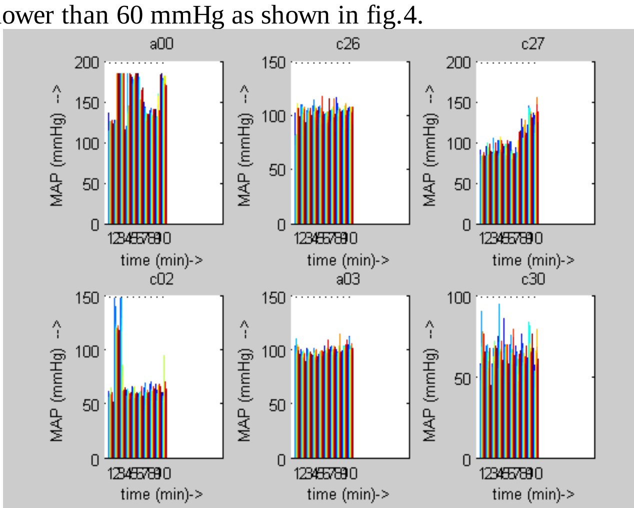

Fig.2. MAP for multiple patients

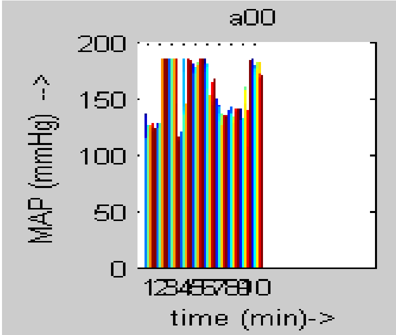

Fig.3. MAP for Non-Hypotensive patient

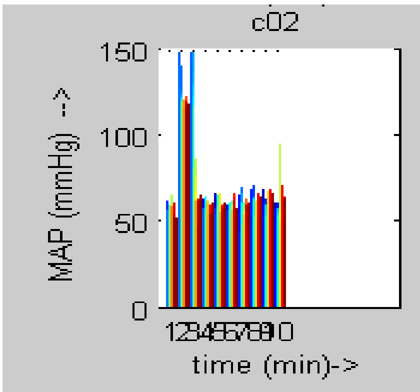

Fig.4. MAP for Hypotensive patient

For detection of AHE by Information Divergence, we first calculated the Probability distribution of MAP values of each patient. We have make group of 5 or 10 AHE patients probability and check the statistical distance with probability of patient to be tested.

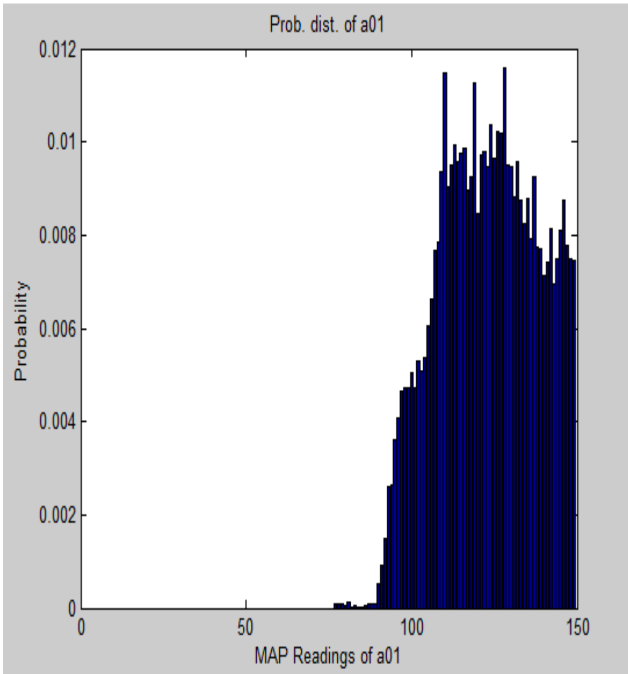

Fig.5. Probability Distribution of MAP (with normal patient).

Probability Distribution of Mean Arterial Blood Pressure of the patient having documented AHE is shown in figure 6.

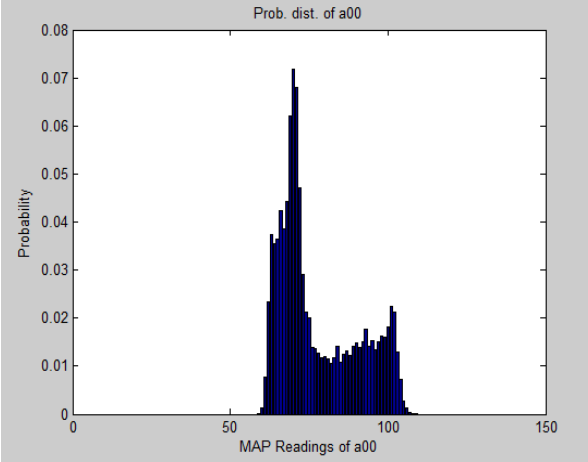

Fig.6. Probability Distribution of MAP (with documented AHE patient).

VI. CONCLUSION

This paper represents the effective technique for predicting the Acute Hypotension Episodes of the ICU patients. In the proposed methodology, the algorithm is developed for calculating mean arterial blood pressure (MAP). For non-hypotensive patient, MAP is greater than 60 mmHg and for hypotensive patient, MAP is lower than 60 mmHg.
The second algorithm of K-L divergence is developed for calculating the probability distribution of MAP. The probability distribution of MAP with normal patient is close to 0 and the probability distribution of MAP with documented AHE patient is close to 1.

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