Disorder Classification in the Regulatory Mechanism of the Cardiovascular System

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Abstract

An approach to classify disorders in autonomic control of cardiovascular system is proposed in this paper. The target of this study is to highlight main features of malfunctions in cardiovascular system due to autonomic disorder. Collecting the data from the physionet archive, we divide patients into two groups of normal and abnormal, based on having autonomic disorder in their cardiovascular system or not. Systolic blood pressure (SBP) and heart rate (HR) time series are evaluated for each patient. We then plot the diagram of SBP against HR for all patients in a single figure. Fuzzy c-means clustering (FCM) method is also applied to cluster data into two groups. A neural network is then implemented to classify and to distinguish the two groups. The network is trained with data of a normal patient and is tested with data of other normal and abnormal patients. Result show that selected features can clearly detect disorders in autonomic system.

1. Introduction

Short-term, beat-to-beat cardiovascular variability reflects the dynamic interplay between ongoing perturbations to the circulation and the compensatory response of neurally mediated regulatory mechanisms. Autonomic nervous system (ANS) provides second to second adjustment of blood pressure and heart rate. allowing humans great flexibility in posture and environment.

Disorders in the function of neural regulatory mechanism can result from disease and environmental conditions. Some diseases such as hypertension (HTN) and congestive heart failure (CHF) are affecting short term regulation. Examples of other common diseases affecting short-term regulation are diabetes mellitus and Parkinson's disease.

Autonomic disorders, also referred as dysautonomias, can be divided according to their effects on blood pressure in the upright posture.

The first group include severe dysautonomias, always causing significant orthostatic hypotension (a fall in blood pressure with standing of more than 20/10 mmHg, measured with the patient lying quietly after 5 minutes of quiet standing.). Although severe disorders are rare, all of them are serious. The second group, mild dysautonomias, are more common but less serious, and orthostatic hypotension is usually absent, though heart rate abnormalities are often prominent. Table 1 list autonomic disorders grouped by severity.

Table 1. Disorders grouped by severity

Type	Dysautonomia
Severe	Baroreflex failure
	Glossopharyngeal neuralgia
	Pure autonomic failure
	Autoimmune autonomic failure
	Autonomic neuropathy
Mild	Postural tachycardia syndrome
	Neurally mediated syncope
	Neurapinephrine transporter-deficiency
	Medications
	Bed rest

Since many clinicians are unfamiliar with disorders in the autonomic nervous system, automatic and noninvasive assessment of disorders in regulatory mechanism of cardiovascular system is valuable in clinical use.

There are some researches which have focused on this area. Javorka et al [1] compared heart rate and blood pressure variablity between young patients with type 1 diabetes mellitus (DM) and control subjects by pioncare plot. They show that there is a siginficant reduction in HRV pioncare plot measure in patients with type 1 diabetes mellitus, indicating heart rate dysregulation.

Pagani et al [2] studied patients with hypertension; they showed that baroreflex gain decrease with hypertension. Mukkamala et al [3] studied patients with diabetic autonomic neuropathy (DAN), they indicated that baroreflex amplitude progressively decrease with increasing severity of diabetic autonomic neuropathy. Belozeroff et al [4] studied patients with sleep apnea (SA) before and after continuous positive airway pressure (CPAP) therapy, they inferred that baroreflex gain increased with CPAP therapy. Voss et al [5] studied patients with dilated cardiomyopathy (DCM), they showed that maximum alternans durations were significantly enlarged in DCM patients.

In this study we propose a method to distinguish patients with dysautonomias from normal. The hypothesis of this study is that there are differences between HR and SBP time series of abnormal patients and normal ones. We then extract features of HR and SBP time series and highlight the differences between normal and abnormal patients.

2. Methods

To evaluate our hypothesis, data of ECG signal and simultaneous arterial blood pressure (ABP) waveform of 7 normal subjects and 11 abnormal patients are collected from physionet, physiobank archive [6]. For each subject 1 hr of data is collected. Figures 1 and 2 show plot of SBP for a normal subject and abnormal patient.

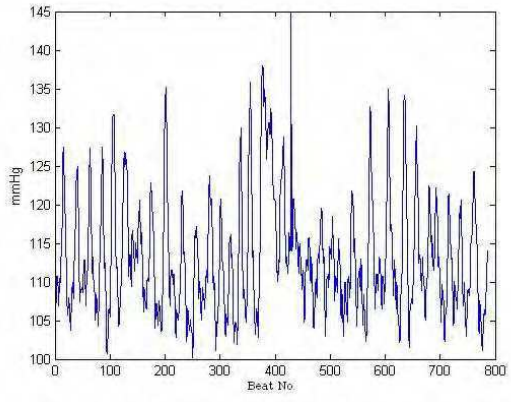

Figure 1. Plot of SBP for a normal subject.

2.1. Preprocessing

In the next step ECG signals of all subjects are denoised using the method discussed in [7]. Signal abnormality index (SAI) algorithm [8] is also applied to remove artifacts and noises from ABP waveforms. Then HR and SBP time series for each subject are evaluated. RR interval for each beat evaluated using corrected annotations available in the physionet archive. SBP for each beat is evaluated by finding maximum of ABP waveform in the 0.3 sec period after annotation.

We neglect first 10 min of both ECG signal and ABP waveform for each subject, to assure that subjects are in their steady condition.

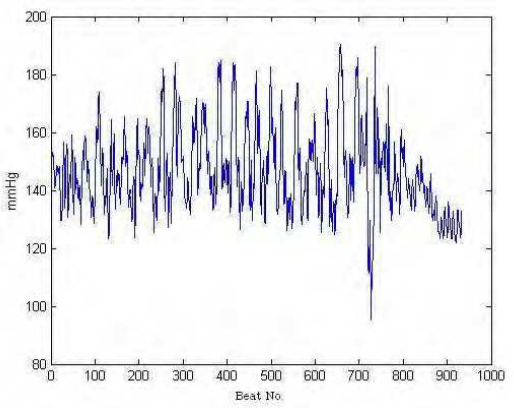

Figure 2. Plot of SBP for a Abnormal patient.

2.2. Data Clustering

To find difference between the two groups first we plot the diagram of SBP against HR for all patients in a single figure. Figure 3 shows the plot of SBP against HR for all patients. Plot shows two distinguishable regions of normal and abnormal patients. The plot indicate that we can cluster subjects into two groups, so we apply a clustering method to classify subjects into two groups.

2.2.1. Fuzzy c-means (FCM)

To cluster two groups we apply fuzzy c-means (FCM) method. Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This method (developed by Dunn [9] and improved by Bezdek [10]) is frequently used in pattern recognition and classification problems. It is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^{n}\sum_{j=1}^{c} u_{ij}^{m} \left\| x_i - c_j \right\|^2$$

where m is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the ith of d-dimensional measured data, c_j is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ij} and the cluster centers c_j by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}}$$

This iteration will stop when:

$$\max_{ij}\left\{u_{ij}^{(k+1)} - u_{ij}^{(k)}\right\} < \varepsilon$$

Where ε is a termination criterion between 0 and 1, whereas k are the iteration steps. This procedure converges to a local minimum or a saddle point of J_m.

The SBP and HR coordinate of cluster centers for each group is obtained using the method.

2.3. Results

In this step a system identification method is used to classify data. For this purpose we assume a nonlinear model of nervous system in the form of the above Equation. This equation represent the model:

$$HR(t) = F\begin{pmatrix} HR(t-1), HR(t-2),..., HR(t-m), \\ SBP(t), SBP(t-1),..., SBP(t-n) \end{pmatrix}$$

Where m and n are order of the model. By application of the affine geometry method discussed in [11], m and n are evaluated for each subject. Selected m and n are average of evaluated m and n for all subjects. The value of m is 11 and the value of n is 12. Then a multi layer preceptron (MLP) network with 24 nodes in input layer, 30 nodes in hidden layer and one node in the output layer, is used for the identification purpose. Network is then trained with data of a normal subject and is tested with data of other subjects.

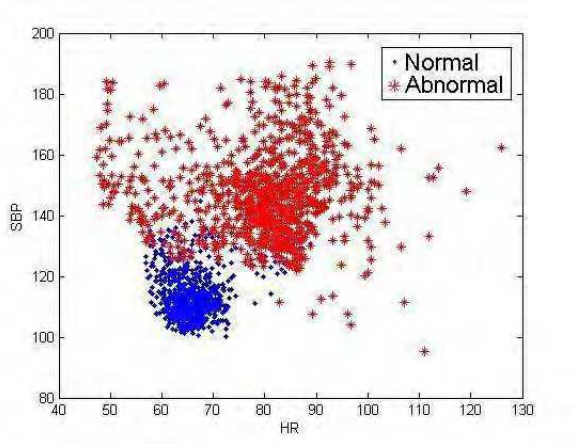

Figure 3. Plot of SBP against HR for all patients

3. Results

The result of clustering method is presented in table 2. As indicated in the table there is major difference between centers of the two groups.

Table2. Clustering results

Group	SBP center	HR center
Narmal	112	66
Abnormal	143	84

It is also obvious from figure 1 that data of normal group is packed but the data of abnormal group is distributed.

Root mean square error (RMSE) in estimation of output in the neural network is calculated for all subjects. Result of RMSE for each group is presented in table 3. It is evident that RMSE result of the normal group is significantly lower than the abnormal group.

Table 3. RMSE results

Group	Mean	Min	Max
Normal	0.083	0.052	0.102
Abnormal	0.671	0.412	0.851

4. Discussion and conclusions

In this paper we present An approach to automatic clustering normal subjects from patients which have dysfunction in their regulatory mechanisms of cardiovascular system.

We demonstrate that there are major differences between data of abnormal patients and normal ones. However this conclusion is true, because in patients which have a type of dysautonomias, autonomic nervous system fail to act properly and so the response of the system will change. The result of neural network based identification show that the system is nearly the same for normal subjects, but it changes for abnormal subjects. This conclusion is correct, because autonomic nervous system is similar for all persons except they have malfunctions in their autonomic nervous system. Although we can use the method only for detection of disorders in regulatory mechanism of cardiovascular system, and we can't use this method to specify what kind of dysautonomias the patient has, But unlike other methods this method is not restricted to specify only one dysautonomia.

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