Detection of Acute Hypotensive Episodes via Empirical Mode Decomposition and Genetic Programming

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***Abstract*—Big data time series in the Intensive Care Unit (ICU) is now touted as a solution to help clinicians to diagnose the case of the physiological disorder and select proper treatment based on this diagnosis. Acute Hypotensive Episodes (AHE) is one of the hemodynamic instabilities with high mortality rate that is frequent among many groups of patients. This study presented a methodology to predict AHE for ICU patients based on big data time series. Empirical Mode Decomposition (EMD) was used to calculate patient's Mean Arterial Pressure (MAP) time series and some features, which are bandwidth of the amplitude modulation, frequency modulation and power of Intrinsic Mode Function (IMF) were extracted. Then, the Genetic Programming (GP) is used to build the classification model for detection of AHE. The methodology was applied in the datasets of the 10th PhysioNet and Computers Cardiology Challenge in 2009 and Multi-parameter Intelligent Monitoring for Intensive Care (MIMIC-II). We achieve the accuracy of 83.33% in the training set and 91.89% in the testing set of the 2009 challenge's dataset; and the 83.37% in the training set and 80.64% in the testing set of the MIMIC-II dataset.**

Keywords—acute hypotensive episodes; empirical mode decomposition; genetic programming; classification

I. INTRODUCTION

Acute Hypotensive Episodes (AHE) is the common phenomenon in the Intensive Care Unit (ICU), which may result in irreversible organ damage and eventually death. As a result, the prognoses of AHE are of fundamental importance in the management of critical ill patients. The most obvious characteristic of AHE is the Mean Artery Pressure (MAP) signal, which is defined for an hour at any time of 30 minutes or more during which at least 90% of the MAP measurements are at or below 60mmHg. Therefore, the early detection of AHE will give professionals much more precious time to determine a proper treatment for patients. Bassale J [1] proposed to generate the statistical summaries of Arterial Blood Pressure (ABP) signals to predict hypotension before hypotension episodes, including the mean, standard deviation, variance, skewness and the quantile-quantile. MA Frolich [2] discovered that the higher baseline heart rate, which possibly reflects a higher sympathetic tone, might be a useful parameter to predict hypotension. Saeed M introduced a temporal similarity metric, which applied a wavelet decomposition to characterize time series dynamics at multiple time scales to utilize classical information retrieval algorithms based on a vector-space model. This algorithm was used to identify similar physiologic patterns in hemodynamic time series from ICU patients by the detection of imminent hemodynamic deterioration [3]. A Ghaffari aimed to detect AHE and MAP dropping regimes using ECG signal and ABP waveforms[4], the proposed method calculated the shock occurrence probability with a adaptive network fuzzy inference system which incorporates the influences of heart rate, systolic blood pressure, diastolic blood pressure, age, gender, weight and some miscellaneous factors. Rocha T [5] used the neural network multi-models to calculate the MAP signal in the forecast window of 1 hour and then predicted the AHE. The 2009 challenge was the tenth in the annual series of open challenges hosted by PhysioNet in cooperation with Computers in Cardiology Conference. The goal of this challenge was to predict the AHE in ICU, and some valid approaches were proposed in that contest [6-7].

This paper demonstrates how AHE can be predicted in the next 1 hour forecast window. In order to achieve this aim, the analytic signals are obtained from MAP with Hilbert-Huang method, and then several features are absorbed in the analytic signals. Genetic programming (GP) is an effective method to select features and constructs a classifier simultaneously [8-10]. In this work, GP is used to classify the AHE and no AHE patients (In particular, AHE means there is an episode of acute hypotension beginning within the forecast window). The validation sets consist of two datasets, A and B. The Set A is comprised of 110 records [11], while the Set B is comprised of 2866 records which are obtained from MIMIC-II database [12]. The experimental shows that our method achieved accuracy 83.33% and 91.89% in the training and testing sets of Set A respectively, and 83.37% and 80.64% in Set B.

In the following section the database and methods of the application are described in detail. In section II, the methodology is introduced, including empirical mode decomposition (EMD), features extraction method and GP classification method. The experiment verification and

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discussion are given in section III. The last section gives conclusions.

II. METHODOLOGY

An overview of the methodology of this work is proposed in Fig1. Firstly, the MAP signal before T_0 in ① is decomposed by EMD method in②. The analytic signals are calculated by the IMF signals using the Hilbert transform in ③. After that, in ④ and ⑤, several features are extracted from the analytic signals. The Amplitude Modulation Bandwidth (AMB) and Frequency Modulation Bandwidth (FMB) in ④ are the features of the high frequency components of the IMF, and power of the last IMF is the feature of the low frequency components. Finally, the features are imported into GP to train a classification model in ⑥, and the model is used to distinguish status of the unlabeled MAP signals in⑦.

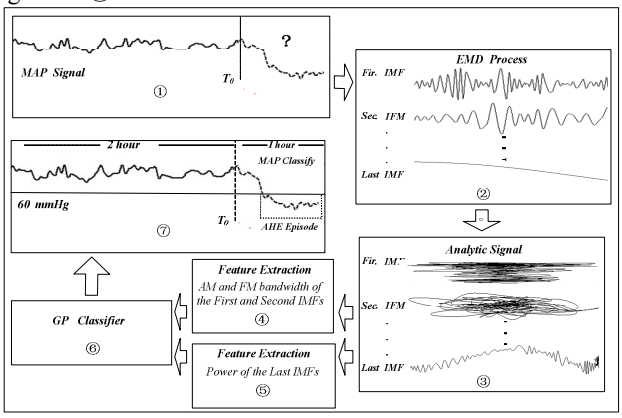

Fig.1. The Methodology of detecting AHE

A. Empirical Mode Decomposition

Hilbert-Huang Transform (HHT) is an adaptive method for time series signal analysis, which is proposed by N.E. Huang [13]. HHT is composed of EMD method and Hilbert spectrum analysis (HSA) method. The HHT is used in many applications, such as gravitational wave, biomedicine, nonlinear system, etc. In this work, the EMD method is applied to data decomposition of patients' MAP signals.

The sifting process of EMD can decompose the complex signal into a finite number of IMFs adaptively, according to the local characteristic time scale of the source signal/data. As a consequence, each IMF component contains the local characteristics of original signals in different time scales. Each IMF must satisfy the following conditions:

1) In the whole data sequence, the number of extreme values and the number of zero crossing points must be same or not more than one at most.

2) At any time, the envelope mean, defined by the signal of local maximum and minimum, is zeros.

For a fixed length time series signal $x(t)$ (for MAP time series ,the length of time series is 2 hours), the EMD process can be summarized as follows:

Step 1: Finding out all the local maximums and minimums of the signal $x_i(t)$, and getting the upper envelopes ($e_{max}(t)$) and lower envelopes ($e_{min}(t)$) by connecting the maximums and minimums respectively with cubic spline. Then, the average curve of envelopes ($m(t)$) can be calculated by:

$$m(t) = \frac{e_{\max}(t) + e_{\min}(t)}{2} \tag{1}$$

Step 2: Defining the intermediate variable $h(t) = x_i(t) - m(t)$, and detecting whether the $h(t)$ is an IMF or not on above conditions (1) (2).

Step 3: When $h(t)$ is an IMF, assigning the $c_i(t)$ to be an basic IMF by $c_i(t) = h(t)$.

Step 4: Repeat the process with the residual signal $x_{(i+1)}(t) = x_i(t) - h(t)$, and the Step 1-3, until residual signal $x_{(i+1)}$ can't be decomposed.

At the end of the decomposition, the original signal $x(t)$ is defined as the sum of N IMFs and residual term $r(t) = x_{(i+1)}$:

$$x(t) = \sum_{i=1}^{N} c_i(t) + r(t) \tag{2}$$

B. Feature Extraction Method

Hilbert spectrum expresses the Time-Frequency-Energy distribution in the source signal. Each of IMF signal means the local information of source signal, meanwhile the HSA can obtain instantaneous significance from the IMF. In a MAP time series, the instantaneous parameters, including the instantaneous amplitude, instantaneous frequency and instantaneous power, are significant for the features extraction through the EMD and HSA (Further information about Hilbert spectrum representation of the non-stationary data can be found in reference [13]). For each IMF signal, the Hilbert transform is defined as follows:

$$\hat{c}_i(t) = c_i(t) * \frac{1}{\pi t} = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{c_i(\tau)}{t-\tau} d\tau \tag{3}$$

The $\hat{c}_i(t)$ is the Hilbert transform of the ith IMF signal $c_i(t)$. The analytic signal of source signal $x(t)$ is defined as:

$$z_i(t) = c_i(t) + j\hat{c}_i(t) = a_i(t)e^{j\theta_i(t)} \tag{4}$$

The $z_i(t)$ is the analytic signal of the IMF signal $c_i(t)$. The ith IMF signal of the instantaneous amplitude $a_i(t)$ and instantaneous phase $\theta_i(t)$ are defined as follows:

$$a_i(t) = \sqrt{c_i^2(t) + \hat{c}_i^2(t)} \tag{5}$$

$$\theta_i(t) = \arctan\left(\frac{\hat{c}_i(t)}{c_i(t)}\right) \tag{6}$$

The polar form of analytic signal reflects the physical meaning of the Hilbert transform, which obtains the local optimal approximation through a sinusoidal frequency and amplitude modulation. Therefore, considering the definition of the instantaneous frequency, the instantaneous frequency $f_i(t)$ of ith IMF signal can be defined as:

$$f_i(t) = \frac{1}{2\pi} \frac{d\theta_i(t)}{dt} \tag{7}$$

In order to measure the instantaneous amplitude $a_i(t)$ and the instantaneous frequency $f_i(t)$, reference [14] developed the concept of instantaneous bandwidth, which is an indication of the frequency spread at a given time. The bandwidth of a signal can be broken up into amplitude modulation and

frequency modulation, which are named as AMB and FMB. The AMB and FMB can be exactly given as follows:

$$AMB = \sqrt{\int_{-\infty}^{+\infty} \left(\frac{a_i'(t)}{a_i(t)}\right)^2 a_i^2(t)dt} \quad (8)$$

$$FMB = \sqrt{\int_{-\infty}^{+\infty} (w_i(t) - \langle w_i \rangle)^2 a_i^2(t)dt} \quad (9)$$

Where $<w_i>$ is the global mean frequency, and the $<w_i>$ can be defined as follows:

$$\langle w_i \rangle = \frac{1}{E} \int_{-\infty}^{+\infty} w_i(t) a_i^2(t)dt \quad (10)$$

$$E = 2 * \lim_{a \to \infty} \int_{-a}^{+a} c_i(t)dt \quad (11)$$

Where E is the energy of analytic signal $z_i(t)$. The energy and the power of $z_i(t)$, P can be given as follows:

$$P = \lim_{a \to \infty} \frac{E}{2a} \quad (12)$$

In this work, we select the first three IMFs signals of AMB and FMB respectively and the last IMF's power as the seven features for classification. Because energy changes more rapidly in the first three AMBs than it does in the other AMBs, and coincidentally, the first three FMBs have more significant changes than the other three ones. Morevoer, the last IMF's power can express the patient's blood pressure level.

C. Genetic Programming Classifier

Based on the Hilbert spectrum method, we have extracted seven classification features. These features can express the AHE signals in both time domain and frequency domain. After that, training the best classifier assists us to predict whether the patients suffered from AHE.

GP is an automatic programming technique for evolving computer programs, which is able to solve problems in a wider range of disciplines (may be more powerful than neural networks and other machine learning techniques)[8]. GP is applied in the classifiers design and feature selection frequently [9]. In this work, binary classifier algorithm based on GP [9-10] is used for classifier and the fitness function is defined as follows:

$$fitness = consig * \exp(compl - 1) \quad (13)$$

$$consig = \left(\frac{p}{p+n} - \frac{P}{P+N}\right) * \frac{P+N}{N}$$

$$compl = \frac{p}{P}$$

Where, P and N are respectively the total numbers of "*AHE*" and "*no AHE*" class. The p and n is the correct number of P and N in the obtained classifier function.

III. RESULT AND DISCUSSION

Because of some data are missed in Set A, only 48 records and 37 records are selected as training set and testing set. Set B is a big data set which contains 2866 records, we selected 1533 records randomly as training set, and the remaining is testing set, which has 1333 records. For all records used in the dataset A and B, the sampling frequency is 1Hz. In addition, a T_0 point on time for each patient's MAP signal is marked (like in Fig.1). The following one hour of T_0 point is the forecast window. If the record contains AHE, the T_0 is always set at the beginning of the first AHE; if the record has no AHE, the T_0 is set casually in the case of sufficient data.

For clarity, one source signal, no AHE patient (No. 3831217nm) is randomly selected to describe the methodology presented in this paper (Fig.2).

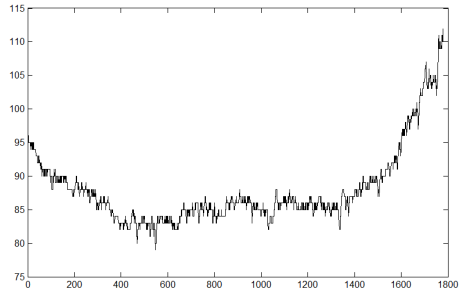

Fig.2. Source Signal of No. 3831217nm

As mentioned before, the EMD method provides an approach to decompose the source signal of patients into a set of IMFs. The IMFs ($C_1(t)$-$C_{10}(t)$) of the no AHE sample (No. 3831217nm) are obtained by EMD and showed in Fig.4.

Then, in order to explain the changes of frequency and amplitude simultaneously, IMFs signals are transformed into the analytic signals by Hilbert transform. According to the obtained analytic signal, the Instantaneous Amplitude (IA) and Instantaneous Frequency (IF) could be calculated and displayed in the Fig.4 and Fig.5 respectively. Generally, the IA can be interpreted as one patient's intensity of blood pressure, and the IF can be interpreted to be the changing speed of blood pressure.

The extracted features, AMB and FMB, are applied to measure the abrupt change of the IA and IF respectively. According to our experiments, the magnitude of first three components can clearly distinguish the changing of patients. Thus, the corresponding values of AMB and FMB are the inputs of classifier. TABLE I present a sample of AMB and FMB values for no AHE (No. 3831217nm) and AHE (No. 3061778nm) patients.

TABLE I. THE AMB AND FMB FOR NO AHE AND AHE PATIENTS

	$a_1(t)$	$a_2(t)$	$a_3(t)$	$f_1(t)$	$f_2(t)$	$f_3(t)$
NO AHE	0.3518	0.1024	0.3518	2.7727	1.9564	1.4410
AHE	0.1988	0.0684	0.1988	1.8754	1.6444	1.3834

Furthermore, the amplitude of the last IMF is much higher than other components, it could be said that the last IMF accumulates the most of the energy of the source signal. The experiment shows that the no AHE patients own the higher energy than the AHE patients. So the signal power, a manifestation of energy, is selected as the measurement parameter for distinguishing the AHE and no AHE patients.

Thus, for GP classifier, the $x_i\,(i = 1,2,3,4,5,6,7)$ represent seven features which are the AMBs ($a_1(t)$~$a_3(t)$), FMBs ($f_1(t)$ ~$f_3(t)$) and the power. The GP classifier parameters setting are as follows: The function sets are {+, -, *, /, *sqrt*, *exp*, *ln*, x^2, x^3, *sin*, *cos*, *atan*}, the population size is 30, the mutation and crossover rate are 0.15 and 0.8 respectively[10], the stop criteria is 1000 generations and the Roulette method is used as the selection method. The average result of 10 independents trials by GP are summarized in TABLE II.

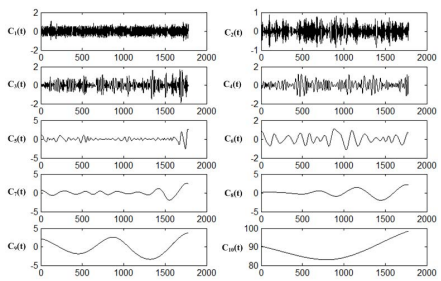

Fig.3. IMFs of No. 3831217nm

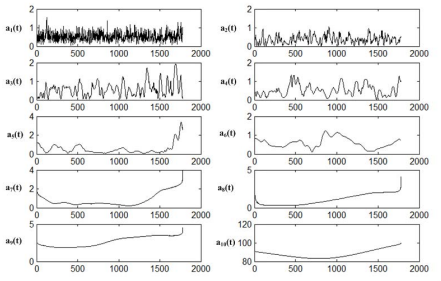

Fig.4. IA of No. 3831217nm

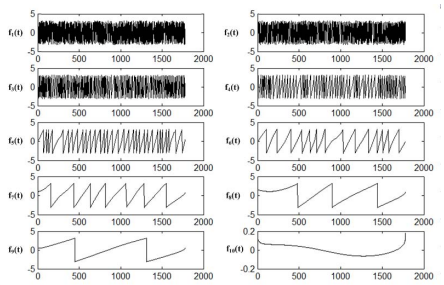

Fig.5. IF of No. 3831217nm

TABLE II. THE RESULTS OBTAINED BY GP AND SVM

	Set A				Set B			
	GP		SVM		GP		SVM	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
Sensitivity	84%	92%	68%	80%	85.88%	83.15%	86.93%	84.98%
Specificity	82.60%	91.66%	86.96%	83.33%	76.25%	74.81%	69.83%	67.59%
Accuracy	83.33%	91.89%	77.08%	81.08%	83.37%	80.64%	82.45%	79.74%

The achieved accuracy of the GP classifier are 83.33% and 91.89% with the proposed features in the training data and test dataset of set A. And, the accuracy of 83.37% and 80.64% with the proposed features in the set B's training data and testing data. Furthermore, within the same training and testing set, the SVM method with radial basis function kernel ($\sigma = 2.4$) is used to compare with GP classification method. The results of experiments confirm that the GP method improves the prediction of AHE with higher accuracy compared with the SVM.

IV. CONCLUSION

Time series data is pervasive across almost all human endeavors, including medicine, finance, science, and entertainment. As such, it is hardly surprising that time series data mining has attracted significant attention. As a typical medical time series data, MAP signals are analyzed tentatively in this work. As a nonlinear and non-stationary signal processing tool, EMD method is used to decompose the MAP time series into a number of IMFs. The complex and unordered MAP data become regular and ordered by the decomposition. After features extraction, GP method is used to establish the classifier for AHE prediction. The result shows that the classification model can provide the medical guidance for predicting, which is significant for the care and cure of AHE in ICU.

For future work, as a much potential method, EMD is worth to be analyzed and applied with more effort. More features can be extracted in the IMFs. After that, we can select useful features based on the GP's ability of feature selection. Furthermore, the methodology of this paper could be applied into other applications, such as internet of things and mobile computing [15-16], etc.

ACKNOWLEDGMENT

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