A Hybrid Approach for Predicting Acute Hypotensive Episodes

M.Hoseinnia
Department of Electrical Engineering
Iran University of Science and Technology(IUST)
mahsahoseinnia@yahoo.com
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Name of the Presenter: Mahsa Hoseinnia

Abstract

This paper describes a hybrid approach for long term prediction of mean arterial blood pressure signal in order to detect an acute hypotensive episode (AHE) during one hour forecasting window. An acute hypotensive episode is defined as any period of 30 minute or more during which at least 90% of the non-overlapping one minute averages of the arterial blood pressure waveform is under 60 mmHg. The proposed method is based on wavelet transform and time-delay embedding neural networks.The wavelet transform is implemented to decompose mean arterial blood pressure (MAP) time series into set of wavelet components. A recurrent neural network architecture with embedded memory is then applied to forecast the wavelet approximation coefficients which represent the trend of the time series. Wavelet detail components were predicted using local radial basis models with time varying parameters. To obtain the predicted MAP time series, the neural network outputs were recombined using the same wavelet technique.The effectiveness of this strategy is validated using 40 records of arterial blood pressure signals from Multi-parameter Intelligent Monitoring in Intensive Care II (MIMIC II) database . Simulation results revealed the reasonable forecasting accuracy in prediction of AHE in one hour forecasting window.

Key words: Acute Hypotensive Episode(AHE), Mean Arterial Blood Pressure(MAP), Neural Network ,Prediction, Wavelet Transform.

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1. Introduction

Acute hypotensive episode is one of the most important events which requires effective treatment in intensive care units (ICUs) to prevent further damages. Such episodes may result in irreversible organ damage and death because vital organs are very sensitive to insufficient blood flow.

An acute hypotensive episode is defined as any period of 30 minute or more during which at least 90% of the non-overlapping one minute averages of the arterial blood pressure waveform is under 60 mmHg.

The development of methodologies to predict abnormally low blood pressure episodes can improve appropriate clinical interventions and increase survival opportunities in intensive care units. In general, the development of automatic hypotensive predictive solutions explore the correlation of patient clinical information, such as arterial blood pressure , heart rate (HR) and oxygen saturation (SO2) with the onset of the hypotension episode. Bassale proposed the use of parametric and non-parametric methods to analyze and characterize ABP before hypotensive episodes. He concluded that ABP variability and shape features have the potential to predict such events. Frolich *et al* suggested the use of baseline HR as a significant predictor of obstetric spinal hypotension. Basically, they showed that higher baseline HR may be a useful parameter to predict postspinal hypotension. Using spectral analysis of HR and ABP variability Pelosi *et al* have identified precursors of hypotensive episodes during renal dialysis. In particular, they investigated the ratio of low to high frequency peaks of the HR variability power spectrum (LF/HF) to the prediction of hypotension events after spinal anesthesia, for the specific cases of pregnant women and elderly men . More recently, Mancini *et al* showed the potential of SO2 short-term variability in anticipating the hypotension onset. Currently the European Avert-IT project proposes the development of a system architecture that can automatically predict adverse hypotensive events over a useful timescale, without the intervention of a health-care professional. The prediction task is performed through a Novel Bayesian Neural Network.

This paper described a hybrid approach for long term prediction of mean arterial blood pressure in order to anticipate acute hypotensive episodes in one hour forecasting window by means of wavelet transform and neural networks.. The wavelet transform is implemented to decompose MAP time series into set of wavelet components.A recurrent neural network architecture with embedded memory is applied to forecast the approximation component which represents the trend of time series. wavelet detail components are predicted using local radial basis model with time varying parameters. To obtain the predicted mean arterial blood pressure, the neural network outputs were recombined using the same wavelet technique.

The effectiveness of this strategy is validated using 40 records of arterial blood pressure signals from MIMIC II database.

The paper is organized as follows: section 2 introduces the dataset and preprocessing approach. In section 3, the proposed methodology is described. In section 4 the results are presented and discussed.

2.Data and Material

The dataset used in this work comes from the MIMIC II database, including physiologic signals and time series from patients in ICUs.

The records included at least 10 hour of arterial blood pressure data before T_0 , the beginning of forecast window, and at least one hour of data after T_0.

These records are assigned to two distinct groups:

- H: those with an AHE within the forecast window (the one-hour period following T0)
- C: those with no AHE within the forecast window

60 cases from these records are selected as training set and selected test set includes records from 15 H patients and 25 C patients, a proportion that very roughly matches the observed incidence of AHE among MIMIC II patients with MAP time series.

All analyzed arterial blood pressure signals are sampled at 125 Hz. The sampled signals are provided to a lowpass filter in order to suppress high frequency noise. We use a second order recursive filter which had been used by Zong (2003) with the aim of preprocessing the arterial blood pressure signals and beat detection. Frequency response of the filter is given by Eq.1.

$$|H(\omega T)| = \frac{sin^2\left(\frac{5\omega T}{2}\right)}{25sin^2\left(\frac{\omega T}{2}\right)} \qquad (1)$$

The 3 dB cutoff frequency of the filter is about 8 Hz. In the next step, mean arterial blood pressure signals are achieved by averaging the ABP time series in non-overlapping one minute windows. To deal with the missing information, MAP time series are linearly interpolated.

3. Research Methodology

This approach introduces a hybrid model to forecast mean arterial blood pressure time series using wavelet transform in combination with neural network techniques .wavelet transform is implemented to decompose time series into set of wavelet components comprising an approximation component and number of detail components. A recurrent network architecture with embedded memory is applied to forecast the approximation component which represent the low frequency component of time series. High frequency components are predicted by local RBF network.

3.1.Wavelet Decomposition

A one-dimensional discrete wavelet transform with an specified resolution level is used to decompose the one hour MAP data before forecasting window. Depending on the selected resolution levels, the time-series signals are decomposed into a low frequency component and several high frequency elements.

The most suitable resolution level is identified based on the smoothness of the approximation signal. For the proposed model, with respect to the length of time series, approximation signal at resolution level two is sufficiently smooth to represent a general pattern of the original signal. Wavelet components of a specified record are illustrated in Fig.1.

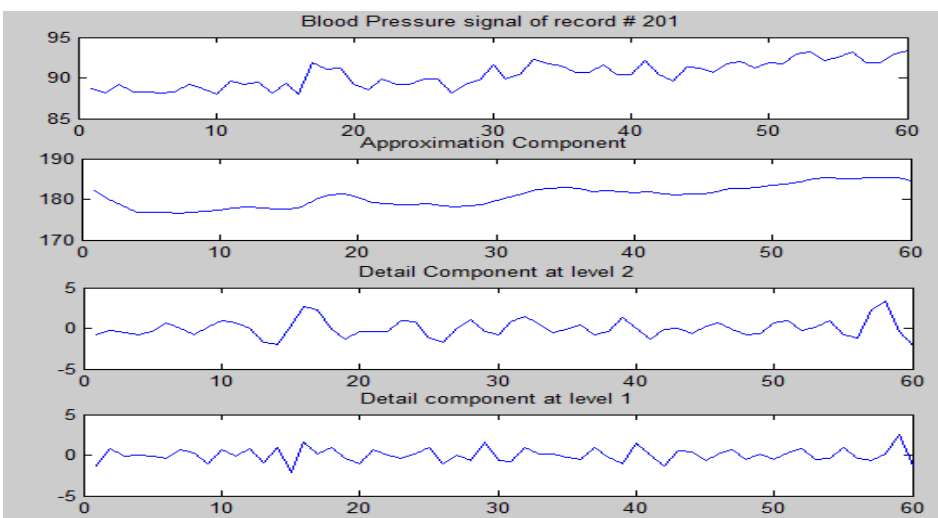

Fig 1: Decomposition of a specified record .

3.2. Wavelet Component Forecasting

3.2.1. Approximation Forecasting

Nonlinear autoregressive model process with exogenous input (NARX), as an architectural approach of recurrent neural network is used to predict approximation coefficient. A NARX model can be determined by following regression vector and predictor:

$$\varphi(t) = [y(t-1), \dots, y(t-n_a)]^T \tag{2}$$
$$\hat{y}(t|\theta) = \hat{y}(t|t-1, \theta) = g(\varphi(t), \theta) \tag{3}$$

Where $\varphi(t)$ is vector containing the regressors , θ is vector containing the weights and g is the function realized by training a two layer network with Levenberg-Marquadt method. NARX recurrent neural networks is a powerful class of models for modeling nonlinear systems and time series.
To complete the model, it is necessary to choose the number of past signals used as regressors or model order.

3.2.1.1. Choice of Model Order

The optimal model order is defined by means of Lipschitz number criterion. He and Asada (1993) introduced this method for the estimation of the model orders of nonlinear system. By evaluating the modification of an order index, which is defined as Lipschitz number with successive modification of the model orders, the appropriate model order can be achieved more simply and reliably by selecting the sufficiently large lag space which does not change the model index considerably.

3.2.2. Detail Forecasting

Detail components are predicted through a numerical algorithm designed by Zhu(2009) in order to forecasting nonlinear time series using time-delay embedding and radial basis function (RBF) neural networks. Unlike the common RBF structures with preselected and fixed centers, the proposed method utilizes a simple selection algorithm to dynamically change the center positions, resulting in a local RBF model with time varying parameters. The model first reconstructs the time series using phase space reconstruction technique, then within this space, a local RBF network model is built for one-step prediction.

3.2.2.1. Phase Space Reconstruction

Phase space reconstruction is a technique used to represent the non-linear characteristics of a dynamic system, consisting of a simple plot of signal time-lagged vectors. Considering the signal as a time series $x(1)$, $x(2)$, …, $x(\mathrm{n})$, where n is the number of points, the time lagged vectors of the multidimensional phase space are determined according to Eq. (4).

$$X_i = [x_i \quad x_{i+\tau} \quad \cdots \quad x_{i+(m-1)\tau}] \qquad i = 1, \dots, (m-1) \tag{4}$$

where τ is the time delay between the points of the time series, and m is the embedding dimension which corresponds to the number of phase space coordinates. The process retains the evolution information of the original dynamical system, and they have the same dynamical properties. It should be emphasized that the choice of delay time and embedding dimension is critical to the quality of phase space reconstruction.

3.2.2.2. Choice of Time Delay

A popular method of calculating optimal time delay is based on the behavior of the autocorrelation function.

$$R_{xx}(\tau) = \frac{1}{N}\sum_{0}^{N-1} x_i x_{i+\tau} \quad (5)$$

τ is the first time the autocorrelation function decreased to 1/e of its original value. This definition seeks to find times where correlation between different points in the time series are negligible.

3.2.2.3. Choice of Embedding Dimension

A common approach to choose an optimal embedding dimension is false nearest neighbor method. Embedding dimension is the dimension of the reconstruction if the mapping from real space to pseudo space is one-to-one and achieved trajectories do not cross each other. The method of false nearest neighbors (FNN) has been developed to search through the data and identify the presence of trajectory crossings. The idea is that if the embedding dimension is too small, portions of the strange limit set will cross over itself. So if the nearest neighbor of a pseudo phase point reconstructed in dimension *m* suddenly becomes far away when the reconstruction dimension is increased, then it will have been considered as a false nearest neighbor. In this work, a nearest neighbor is labeled “false” if $R_{m+1}/R_m > 15$, where R_m is the distance between the points in the *m*-dimensional reconstruction space. When a dimension is reached in which there are essentially no false nearest neighbors, the appropriate embedding dimension is found. This test can be applied after the appropriate choice of τ has been made.

3.2.2.4. Local RBF Network Modeling

Local models make predictions by investigating local neighbors that are close to the end point of the time series in phase space. The prediction is an estimate of the average change that occurred immediately after these neighbors. The proposed prediction method using local RBF network model is as follows:

1. Find the k-nearest neighbors of the last time-delay vector **x** using an efficient neighbor-searching algorithm. K is determined through investigation of training set. Use the minimum distance between **x** and neighbors as the width of the centers.
2. Construct a regression RBF network using these k-nearest neighbors as centers and inputs, the corresponding immediate time-delay vectors of the neighbors are determined as the network outputs.
3. Make a prediction using **x** as input.
4. Use the previous prediction as the input for next step, and go back to the first step.

3.3. Wavelet Recombination

The outputs of the neural networks are recombined through the same wavelet technique and resolution level as data decomposition to form the final predicted output.

4. Results and Analysis

By investigating the training set, four different classes of patients are determined. In the first group , the one hour recorded mean arterial blood pressure before forecasting window is near

60 mmHg and remains in this region. Second group has MAP signal within the range between 65 and 80 mmHg. Mean arterial blood pressure waveforms in the third group have a descending trend. The initial values of these time series are above 80 mmHg while the signal magnitude decreases proceeding in the time. Recorded mean arterial blood pressure time series in the last group are above the 80 mmHg.
Required parameters are determined guided by different kinds of groups to minimize the prediction error.

	# of neighbors in Group1	# of neighbors in Group2	# of neighbors in Group3	# of neighbors in Group4
First Level Detail Prediction	n=8	n=14	n=15	n=7
Second Level Detail Prediction	n=8	n=20	n=10	n=7

Table 1. Determination of Model Parameters

Local averaging property of the RBF network decreases the sensivity of model to the number of neighbors. The prediction results of the approach applied to the test set, are summarized in table 2.

	Prediction Result	Actual Result		Prediction Result	Actual Result
#201	C	C	#221	C	C
#202	H	H	#222	C	H
#203	H	H	#223	H	H
#204	C	C	#224	H	H
#205	C	C	#225	H	H
#206	C	C	#226	C	C
#207	H	H	#227	H	H
#208	C	C	#228	C	C
#209	H	H	#229	C	C
#210	C	C	#230	C	C
#211	C	C	#231	C	C
#212	C	C	#232	C	C
#213	C	C	#233	C	C
#214	H	H	#234	H	H
#215	C	C	#235	C	C
#216	C	C	#236	C	C
#217	H	H	#237	C	C
#218	H	H	#238	H	H
#219	H	C	#239	H	H
#220	C	C	#240	C	C

Table 2. Prediction Results

Among the test records, records 222 is incorrectly identified as unlikely to be followed by AHE. In record 222 MAP is declining just before beginning of the forecasting window, T_0 , but rapidly rises in the first minutes after T_0 in response to administration of IV fluids. This is followed by a rapid decline to 63-70 mmHg in the next 5-10 minutes, following a pattern that can also be seen during the previous 10 hours of this record. This time, however, an AHE begins at about T0 + 25 minutes, reaching a minimum of 54 mmHg. The proposed model can not trace these kind of sharp changes. Three examples of prediction results are illustrated in Figs.2~4.

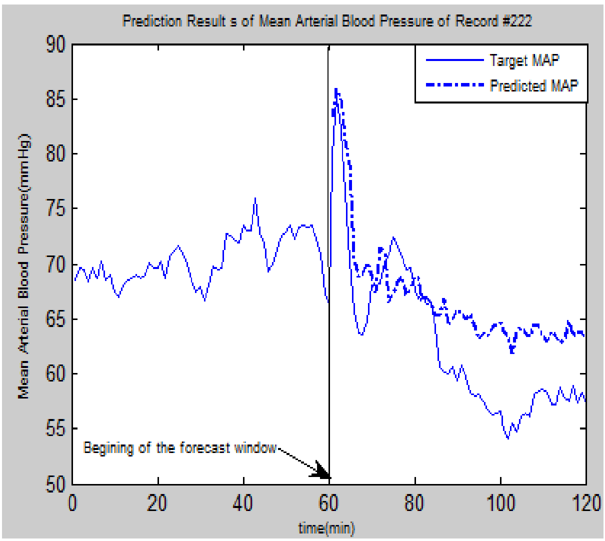

Fig 2 : Prediction Result of Record # 222

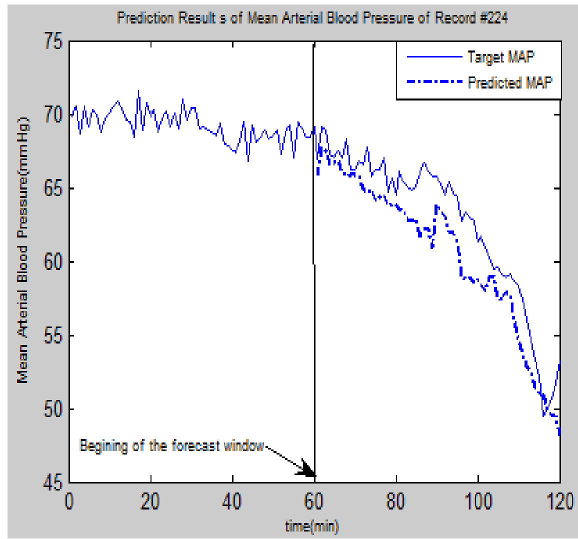

Fig 3 : Prediction Result of Record # 224

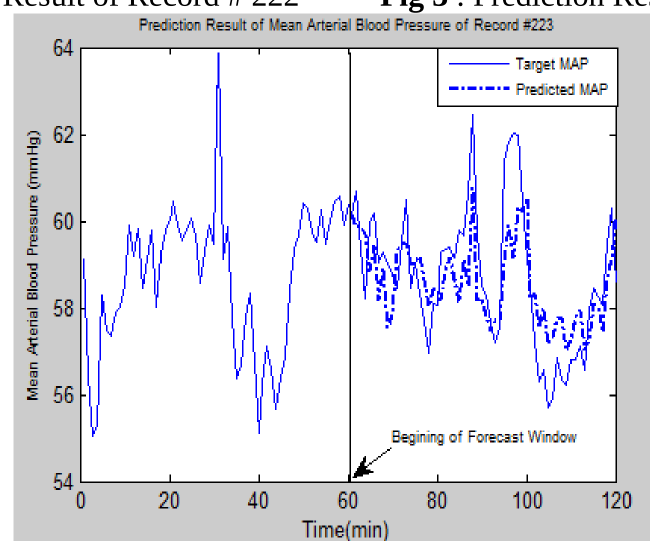

Fig 4 : Prediction Result of Record # 223

As the result shows, decomposing the time series into wavelet component leads to exploring the details of dynamic system and improves the forecasting accuracy. Although the application of NARX network in time series prediction reduces the structure to a time delay neural network architecture (TDNN) and decreases its capabilities due to the lack of output memory ,NARX network as a powerful nonlinear system identification structure shows satisfactory results in combination to local RBF network. Local RBF network is an efficient

structure in analysis the nonlinear dynamic system with time varying parameter specially when the available training data set is small.
Performance of the proposed model is measured by the following parameters and the performance results are summarized in table 3.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \tag{6}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100 \tag{7}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{8}$$

	FNR	FPR	TNR	TPR	Sensivity	Specificity	Accuracy
Proposed Approach	1	1	24	14	%93.3	%96	%95

Table 3. Performance Results

5. Conclusions

This work proposes a hybrid methodology to predict acute hypotensive events over a specified time using mean arterial blood pressure time series of MIMIC II database, the modeling strategy incorporating the discrete wavelet transform and neural network structures is implemented, enabling to estimate prediction over a forecast horizon. Applied to MAP time series, the referred strategy allows to adequately capture its dynamics and predict the onset of hypotensive episodes.
This study is only based on arterial blood pressure signals. Further studies maybe take into account the heart rate variability to improve the capability of the model in forecasting sharp changes of MAP time series. In addition, longer blood pressure records can be used to investigate the hidden patterns more accurately.

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