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Generalized discriminant analysis for congestive heart failure risk assessment based on long-term heart rate variability☆

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ABSTRACT

The aims of this study are summarized in the following items: first, to investigate the class discrimination power of long-term heart rate variability (HRV) features for risk assessment in patients suffering from congestive heart failure (CHF); second, to introduce the most discriminative features of HRV to discriminate low risk patients (LRPs) and high risk patients (HRPs), and third, to examine the influence of feature dimension reduction in order to achieve desired accuracy of the classification. We analyzed two public Holter databases: 12 data of patients suffering from mild CHF (NYHA class I and II), labeled as LRPs and 32 data of patients suffering from severe CHF (NYHA class III and IV), labeled as HRPs. A K-nearest neighbor classifier was used to evaluate the performance of feature set in the classification. Moreover, to reduce the number of features as well as the overlap of the samples of two classes in feature space, we used generalized discriminant analysis (GDA) as a feature extraction method. By applying GDA to the discriminative nonlinear features, we achieved sensitivity and specificity of 100% having the least number of features. Finally, the results were compared with other similar conducted studies regarding the performance of feature selection procedure and classifier besides the number of features used in training.

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1. Introduction

By definition, heart failure is the inability of the heart to maintain or increase cardiac output at a rate commensurate with somatic aerobic requirements [1]. This may happen when the heart muscle itself is weaker than normal or when there is a defect in the heart that prevents blood from getting out into the circulation [2,3]. When the heart does not circulate blood normally, the kidneys receive less blood and filter less fluid out of the circulation into the urine. The extra fluid in the circulation builds up in the lungs, the liver, around the eyes, and sometimes in the legs. This is called fluid “congestion” and for this reason doctors call this “congestive heart failure” (CHF) [2]. CHF is chronic, degenerative and age related [4]. Therefore, the growing number of elderly people in western countries could be one of the reasons that the number of patients with CHF is increasing [5]. It is said that CHF is asymptomatic in its first stages. A decreased heart functioning may be diagnosed by several tests, including the “echocardiogram”, “heart catheterization”, “chest X-ray”, “chest CT scan”, “cardiac MRI”, “nuclear heart scans (MUGA, RNV)”, and “ECG”

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[6]. Obviously, detecting patients' conditions at the starting phases of disease would lead to a reduction in medical cost as well as prevention of the disease progress. However, patients with heart failure can have an enjoyable life by controlling the disease with medicine besides changing their life style. CHF severity can be measured by symptomatic classification scale developed by New York Heart Association (NYHA) [1]. Classification via NYHA scale has been proved to be a risk factor for mortality [7]. According to the estimation via NYHA scale [1], patients suffering from mild CHF (NYHA classes I and II) are considered as low risk patients (LRPs) while the ones suffering from severe CHF (NYHA classes III and IV) are considered as high risk patients (HRPs).

Heart rate variability (HRV) is the variation over time of the period between consecutive heartbeats (RR intervals) [8]. It is calculated using ECG signals and commonly used to assess the influence of the autonomic nervous system (ANS) on the heart [9]. Many studies used HRV analysis in order to classify different arrhythmias [5,6,9–26]. Some of these studies used long-term [21–23] and short-term [5,6] HRV analysis for distinguishing CHF patients from normal subjects. Also the effect of HRV analysis in order to assess risk and mortality of CHF patients is mentioned in some studies [27,28].

Recent clinical studies have demonstrated that HRV analysis may be a useful tool to assess the balance of cardiac autonomic nervous system. HRV indices are closely related and reflect parasympathetic, mixed sympathetic, and parasympathetic and circadian rhythms [29]. On the other hand, it has been recognized that, in heart failure, the sympathetic nervous system (SNS) is activated and the imbalance of the activity of the SNS and vagal activity interaction occurs. The abnormal activation of the SNS leads to further worsening of heart failure [30,31]. So, based on this rational relationship, in this study, we used HRV analysis to investigate the power of linear and nonlinear HRV measures to individuate low risk (LR) and high risk (HR) CHF patients. In 2011, a classifier was presented by Mellilo [28] which took advantage of short-term HRV measures to individuate severity of CHF. He also used long-term HRV analysis for risk assessment in patients suffering from CHF [27]. He used linear HRV analysis and classification tree to classify patients in LR and HR classes and achieved sensitivity and specificity rates of 93.3% and 63.6%, respectively. The method we used for the aforementioned purpose is based on the use of discriminative nonlinear features of HRV. Some studies on the CHF detection such as [6,22,23] have used $SD1/SD2$ with other features extracted from HRV time series. Voss [32] showed that besides clinical indices, nonclinical parameters, especially nonlinear ones such as DFA revealed significant differences between LR and HR groups of CHF patients. He also showed that α_1 from DFA is a powerful independent predictor of mortality in CHF. In 1991 Pincus [33] evaluated and quantified nonlinear dynamic changes based on chaos theory for analysis of heart failure subjects using FD, DFA, and ApEn. Krstacic et al. [34] studied the nonlinear dynamics (DFA, FD, and ApEn) in 250 patients with heart failure during 12 months and found that the patients with heart failure had lower ApEn while higher FD.

In the next step of our algorithm, we proposed a new method which enabled us to individuate LR and HR patients. The proposed algorithm uses the generalized discriminant analysis (GDA) which is a sort of generalization to the widely accepted linear discriminant analysis (LDA) algorithm. Recently, Asl [35] used GDA and support vector machine (SVM) methods to classify cardiac arrhythmia. Yaghouby [26] used GDA as a feature dimension reduction method besides MLP as a classifier to classify four different types of cardiac arrhythmias. Soleymani [25] presented an algorithm for classification of seven heart arrhythmias by neural networks using chaotic features of HRV signal and GDA. In GDA method, the input data is mapped into a convenient higher dimensional feature space F and instead of the original input space, the LDA algorithm is performed on the obtained space F. Therefore, by using GDA we achieved dimensionality reduction of the input feature space as well as selection of the most useful discriminating features at the same time.

In the last part of our study we classified CHF patients in two classes of LRP and HRP by using k-nearest neighbor (KNN) as a classifier which was previously used by Isler [6] for diagnosing CHF patients. In the following sections, the details of the proposed algorithm are explained.

In Section 2, our method is described and some information about the linear and nonlinear features extracted from HRV, feature dimension reduction and classifier are presented. The results of the proposed algorithm are presented in Section 3. Finally, we compared this work to the previous relevant studies and the arguments are presented in Section 4.

2. Methods

2.1. Data

The dataset we used herein was retrieved from two databases, both of which are available on the PhysioNet. It includes 29 data obtained from Congestive Heart Failure RR intervals Database [36] with patients suffering from CHF (NYHA classes I–III) and 15 data obtained from BIDMC Congestive Heart Failure Database [36] with patients suffering from severe CHF (NYHA class III and IV). The first database includes RR Intervals extracted from 24-h ECG Holter recordings of 8 men, 2 women and 19 unknown-gender subjects with the age of 34–79, and the original ECG recordings of this RR interval database digitized at 128 samples per second. The latter database includes long-term ECG recordings of 11 men and 4 women subjects with the age of 22–71, and the original ECG recordings of this database digitized at 250 samples per second. These 44 nominal 24-h recordings were divided into two sets based on the NYHA criterion: low risk patients (LRPs) and high risk patients (HRPs). The LRP subdataset includes 12 data of patients suffering from mild CHF (NYHA classes I and II) and the HRP subdataset includes 32 data of patients suffering from severe CHF (NYHA classes III and IV). We just selected the patients with a fraction of total heartbeats intervals (RR) classified as normal-to-normal (NN) intervals (NN/RR) higher than 80% as explained in Section 2.2.

2.2. Long-term HRV measures

In order to compute HRV measures, standard long-term HRV analysis on nominal 24-h recordings was used according to international guidelines [9].

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