Discrimination of Heart Arrhythmias using Novel Features in Heart Rate Phase Space

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Abstract

In this paper, we try to recognize and distinguish different groups of arrhythmia using novel features which have been obtained from the heart rate's phase space in recent years. For this purpose, we used Triangular Phase Space Mapping (TPSM) and Parabolic Phase Space Mapping (PPSM). For recognition, we used three groups of 15 subjects using the Physionet database (Arrhythmia, Congestive Heart Failure (CHF), and Atrial Fibrillation (AF)) with Normal Sinus Rhythm (NSR). The obtained features discriminate arrhythmia from NSR by p<E-5; CHF from NSR by p<E-4; AF from NSR by p<E-5; CHF from arrhythmia by p<2E-2; CHF from AF by p<6E-4; and arrhythmia from AF by p<2E-3. The results show that PPSM is more useful in detection of cardiac arrhythmia from normal, while TPSM is more effective to recognize different arrhythmia from together.

1. Introduction

The recorded potential between two electrodes placed on the surface of the skin is referred to as the surface electrocardiogram (ECG) [1]. The successive atrial de/repolarization and ventricular de/repolarization, which occur with every heartbeat, are represented in a single cycle of normal ECG [2]. These events are associated with the peaks and valleys of the ECG signal which are Labeled P, Q, R, S, and T which are shown in Figure 1 [1].

The largest amplitude of the ECG signal corresponds to the R-wave [3]. The RR-interval is the time between successive peaks, and the inverse of this time interval gives the instantaneous heart rate [4]. A series of RR intervals is known as an RR tachogram, and variability of these RR-intervals reveals important information about the physiological state of the subject [4-6]. Analysis of variations in the instantaneous heart rate time series, using the beat-to-beat RR-intervals, is known as *heart rate variability* (HRV) analysis [1] which is shown in Figure 2. This analysis is a powerful tool for estimation of autonomic nervous system activities. Beat-to-beat variations of human RR-intervals display fluctuations over a number of different time scales ranging from seconds to days [7].

The nonlinear analysis of HRV is a valuable tool in both clinical practice and physiological research reflecting the ability of the cardiovascular system.

One of the chaos tools that has been used extensively in the initial development of HRV has been the phase space Poincare plot, sometimes also referred to as Lorenz plot [8, 9]. But standard analyses of Poincare plot are linear statistics and hence the measures do not directly quantify the nonlinear temporal variations in the time series contained in the Poincare plot [10]. Moreover, it has some limitation to investigate all the physiological mechanisms in a time series. So for distinguishing the behavior of different arrhythmia, accessing to more information of HRV dynamics is necessity.

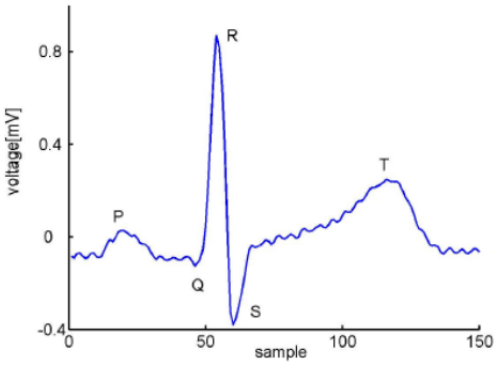

Figure 1. Cycle of normal ECG signal.

For this purpose, nowadays, a lot of different methods and mappings have been introduced for analysing the HRV signal. In this paper, we used two novel mapping for heart rate which are introduced in 2010 that are called Triangle Phase Space Mapping (*TPSM*) [11] and

Parabolic Phase Space Mapping (PPSM) [12]. Then, we extract geometric features in these new maps to detect new aspects of HRV dynamics. We try to use them for distinguishing four groups of subjects (Arrhythmia, Congestive Heart Failure (CHF), Atrial Fibrillation (AF) and Normal Sinus Rhythm (NSR)).

At first, we review these two mentioned mappings and their extracted parameters, then review the groups of arrhythmia and at the end, we will evaluate and analyses the obtained results.

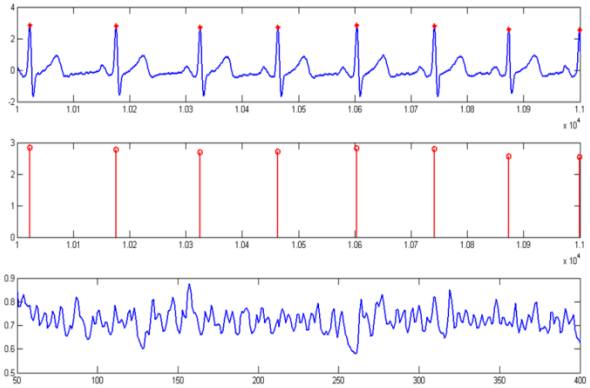

Figure 2. ECG of a normal subject with R detection and derived HRV.

2. Triangle phase space mapping

TPSM is a novel method for representation of heart rate which is obtaining by using RR interval time series signal to plot the triangle mapping consist of all the ordered pairs [11]:

$$(RR_i, |\overline{RR} - RR_i|) \tag{1}$$

in which $RR = \{RR_1, RR_2, \ldots, RR_n\}$, $i = 1, 2, 3, \ldots, n$ and $\overline{RR}$ is the mean of RR intervals which is defined as:

$$mean(RR) = \overline{RR} = \frac{1}{n+1}\sum_{i=1}^{n} RR_i \tag{2}$$

As shown in Figure 3, we obtained a triangle from the distribution of these points and by analyzing it, we could extracted some geometric features such as Angles, Area of the triangle, the slope of the line, the length of them and so on which are explained in details in [11].

The first step in geometrical analysis of *TPSM* is finding the coordination of three vertices of the triangle. There are a lot of ways for measuring the following geometric features of a triangle. One of them is as follows [11]:

$$A(\min(RR), |\overline{RR} - \min(RR)|)$$

$$B(\max(RR), |\overline{RR} - max(RR)|) \tag{3}$$

$$C(RR_C, |\overline{RR} - RR_C|) \| \overline{RR} - RR_C| = \min(|\overline{RR} - RR_i|)$$

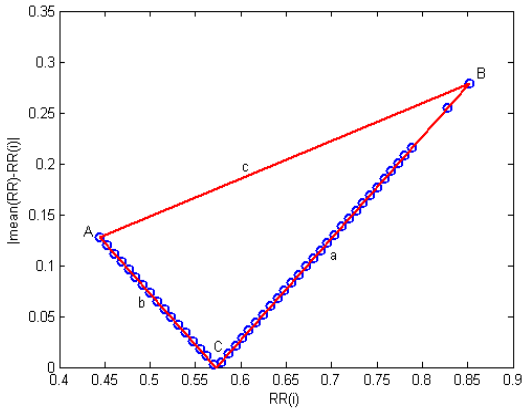

Figure 3. Estimation a triangle for point distribution in TPSM.

After finding the coordinates of three vertices, we can find the slope of the sides. As mentioned in [11], the slope of sides a and b are respectively 1 and -1. So it's enough to find the slope of side c (m_c) which is obtained as follows [11]:

$$m_c = \frac{y_B - y_A}{x_B - x_A} \tag{4}$$

For calculating the length of the sides, we used the relation for finding the distance between two points. So we have [11]:

$$a = \sqrt{(x_B - x_C)^2 + (y_B - y_C)^2}$$

$$b = \sqrt{(x_A - x_C)^2 + (y_A - y_C)^2} \tag{5}$$

$$c = \sqrt{(x_B - x_A)^2 + (y_B - y_A)^2}$$

Now, by knowing the lengths of all three sides of triangle, the three internal angles can be calculated as follows [11]:

$$A = \cos^{-1}\left(\frac{b^2+c^2-a^2}{2bc}\right)$$

$$B = \cos^{-1}\left(\frac{a^2+c^2-b^2}{2ac}\right) \tag{6}$$

$$C = \cos^{-1}\left(\frac{a^2+b^2-c^2}{2ab}\right) = 90^\circ$$

The perimeter of the triangle is defined by adding three sides of it [11]:

$$P = a + b + c \tag{7}$$

By knowing the coordinates of the three vertices of the triangle, the area can be computed as $1/2$ times the absolute value of the determinant [11]:

$$S = TriangleArea = \frac{1}{2}\left|det\begin{pmatrix} x_A & x_B & x_C \\ y_A & y_B & y_C \\ 1 & 1 & 1 \end{pmatrix}\right| \quad (8)$$

$$= \frac{1}{2}\left|(x_A - x_C)(y_B - y_A) - (x_A - x_B)(y_C - y_A)\right|$$

The last geometric feature extracted from *TPSM* is measuring the quality of the triangle which is obtained as follows [11]:

$$q = \frac{4\sqrt{3}S}{a^2+b^2+c^2} \quad (9)$$

3. Parabolic phase space mapping

As mentioned in [12], this new phase space is based on typical Poincare plot points in relation to the mean of *RR* intervals which consists of all the ordered pairs:

$$(x_i, (\overline{RR} - y_i)^2) \quad (10)$$

in which i = 1, 2, 3, …, n.

By evaluating the distribution of points in *PPSM* which is shown in Figure 4, we could estimate a two degree polynomial equation in the form of $Y = Ax^2+Bx+C$, in which [12]:

$$Y = (\overline{RR} - y_i)^2 \quad (11)$$

As mentioned and explained in [12], the useful features obtaining of this map are the coefficients of the estimated polynomial (*A*, *B*, and *C*) which fit the set of data in *PPSM*.

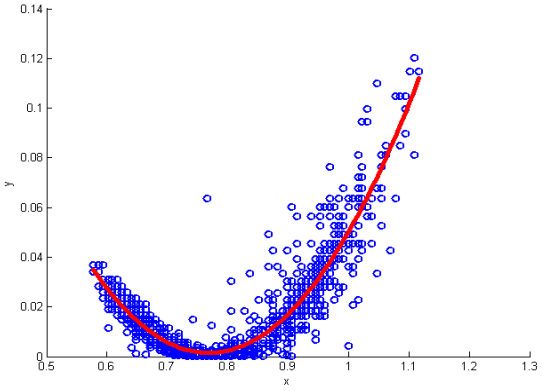

Figure 4. Point distribution in *PPSM* and the estimation of their quadratic equation.

4. Discrimination of heart arrhythmia

For discrimination of heat arrhythmia we used four groups of subjects (Arrhythmia, Congestive Heart Failure (CHF), Atrial Fibrillation (AF) and Normal Sinus Rhythm (NSR)). For each groups, we calculate these features separately.

The data from MIT-BIH Physionet database are used in the experiment. In this study, we have used 15 long-term ECG recordings of subjects in normal sinus rhythm from Physionet Normal Sinus Rhythm database [13].

Furthermore, we have also used NHLBI sponsored Cardiac Arrhythmia Suppression Trial (CAST) RR-Interval Sub-study database for the arrhythmia data set from Physionet [13]. Subjects of CAST database had an acute myocardial infarction (MI) [13]. The database is divided into three different study groups among which we have used the Encainide (e) group data sets for our study [13]. From that group we have chosen 15 subjects belong to subgroup baseline (no medication). Also, we have used 15 long-term ECG recordings of subjects with CHF from Physionet Congestive Heart Failure database along with 15 ECG recordings of subjects with Atrial Fibrillation from Physionet Atrial Fibrillation database [13]. The original long term ECG recordings in every four groups were digitized at 128 Hz [13].

5. Results

In this study, we have used Kruskal-Wallis test to define the level of significance of our proposed features.

Kruskal-Wallis test is a nonparametric version of the classical one-way ANOVA, and an extension of the Wilcoxon rank sum test to more than two groups [5]. The assumption behind this test is that the measurements come from a continuous distribution, but not necessarily a normal distribution. The test is based on an analysis of variance using the ranks of the data values, not the data values themselves.

In case of $p < 0.05$ to be considered as significant, we can see that *TPSM* and *PPSM* features would show the significant difference between groups which *p* value is shown in Table 1 and Table 2.

The results show that these parameters don't depend on the type of arrhythmia and are able to distinguish different groups. They discriminate CHF from NSR by *p<1E-4*; AF from NSR by *p<2E-4*; CAST from NSR by *p<5E-5*; CHF from CAST by *p<3E-3*; CHF from AF by *p<2E-4*; and CAST from AF by *p<7E-4*. It's shown in this tables that these features are able to classify all four groups by *p<E-5*.

6. Discussion

In this novel methods, we have used the function between data of time series in relation to the mean of whole data. It was shown that these new mappings were able to differentiate four groups of subjects significantly.

Table 1. p-Value Results for TPSM features.

Groups	*TPSM* Features							
	A	a	b	c	m_c	P	S	q
NSR, CHF	0.0043	0.7001	0.0028	0.0009	0.0033	0.0008	0.0015	0.0008
NSR, CAST	0.0014	0.0078	0.0005	0.0003	0.0024	0.0003	0.0003	0.0024
NSR, AF	0.3195	0.0008	0.0536	0.0077	0.3982	0.0088	0.0169	0.9268
CHF, CAST	0.0036	0.0274	0.5813	0.5813	0.9633	0.5813	0.0038	0.8903
CHF, AF	0.0007	0.0015	0.0021	0.0051	0.0008	0.0051	0.0274	0.0002
CAST, AF	0.0007	0.1543	0.0008	0.0011	0.0007	0.0011	0.0015	0.0015
Total	1.03E-4	4.81E-4	5.38E-5	2.52E-5	1.06E-4	2.39E-5	6.57E-5	5.50E-5

The results show that PPSM is more useful in detection of cardiac arrhythmia from normal, while TPSM is more effective to recognize different arrhythmia from together.

Table 2. p-Value Results for PPSM features.

Groups	*PPSM* Features		
	Coefficient A	Coefficient B	Coefficient C
NSR, CHF	0.0001	0.0006	0.1734
NSR, CAST	0.00005	0.0058	0.5503
NSR, AF	0.0003	0.0002	0.0006
CHF, CAST	0.9633	0.0274	0.5813
CHF, AF	0.0008	0.0015	0.0021
CAST, AF	0.0007	0.1543	0.0008
Total	1.06E-4	4.81E-4	5.38E-5

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