Application of Empirical Mode Decomposition in Prediction of Acute Hypotension Episodes

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Abstract — Acute hypotension episodes are one of the hemodynamic instabilities with high mortality rate that is frequent among many groups of patients. Prediction of acute hypotension episodes can help clinicians to diagnose the cause of this physiological disorder and select proper treatment based on this diagnosis. In this study Empirical Mode Decomposition of Mean Arterial Pressure (MAP) time series were calculated and some features such as statistical features of Intrinsic Mode Functions (IMFs) were extracted. Finally, a Support Vector Machine (SVM) was applied for classification of these features and prediction of acute hypotension episodes. The accuracy of prediction was 92% with Leave One Out cross validation method.

Keywords—Hypotension, Empirical Mode Decomposition, Prediction, Statistical feature

I. INTRODUCTION

Hypotension is a clinical condition in which patient's blood pressure has abnormally low values below 60 mmHg. If the blood pressure stays down for a long time, as a result of inadequate tissue perfusion a clinical syndrome occurs that is named "shock". If shock persists for a long time, inadequate oxygen delivery leads to irreversible cell injury and even can cause patient’s death [1].

Several groups of patients are exposed to hypotension. 22% of patients in MIMICII database experienced hypotension episodes and the mortality rate of this group is more than twice of MIMICII population as a whole [2]. In addition, hypotension is one of the most frequent side effects of spinal anesthesia with incidence of 33% [3] and hemodialysis with incidence of 15-25% [4].

Delaying in treatment of acute hypotension episodes may result in organ damage and death. Timely and rapid intervention can help to save patient's life. Determining proper treatment depends on diagnosing the cause of acute hypotension which might be sepsis, myocardial infarction, cardiac arrhythmia, pulmonary embolism, hemorrhage, dehydration, anaphylaxis and also anything which causes hypovolemia. To this end, some clinical examinations are required which normally are very time consuming. Therefore, prediction of acute hypotension at the right time and before onset of the disease can help clinicians to select an effective and suitable treatment without exposing the patient to the risks of delay in receiving treatment.

Chiarugi [5] extracted significant features from arterial blood pressure and heart rate time series and used decision tree and SVM for classification of these features in order to predict acute hypotension episodes. However, Jousset [6] applied the SVM to classify the statistical features from biological time series and then could predict which patient will experience acute hypotension episodes within a forecast window of 1 hour.

Mneimneh [7], though, used a rule based approach for prediction of acute hypotension episodes. This paper demonstrates how acute hypotension episodes can be predicted in the next 1 hour time interval. In order to achieve this aim, Empirical Mode Decomposition (EMD) analysis was applied on Mean Arterial Pressure time series and these time series was decomposed to their Intrinsic Mode functions (IMFs) that is explained in section 2. Some features were extracted from these IMFs and classification of patients was done based on these features and with a SVM classifier.

In the following section the database and methods of the application are described in detail. In section 3, the results of methods are presented and discussed. Finally section 4 concludes the paper with a summary of the study and a comparison between results of this research and the results of previous studies.

II. METHODE

A. Database

The database which was used in this study is from the 10th annual physionet/computer in cardiology challenge on predicting acute hypotension episode in the intensive care unit (ICU). This database is comprised of two groups of patients, group H (patients with acute hypotension episode in forecast window) and group C (patients without acute hypotension episode in forecast window) [8]. The records include at least the data of Heart Rate (HR), Systolic Arterial Pressure (SAP), Diastole Arterial Pressure (DAP) and Mean Arterial Pressure (MAP) time series. Train set of the challenge database were used in this study for prediction of acute hypotension episodes.

B. Empirical Mode Decomposition

EMD is an adaptive method for decomposing a signal into AM-FM modulated components. It was introduced by N.E.
Huang in 1998 as a nonlinear and non-stationary signal processing tool and it has been used in many applications [9]. EMD is used in denoising and signal enhancement [10]-[12] and also in detection and classification [13], [14].

EMD decomposes complicated signals into a few components called IMF. Each IMF has some specifications:
1) The number of extrema (maxima and minima) is equal to number of zero crossings of signal or differs only by one
2) They are locally symmetric and the mean of top and bottom envelope of each IMF is zero

As discussed in [14], the IMFs are not only some components extracted from the original signal which sum of them is equal to the original signal, but also each of them is related to a physical characteristic existing in signal nature. It is true that the frequency content of the IMFs is decreased from first to last, but each of them has a frequency band, rather than a single frequency, with respect to sinusoidal waves as reference, and they are suitable (locally narrow-band) for Hilbert Transform. Decomposition of original signal into IMFs is called Sifting Process which is an iterative algorithm until some conditions are satisfied. The sifting process stops upon reaching any of the following criteria:
1) The residual signal will become less than a predefined threshold
2) The residual signal is a monotonic function that cannot be decomposed into more IMFs

The sifting process can be summarized into the following steps:
1) Assign \( i = 1 \)
2) Find all extrema (maxima and minima) of signal \( x(n) \)
3) Get the envelops of minima (\( e_{\text{min}}(n) \)) and maxima (\( e_{\text{max}}(n) \)) of the signal \( x(n) \)
4) Compute the mean of minima and maxima envelopes:
\[
m(n) = \frac{e_{\text{min}}(n) + e_{\text{max}}(n)}{2}
\]
5) Compute the difference of the main signal and the mean signal:
\[
h(n) = x(n) - m(n)
\]
6) Continue the steps 1-4 with \( h(n) \) as a new signal or Stop depend on stop criteria in [14] and assign \( c_i(n) = h(n) \) and continue the process with the residual signal \( x(n) - h(n) \) as a new \( x(n) \) and increase \( i \) by one

After performing the sifting process, the original signal can be written as sum of its IMFs \( c_i(n) \):
\[
x(n) = \sum_{i=1}^{N} c_i(n)
\]

**C. Feature Extraction Method**

For feature extraction, first the EMD of each patient's MAP time series was calculated and the IMFs were obtained. In Fig.1 and Fig.2 the IMFs of MAP time series from a patient in group C and a patient in group H are shown.

After decomposition of the MAP time series some features such as statistical features (minimum, mean, max, skewness and percentiles) were extracted from the IMFs and the best result was obtained based on these 5 features:

1) High frequency energy to low frequency energy ratio:
After that the sifting process was done and \( N \) IMFs of MAP time series were obtained, the MAP time series could be written as:
\[
\text{MAP}(n) = \sum_{i=1}^{N} c_i(n)
\]

Where \( c_i(n) \) is the \( i^{\text{th}} \) IMF of the MAP\((n)\) after its decomposition by EMD. \( E_1, E_2 \), the energy of high frequency and low frequency part of the signal respectively, could be defined as:
\[
E_1 = \sum_{i=1}^{N} \varepsilon\{c_i(n)\}
\]
\[
E_2 = \sum_{i=N+1}^{N} \varepsilon\{c_i(n)\}
\]

where \( \varepsilon\{c_i(t)\} \) shows the energy of \( c_i(t) \), simply the sum of squared values of \( c_i(t) \) :
\[
\varepsilon\{c_i(n)\} = \sum_{i=0}^{\infty} c_i^2(n)
\]

This definition of \( E_1, E_2 \) is reasonable because the frequency content of each IMF will shift toward zero as the sifting process proceeds, so the first IMF has more high frequency components than the last one Fig.3 shows frequency content of Fig.1 MAP time series IMFs.

2) Minimum of last IMF: Last IMF could be defined as the trend of signal. The minimum of the trend can be a good feature for discrimination between patients from group H and patients from group C because of acute hypotension episodes definition based on the MAP time series and variations of it.

3) Maximum instantaneous frequency of the last IMF: This feature means the most instantaneous variations of the signal’s trend. The instantaneous frequency is defined as:
\[
\text{IF}(c_N(t)) = \frac{d}{dt} (\angle \text{hilbert}(c_N(t))
\]

Hilbert is a well known mathematical transformation that results in complex signal and the \( \angle \) means the phases of this complex signal. This feature is scale of MAP time series variation too.
4. 12th percentile of the last IMF (percentile is the value of a variable below which a certain percent of signal values fall. So the 12th percentile is the value below which 12 percent of the signal values are found.

5. Skewness (third statistical momentum) of the last IMF

All of selected features were extracted from last IMF that is somehow the trend of MAP time series. These features were classified with a SVM classifier in order to predict which patient will experience acute hypotension episodes in future 1 hour time interval.

III. RESULTS

Evaluating the accuracy of the classification was performed based on Leave One Out (LOO) cross validation method. The LOO is one of the most reliable cross validation methods in which a patient is selected as test set while all the others are used as train set. Then the single test patient is classified with trained classifier. All of the patients would be tested in the same process. Ultimately, the overall accuracy for all of the data set is counted by calculating all of true test set classifications.

The best result for prediction of acute hypotension episodes was achieved by using SVM classifier with RBF kernel (\( \sigma = 2.4 \)) for classification of the aforementioned features. The achieved accuracy of this method was 93% with those 5 features.

IV. CONCLUSION

In this study EMD of patient’s MAP time series was calculated and their IMFs were obtained. After decomposition of MAP time series some features such as statistical features were extracted from IMFs and these features were classified with SVM in order to prediction of acute hypotension episodes. The accuracy of prediction with this method was 92% while in the research which was conducted by Mneimneh [7] the classification accuracy of train set was 68.3%. Meanwhile, the classification accuracy of train set with LOO cross validation method which was tested by Chiarugi [5] was 83%. However, Jousset [6] concluded 82% accuracy in classification of train set. Considering the results of the similar studies confirms that some features extracted from IMFs of MAP time series improves prediction of acute hypotension episodes with higher accuracy.
Figure 3: frequency content of MAP time series IMFs of Fig.1

REFERENCES


