Using Heart Rate Fragmentation and Heart Rate Asymmetry to Discriminate Congestive Heart Failure

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Abstract

Heart Rate Asymmetry (HRA) quantifies the imbalance of heart rate acceleration and deceleration. Furthermore, Heart Rate Fragmentation (HRF) refers to a pattern of irregular heart rate variability characterized by frequent, short-lived accelerations or decelerations in heart rate while analyzing beat-to-beat intervals. This paper uses HRA and HRF features to distinguish Congestive Heart Failure (CHF) from Normal Sinus Rhythm (NSR). We have used 29 ECG recordings of subjects with CHF from the Physionet Congestive Heart Failure database and 54 ECG recordings of subjects in normal sinus rhythm from the Physionet Normal Sinus Rhythm database. Using 3000 RR intervals, three common HRA indexes and four HRF indexes were calculated. K-Nearest Neighbors (KNN) was trained on 70% of the data as a training set, and the accuracy was evaluated on 30% as a test set. The first case is when all seven extracted features are used in the classifier. Only four HRF parameters are considered in the second case, and in the third case, only three HRA parameters are included. The result shows that the extracted descriptors of the HRF are 100% accurate compared to the HRA, which obtained an accuracy of 81%. The results showed that although both HRF and HRA have promising results in diagnosing CHF, the parameters extracted from HRF alone can obtain promising results.

1. Introduction

Congestive Heart Failure (CHF) is a chronic condition in which the heart is unable to pump blood efficiently [1]. This leads to fluid buildup in the body, causing symptoms like shortness of breath, fatigue, and swelling. CHF represents a significant public health issue in industrialized countries, with rising prevalence and incidence rates [2]. Therefore, timely detection of CHF is crucial as it allows for better intervention and management of the condition, which can help improve outcomes, enhance the quality of life, and reduce the risk of complications such as hospitalizations and mortality.

Studies have shown that CHF affects the autonomic nervous system (ANS), leading to altered heart rate variability (HRV) patterns [3-6]. Specifically, research suggests that CHF reduces the complexity of autonomic fluctuations in HRV, making it possible to diagnose CHF through HRV analysis [3]. In recent years, new approaches for analyzing ANS, including heart rate asymmetry (HRA) and heart rate fragmentation (HRF), complemented HRV analysis. HRA is the phenomenon where the contribution of heart rate decelerations and accelerations to HRV is unequal [7]. This concept has been explored in various contexts, including long-term electrocardiogram (ECG) recordings in healthy individuals [7] and emotion/psychology studies [8]. HRF refers to the breakdown of heart rate regulation, resulting in irregularities in the pattern of heartbeats. It manifests as an increase in the density of changes in heart rate acceleration sign, which cannot be explained by physiological cardiac vagal tone modulation [9]. Different HRF metrics aim to capture the complexity and variability of heart rate dynamics, providing insights into ANS activity and cardiovascular health [10]. Studies have linked HRF to various conditions, including small vessel disease [11] and cardiovascular events [9]. Previous studies have shown that CHF is associated with reduced complexity of autonomic fluctuations in HRV [3]. However, the impact of CHF on HRA and HRF has not been explored. The main goal of this paper is to study if HRA and HRF metrics differ between CHF and NSR, and whether a classifier using these metrics can distinguish between HRA and HRF.

2. Data and Method

In Figure 1, the research comprises three main stages. Firstly, the process involves determining and preparing the required data, which includes CHF and NSR. The next step consists of feature extraction, where two analyses are conducted on the RR interval time series: Heart Rate

Asymmetry (HRA) and Heart Rate Fragmentation (HRF). This step results in the extraction of 3 and 4 features, respectively. Subsequently, a kNN classifier is employed to differentiate between CHF and NSR following statistical analysis. These steps will be elaborated upon in the following sections.

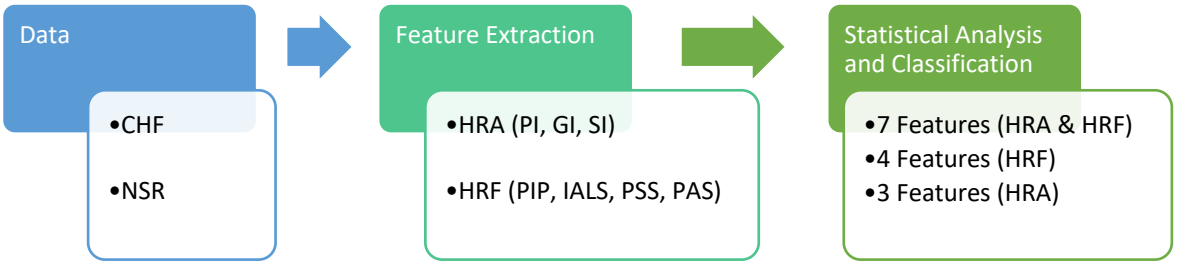

Figure 1. Research Process

2.1. Data

The Congestive Heart Failure RR Interval Database from Physionet includes beat annotation for 29 long-term ECG recordings for subjects with congestive heart failure [12]. As a control group, RR interval time series of the same length were used from the Normal Sinus Rhythm RR Interval Database in Physionet. For this research, 3000 RR intervals for 29 subjects of CHF and 54 subjects of NSR were used. The original long-term ECG recordings in both databases were digitized at 128 Hz, and the beat annotations were obtained by automated analysis followed by manual correction [12].

2.2. Feature Extraction

Feature extraction is critical in detection and classification, especially in biomedical signal processing, to detect and classify healthy versus unhealthy conditions. Feature extraction helps reduce the dimensionality of the data, making it more manageable and computationally efficient. Focusing on the most relevant features can significantly improve the accuracy of detection and classification algorithms. Extracted features often have more meaningful interpretations than raw data, leading to faster training and prediction times for machine learning models. As mentioned, HRA and HRF techniques are used in this study to extract hidden information using databases.

2.2.1. Heart Rate Asymmetry

Heart Rate Asymmetry (HRA) refers to the phenomenon where the increase and decrease in heart rate are not symmetrical [13]. In other words, the time intervals between heartbeats (RR intervals) do not change uniformly. This asymmetry can provide valuable insights into the autonomic regulation of the heart and has been linked to various cardiac and non-cardiac conditions [8, 13-15]. Porta Index [16], Guzik Index [13], and Slope Index [14] were calculated in this research, which are explained in the following:

2.2.1.1. Porta Index (PI)

An index that represents the prevalence of acceleration of heart rate based on quantifying the distribution of points in the Poincare plot relative to Identity Line (IL) [16]:

$$PI\ [\%] = \frac{n_{PB}}{n_{PA} + n_{PB}} \times 100 \qquad (1)$$

where, n_{PA} and n_{PB} are number of points above and below IL. Of note, each RR interval is plotted against the next RR interval in the Poincaré plot.

Table 1. The mean and standard deviation of HRA and HRF indexes across NSR and CHF. Statistically significant (p-value<0.05) marked in bold. (PI: Porta Index, GI: Guzik Index, SI: Slope Index).

FEATURES	NSR	CHF	*P*-VALUE
PI	49.89 ± 1.84	51.46 ± 1.92	**0.014**
GI	50.01 ± 0.06	50.00 ± 0.05	0.658
SI	50.00 ± 0.07	49.78 ± 0.28	**0.003**
PIP	65.77 ± 7.84	83.25 ± 10.17	**<0.05**
IALS	0.62 ± 0.06	0.75 ± 0.06	**<0.05**
PSS	13.84 ± 4.94	6.09 ± 3.59	**<0.05**
PAS	24.82 ± 9.42	43.13 ± 11.27	**<0.05**

2.2.1.2. Guzik Index (GI)

GI is defined as a percentage of the distance of points above IL relative to the total distance of all points relative to IL [13]:

$$GI\,[\%] = \frac{\sum_{i=1}^{n_{PA}} d_i^+}{\sum_{i=1}^{n_{PA}} d_i^+ + \sum_{i=1}^{n_{PB}} d_i^-} \times 100 \qquad (2)$$

where d_i^+ and d_i^- are distances of points above and below IL from the identity line, respectively.

2.2.1.3. Slope Index (SI)

SI is defined as a percentage of the phase angle difference of points above IL relative to the total phase angle difference [14]:

$$SI\,[\%] = \frac{\sum_{i=1}^{n_{PA}} \Delta\theta_i}{\sum_{i=1}^{n_{PA}} \Delta\theta_i + \sum_{i=1}^{n_{PB}} \Delta\theta_i} \times 100 \qquad (3)$$

where, $\Delta\theta_i = \theta_{IL} - \theta_i = 45^\circ - \theta_i$ and $\theta_i = \operatorname{atan}\left(\frac{RR_{n+1}}{RR_n}\right)$ θ_i is the phase angle of consecutive RR intervals $(RR_n\, RR_{n+1})$.

2.2.2. Heart Rate Fragmentation

Heart Rate Fragmentation (HRF) refers to irregularities and disruptions in heart rate patterns. This concept is essential in understanding the complexity and stability of heart rhythm. Fragmented heart rate dynamics may indicate impaired autonomic regulation and have been associated with various cardiovascular and non-cardiovascular conditions, including sleep apnea and increased mortality risk. The Percentage of Inflection Points, the Inverse of the Average Length of the Acceleration/ Deceleration Segments, the Percentage of Short Segments, and the Percentage of RR Intervals in Alternation Segments were calculated in this research, which are explained in the following [9, 17, 18]:

2.2.2.1. The Percentage of Inflection Points (PIP)

PIP is calculated by the combined percentage of transitions from HR acceleration to HR deceleration or vice versa and from HR acceleration/deceleration to stability (no change) or vice versa [18].

2.2.2.2. The inverse of the average length of the acceleration/deceleration segments (IALS)

IALS is calculated by the inverse of the average number of ΔRR intervals in acceleration/deceleration segments [18]. An acceleration/deceleration segment is a sequence of RR intervals between consecutive inflection points for which the difference between two RR intervals is <0 and >0, respectively. The length of a segment is the number of RR intervals in that segment [17].

2.2.2.3. The Percentage of Short Segments (PSS)

The percentage of long segments (the number of ΔRR intervals in acceleration/deceleration segments with ≥3 ΔRR intervals over the total number of ΔRR intervals) is calculated, and its complement is PSS [18].

2.2.2.4. The Percentage of RR Intervals in Alternation Segments (PAS)

An alternation segment is a sequence of at least four RR intervals, for which heart rate acceleration changes sign every beat [17].

Higher values of indices mentioned above indicate a more fragmented heart rate structure. A higher PIP indicates more HRF, which may be a sign of atrial myopathy or disruption of the sinus node's regulation of the heart rate.

HRF is a component of short-term HRV and is linked to a breakdown of the ANS. Increased HRF has been associated with a higher risk of atrial fibrillation and major adverse cardiovascular events.

Table 2. The classification performance in three feature configurations

	ACCURACY	SENSITIVITY	SPECIFICITY
HRF & HRA	100	100	100
HRF	100	100	100
HRA	81	85	85

2.3. Statistical Analysis and Classification

Table 1 reports the mean and standard deviation of extracted features. To identify features significantly different in the two groups of CHF and NSR, the Kruskal-Wallis test was used with the level of significance set to 0.05. Furthermore, a K-nearest neighbor (KNN) classifier was used to classify two groups of CHF and NSR. The classifier was trained on 70% of the data as a train set, and the accuracy was evaluated on 30% as a test set.

As mentioned, the kNN classifier is used to classify CHF from NSR, considering three different feature configurations. The first case is when all seven extracted features are used in the classifier. In the second case, only four HRF parameters and in the third case, only three HRA parameters were considered. The results are shown in Table 2.

3. Discussion

This paper uses HRF and HRA for CHF detection versus NSR. The analysis reveals significant differences in HRA and HRF metrics between CHF and NSR. A classifier developed using HRA and/or HRF features demonstrates promising potential for accurately distinguishing between CHF and NSR. The results showed that although both HRF and HRA have significant results in diagnosing CHF, the parameters extracted from HRF alone can obtain promising results. These findings necessitate further validation through studies involving larger datasets. Furthermore, the impact of RR outliers due to ectopic beat on results reported in this paper must be explored in future studies.

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