Quantitative Analysis of Heart Rate Baroreflex in Healthy Subjects Using Adaptive Neuro Fuzzy Inference System Approximation

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Abstract

This paper is focused on the identification of the heart rate (HR) baroreflex mechanism using new nonlinear system identification approach.

The proposed HR baroreflex model is based on inherent features of the autonomic nervous system for which we develop an adaptive neuro-fuzzy inference system (ANFIS) structure.

The simulation results show significant improvements in prediction of HR as a model output by calculating the normalized root mean square error (NRMSE) in comparison with other reported methods.

We have shown that for modeling of cardiovascular system regulation, our proposed nonlinear model is more accurate than other recently developed methods.

1. Introduction

The cardiovascular system is responsible for maintaining an appropriate environment for normal functioning of the cells in our body. The autonomic nervous system is responsible for regulation of the cardiovascular system over short time scales usually through mediation of the arterial baroreflex system. The arterial baroreflex system consists of four mechanisms: (1) the heart rate (HR) baroreflex; (2) the ventricular contractility (VC) baroreflex; (3) the total peripheral resistance (TPR) baroreflex and (4) the systemic venous unstressed volume (SVUV) baroreflex.

A schematic presentation of this mechanism is given in Figure (1). Arterial blood pressure (ABP) is sensed via baroreceptors that lie in two locations; the carotid sinus and the aortic arch. Afferent nerves transmit the sensed ABP to the brainstem. The ANS communicates with the sino-atrial (SA) node to preserve ABP near its desired value; this communication is through the sympathetic and parasympathetic nerves.

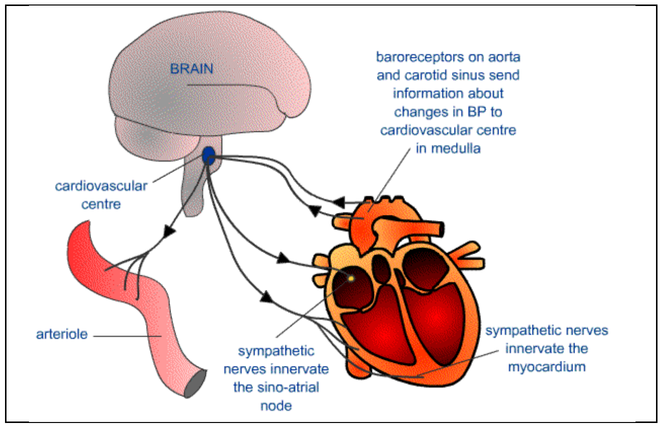


Figure 1. Schematic of the HR baroreflex.

During the past years, there have been many studies in the literature in the field of cardiovascular system identification. Both linear and nonlinear system identification techniques have been applied in these studies for investigating cardiovascular regulation.

Appel et al. [1] implemented the auto regressive with exogenous input (ARX) model for coupling of HR, ABP and instantaneous lung volume (ILV). They identified a closed-loop relationship between these three signals. Xiao et al. [2] introduced a cardiovascular system identification method based on weighted-principal component regression (WPCR). Their method allows incorporation of pre-knowledge about the system through a weighting scheme. They show that the WPCR method is more accurate in identification of the system impulse response function than the other methods when the input signal is colored.

Considering high complexity of the cardiovascular system, some researchers have attempted to implement nonlinear system identification techniques for the physiological mechanism analysis. Chon et al. [3] performed a nonlinear analysis of the effect of fluctuation in ILV and ABP on the HR variations utilizing a Laguerre expansion-based method. They found that the linear model accounted for approximately 67% of variance in the heart rate, while the nonlinear model accounted for approximately 80%. . In the other study presented by Chon et al. [4], they applied the artificial neural network (ANN) method to study the coupling between the HR and ILV and they compared their results with the traditional least square estimation (LSE) method. They also indicated that there are no major differences between the results of these two methods. In the research conducted by Liu et al. [5], they utilized a neuro-fuzzy inference system (NFIS) in combination with AR model in the task of the cardiovascular system identification which resulted in a 78% accuracy of in the HR prediction.

In this study, and in order to improve the accuracy of the estimation of the HR time series as the HR baroreflex output, a nonlinear model is developed to identify the HR baroreflex system. Our method is based on the intrinsic characteristics of the nervous system. An adaptive neuro-fuzzy inference system (ANFIS) structure is also used for the model estimation.

2. Method

Normally, three basic steps are involved in the process of system identification. These three steps are: data generation, model determination, and model validation [6]. In the case that the model is not validated, the first two steps should be repeated until the model becomes validated. The three steps are explained with more detail in the following sections.

2.1. Data generation

In data generation, the first step of system identification, the input and output data of the system should be collected. The input data for the HR baroreflex mechanism identification is ABP, and the output data is HR. The required data are collected from the polysmonographic database in Physionet. This collected data consist of the electrocardiogram (ECG) waveform and the ABP signal of eight subjects over duration of 40 minutes.

2.2. Model determination

The next important step of system identification method is the determination of a mathematical model. Model determination is consists of three sub steps which will be described in the following part:

2.2.1. Candidate model set selection

In order to estimate the HR series as the output of the HR baroreflex mechanism, a nonlinear ARX (NARX) model is employed in our method. Choosing NARX models helps avoid the complexities of the Volterra-Weiner and Hammerstein series. The NARX models are represented by the following general equation:

$$Y(t) = F\big(y(t-1), y(t-2), \dots, y(t-n_a), u(t-n_k), \dots, u(t-n_b-n_k-1)\big) \quad (1)$$

Where y(t) is the current HR, and u(t-m) is the SBP in the time (t-m), n_a, n_b, and n_k are the components of the model order matrix.

2.2.2. Criterion of Fit

The assessment of the model quality is typically based on how the models perform when they are used to reproduce a fresh set of measured data. The model order is an indicator of the sympathetic and parasympathetic nerves function and it reveals the closed-loop properties of the regulatory mechanism of the cardiovascular system; it also delineates the delay in the system under study. Note that the delay in the HR baroreflex mechanism is caused by the parasympathetic nerve function [7]. In this paper we apply A-information criterion (AIC). Physical meaning of this criterion is a metric of the difference between the actual and the estimated unobserved disturbances. The range of model orders, n_a, n_b, and n_k, were chosen experimentally as following:

$$1 \le n_a \le 15$$
$$1 \le n_b \le 15$$
$$1 \le n_k \le 15$$

The results of the selected model order are listed in Table 1.

Table 1. Selected model order

Model order	Value
n_a	9
n_b	6
n_k	3

These results agree with the natural characteristics and physiological understanding of the system under study such as delay in the parasympathetic function, durability in the function of sympathetic nerves and the correlation between the HR and the ABP signals.

The percent of unexplained output variance versus the number of parameters is shown in Figure 2. This figure indicates that the selection of 15 parameters is the best choice for this experiment.

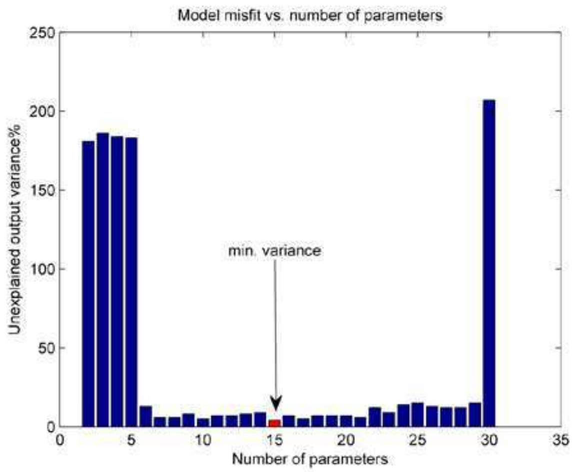


Figure 2. Percent of unexplained output variance versus number of parameters.

2.2.3 Model estimation

There are many methods such as the wavenet estimators and the artificial neural networks developed for estimation of the NARX models. In our model in this study, an adaptive neuro-fuzzy inference system (ANFIS) structure is selected among a variety of methods to estimate the HR baroreflex model. The reason to prefer ANFIS structure rather than other methods in model estimation is that, by using ANFIS in the process of identification, we can implement our prior knowledge about the system physiology to the model. The key feature of this study is to apply prior physiological knowledge about the sympathetic and parasympathetic nerves for system modeling. From the physiological point of view, we know that the ANS controls the HR through the sympathetic and parasympathetic nerves. This knowledge inspires us to design membership functions based on the functions of these two nerves. One membership function represents the sympathetic nerve function. It has been recognized that the maximum functioning of the sympathetic nerves causes maximum amount of the physiologic variable such as HR or SBP. On the other hand the parasympathetic nerve acts in an inverse manner, and hence the second membership function mirrors the first one. Two membership functions are designed for each input to the ANFIS structure. One of them represents the function of the sympathetic nerve and the other is an indicator of the parasympathetic nerve. The membership function that best describes the sympathetic and parasympathetic nerves is the generalized bell membership function. The two membership functions which represent the sympathetic and parasympathetic nerves before training are shown in figure 3.

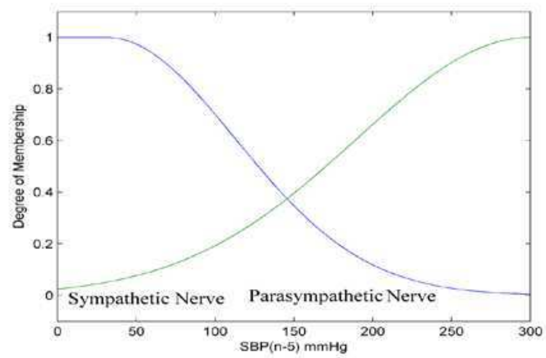


Figure 3. Membership functions which represent the sympathetic and parasympathetic nerves before training.

The proposed ANFIS structure has fifteen inputs and one output. Five hundred data pairs are selected from each subject for the training of the ANFIS model. The number of epochs for training is selected to be 100 and the error method used is a trial and error method. Moreover, a hybrid learning method is applied as a learning algorithm of the ANFIS structure.

2.3. Model Validation

In this step, the proposed model should be validated. It is of great importance to validate the identified model once the preceding two steps are completed. For model validation, 400 data pairs from each subject are selected to test the ANFIS structure. These data pairs are picked at least one minute after the end of the training for each individual subject.

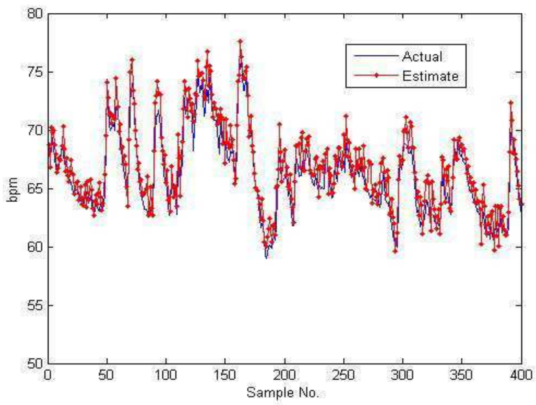
3. Simulation Results

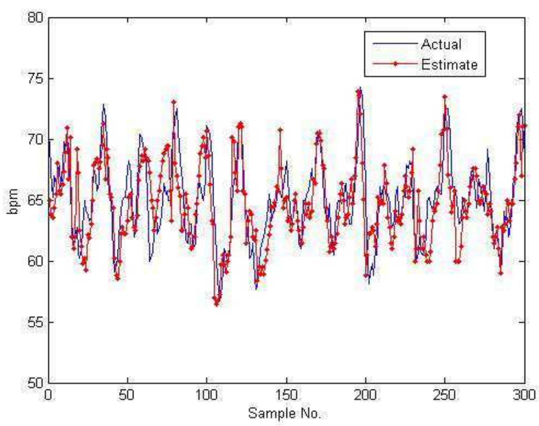
The validity of the model in estimation of the output is calculated based on the normalized root mean square of error (NRMSE) criterion. The NRMSE is then calculated based on the simulation results. The results of this calculation are listed in Table 2.

In Table 3 the results of this study is compared with the other related studies. The results show significant improvements in predicting the HR using the proposed model.

Table 2. Calculated NRMSE in HR estimation

Subject number	Error
1	0.221
2	0.119
3	0.175
4	0.238
5	0.227
6	0.164
7	0.176
8	0.215





Figures 4 and 5. Estimated versus actual HR for the Cases 2 (up) and 5 (down). The simulation results show that estimation results follow actual data very closely.

The plots in Figures 4 and 5 are represented as examples of the simulation. The plots show an excellent match between the estimated and the actual HR data.

4. Conclusion

In this study a new approach in the nonlinear identification of the HR baroreflex is presented. The NARX structure is selected because of its simple implementation and also because it is comparable with the linear ARX model in term of relating current output of system to the previous inputs and outputs.

Table 3. Comparison between results of this study and other related studies.

Method	Mean NRMSE	MODEL
Appel et al.	0.356	ARX
Xiao et al.	0.215	
Liu et al.	0.237	
This paper	0.191	NARX-ANFIS

The ANFIS structure is applied for the task of the NARX model estimation. The soft computing techniques are the most powerful methods among a wide variety of methods for the NARX model estimation. By implementing the ANFIS structure we are able to include our prior knowledge about afferent nervous system in modeling of cardiovascular regulationThe simulation results show that this idea leads to significant improvements in the HR baroreflex estimation in comparison with the previously published methods.

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