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Predicting Acute Hypotensive Episode by Bhattacharyya Distance

Vaibhav Awandekar *, Prof. A.N. Cheeran **
*(M. Tech. in Electronics, Department of Electrical Engineering VJTI, Mumbai University , INDIA)
** (Professor, Department of Electrical Engineering VJTI, Mumbai University, INDIA)

ABSTRACT

Acute hypotensive episode (AHE) is a serious clinical event, which can lead to irreversible organ damage and sometimes death. When detected in time, an appropriate intervention can significantly lower the risks for the patient. An algorithm is developed for automated statistical prediction of AHE in patients, using mean arterial pressure (MAP). The dataset used for this work is from MIMIC II of PhysioNet/Computers in Cardiology. The algorithm consists of probability distributions of MAP and information divergence methods for calculating the statistical distance between two probability distributions. The Bhattacharyya Distance is found out to be most accurate method for calculating such statistical distance. Beat classification of AHE patients with respect to Non-AHE patient is carried out by using training set of MIMIC II database. The comparison is also carried out for feasibility of Bhattacharyya distance with another divergence method like K-L ivergence.

Keywords - **AHE, DABP, MAP, MIMIC II, SABP**

I. INTRODUCTION

Acute hypotensive episodes (AHE), defined here as incidences of mean arterial pressure (MAP) falling below 60 mmHg for at least 90% of any 30 minute period, are serious clinical events in intensive care units. Thus AHEs by this definition may contain short intervals of signal loss or MAP in the hypotensive range, but these can be no longer than three minutes in any half hour, and any AHE must contain at least 27 minutes of MAP measurements in the acute hypotensive range. Several clinical studies have proved that AHE could result in multiple organ failure and they are strongly linked to morbidity and mortality [2]. Such episodes may result in irreversible organ damage and sometimes death.

Determining what intervention is appropriate in any given case depends on rapidly and accurately diagnosing the cause of the episode, which might be sepsis, myocardial infarction, cardiac arrhythmia, pulmonary embolism, hemorrhage, dehydration, anaphylaxis, effects of medication, or any of a wide variety of other causes of hypervolemia, insufficient cardiac output, or vasodilatory shock. Identifying patients with AHE would be an important step for clinicians or physicians to respond in a timely manner and perform necessary patient-specific therapeutic intervention. Timely and appropriate interventions can reduce these risks.

In this paper the analysis is constrained to the largest common subset of features available for all patients (arterial blood pressure measurements). We used information divergence between two distributions to identify the most discriminative features. We used these features in training set to classify the samples in the test sets using Bhattacharyya Distance algorithm. Preliminary results showed that this method leads to significantly better results; therefore it increases the information about the samples in the test sets.

Using information divergence, the statistical measurement of mean arterial pressure was performed. To obtain statistical result for prediction of AHE, we used K-L divergence on the probability distribution of MAP. For best result we used then Bhattacharyya distance to find the class of patient to be tested.

II. DATASET

Data was provided by the 2009 PhysioNet/Computers in Cardiology Challenge which was comprised of training and test sets. 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.

The Multi-Intelligent Monitoring in Intensive Care (MIMIC) II project has collected data from about 30,000 ICU patients to date. 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). About 5,000 of the records also include physiologic waveforms typically including ECG, blood pressure, and respiration etc., and time series that can be observed by the ICU staff. 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.

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) is a combination of the two above quantities, most often calculated as:

$$DABP + \frac{SABP - DABP}{3} \tag{1}$$

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.

III. DETECTION OF AHE BY INFORMATION DIVERGENCE

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, then development of template (class) of patient having AHE was carried out.

In the training data set we calculate the probability of each patient's with respect to mean arterial pressure (MAP), MAP is the mathematical combination of systolic blood pressure and diastolic blood pressure, which is generally acquired from continuous blood pressure measurement.

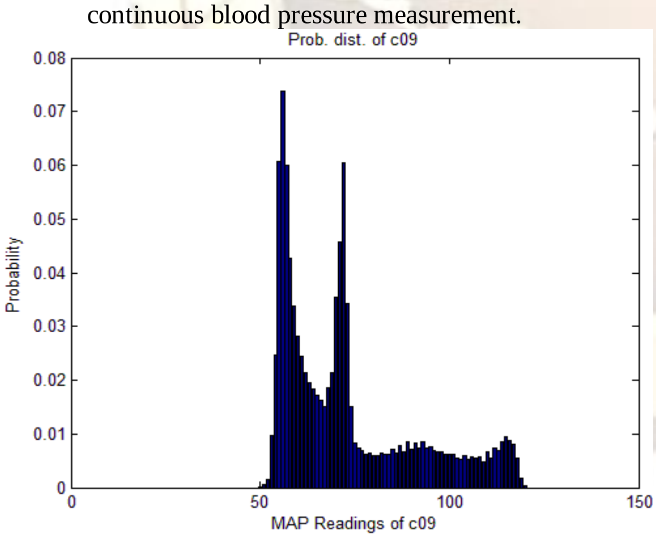

Fig. 1. Probability distribution of mean arterial blood pressure (with documented AHE patient).

Probability Distribution of Mean Arterial Blood Pressure of the patient having documented AHE is shown in figure 1

When the MAP reading of patient below 60mmHg or closed to it, the probability of occurrence of next readings more closely to 50 as shown above.

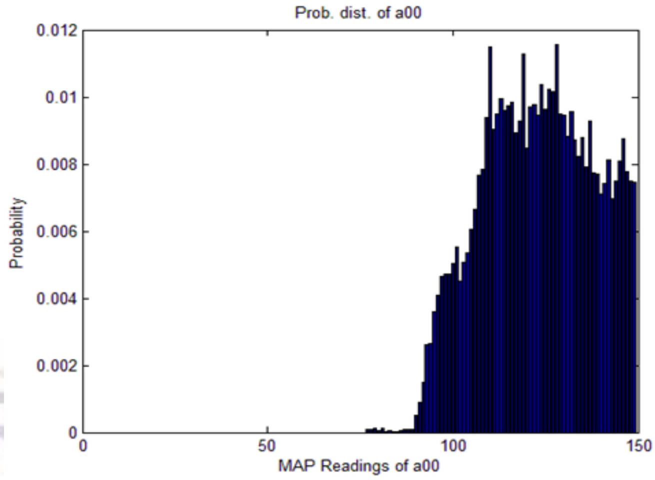

Fig. 2. Probability distribution of mean arterial blood pressure (with normal patient).

A. KULLBACK–LEIBLER DIVERGENCE

For probability distributions P and Q of a discrete random variable their K–L divergence is defined as in equation (2) [4]

$$D_{KL}(P,Q) = \sum_i P(i)\log\left\{\frac{P(i)}{Q(i)}\right\} \tag{2}$$

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. The features θ that made the distributions P and Q the most divergent is then found out.

There are many ways to see time series from a statistical perspective. 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. Since we used the information divergence factor as the decision factor, we required a single value for each feature.

When many consecutive windows have been used, we kept only the window with the minimum value for each feature. This is justified because we are trying to identify AHE, which is by definition a lower value of the Atrial Blood Pressure.

B. BHATTACHARYYA DISTANCE

In statistics, the Bhattacharyya distance measures the similarity of two discrete or continuous probability distributions. It is closely related to the Bhattacharyya coefficient which is a measure of the amount of overlap between two statistical samples or populations. The coefficient can be used to determine the relative closeness of the two samples being considered.

For discrete probability distributions Bhattacharyya Distance between p and q over the same domain X is defined as:

$$B_D(p,q) = -\ln(BC(p,q)) \quad (3)$$

where, BC (p,q) is Bhattacharyya Coefficient.

$$BC(p,q) = \sum_{x \in X} \sqrt{p(x)q(x)} \quad (4)$$

Calculating the Bhattacharyya coefficient involves a rudimentary form of integration of the overlap of the two samples. The interval of the values of the two samples is split into a chosen number of partitions, and the number of members of each sample in each partition is used.

Results

Table 1. Bhattacharya distance between probability distribution of AHE patients (P) verses probability distribution of Non AHE patients (Q).

	Q11	Q21	Q31	Q41	Q51
P11	2.8294	0.8899	0.9809	0.6151	0.6832
P21	3.0249	0.8921	0.9208	0.7395	0.8296
P31	3.0614	0.4537	0.6111	0.7763	0.9206
P41	2.9194	0.5109	0.5886	0.6582	0.7715
P51	3.0104	0.7851	0.5563	0.7271	0.8708

Table 2. Bhattacharya distance between probability distribution of AHE patients (P) verses probability distribution of AHE patients (P).

	P11	P21	P31	P41	P51
P11	0.0022	0.1469	0.5113	0.4198	0.4512
P21	0.1469	0.1698	0.3321	0.3258	0.3985
P31	0.4113	0.3321	0.0778	0.1762	0.1285
P41	0.4198	0.3258	0.1762	0.2055	0.1982
P51	0.4512	0.3985	0.1285	0.1982	0.1417

These two table (table1 and table 2) clearly shows that the distance between AHE patient and Non AHE patients is more compare to distance between AHE patient with AHE patient. For example; if we take two AHE patience, due to more overlapping in their probability distribution the statistical distance will be less. Similarly if we take one AHE patient and other Non AHE patient, there will be less overlapping between their distributions and due to less overlapping the Distance will be more. By using same principle we make group of probability distribution of AHE patients and then the probability distribution of ICU patient (Patient to be tested) has been checked, the information divergence matrix of 2-dimensional distributions using every pair of features is presented. The matrix is symmetric.

There were total 10 patients record tested from test set A, and 40 records tested from test set B, The accuracy matrix is 9/10 (90%) for test set A, 37/40 (92.5%) for test set B, which were obtained from Computer in Cardiology MIMIC II database. By selecting correct values of threshold and taking more training set into account, we can certainly increase our accuracy matrix.

IV. CONCLUSION

Algorithms have demonstrated the feasibility of developing algorithms for automatic prediction of AHE in the ICU using blood pressure only. We achieved modest accuracy of predicting AHE events with the help of Bhattacharyya Distance.

The algorithms could be further developed to increase accuracy by combining the algorithms so that both average MAP and Bhattacharyya Distance contribute to the prediction. For example, a patient with low average MAP, experiencing less distance in probability distribution of MAP is more likely to experience an AHE than a patient with low average MAP and more distance in probability distribution of MAP

REFERENCES

[1] Moody GB, Lehman LH. "Predicting acute hypotensive episodes" *the 10th annual Physio -Net/Computers in Cardiology Challenge. (Computers in Cardiology 2009; 36).*

[2] PA Fournier, JF Roy. "Acute Hypotension Episode Prediction Using Information Divergence for Feature Selection, and Non-Parametric Methods for Classification" (*Computers in Cardiology 2009;36:625−628).*

[3] P Langley, ST King, D Zheng, EJ Bowers,K Wang, J Allen, "Predicting Acute Hypotensive Episodes from Mean Arterial Pressure" (*Computers in Cardiology 2009;36:553−556)*

[4] Kullback S, Leibler R. On information and sufficiency.*(Ann Math Statics 1951;22:79-86)*

[5] Hastie, Tibshirani R,Friedman J. The elements of statistical learning . *(New York,NY: Springer,2001)*

[6] Bellman R. Adaptive Control Processes. Princeton UniHolland P.W., R. E.Welsch. Robust Regression Using Iteratively Reweighted Least-Squares. *Communications in Statistics: (Theory and Methods, A6, 1977, pp. 813-827)*

[7] Vapnik V. The nature of statistical learning Theory. (*New York,NY: Sringer-Verlag,1996)*

[8] Bellman R. Adaptive Control Processes. *(Princeton University Press, 1961).*

[9] The MIMIC II Project database via the Physionet website (*http://www.physionet.org/physiobank/databas e/ mimic2db/)*