# Extended Parabolic Phase Space Mapping (EPPSM): Novel Quadratic Function for Representation of Heart Rate Variability Signal

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## Abstract

*In this paper, Extended Parabolic Phase Space Mapping (EPPSM) is introduced. This mapping is a novel method for representation of heart rate which is obtained using RR interval time series signal consist of all the ordered pairs:* $(RR_i,(\overline{RR}-RR_i)^2)$, $i=1,\dots,N-1$ *where* $\overline{RR}$ *is the mean of RR intervals. By analyzing the point's distribution in this map, we could estimate a two degree polynomial equation in the form of* $y = Ax^2 + Bx + C$ *in which y is* $(\overline{RR}-RR_i)^2$ *and x is* $RR_i$*. The useful features obtaining of this map are the coefficients A, B, and C. These features were evaluated in distinguishing four groups of subjects (Arrhythmia, Congestive Heart Failure (CHF), Atrial Fibrillation (AF) and Normal Sinus Rhythm (NSR)) obtained of Physionet database. Kruskal-Wallis test was used to define the level of significance of each feature. The results show that these features discriminate CHF from NSR by p<E-5; arrhythmia from NSR by p<E-7; and AF from NSR by p<E-6.*

## 1. Introduction

RR interval is the time between successive R-waves in ECG and the variation in the time series of RR intervals (consecutive heartbeats) is referred as Heart Rate Variability (HRV) [1].

Heart rate and HRV is an indicator of heart's condition [1]. Assessment of heart rate and HRV has been shown to aid clinical diagnosis and intervention strategies. It has been proved that nonlinear analysis of HRV might provide more valuable information for the physiological interpretation of heart rate fluctuations [1]. However, the variety of contradictory reports in this field indicates that there is a need for a more rigorous investigation of methods as aids to clinical evaluation. The nonlinear analysis of HRV is a valuable tool in both clinical practice and physiological research reflecting the ability of the cardiovascular system [1].

For distinguishing the behavior of the heart, accessing to more information of HRV dynamics is necessity and different geometric mapping has been proposed for HRV [5, 7, 11, and 12]. Also, in our previous article, a novel mapping, Parabolic Phase Space Mapping, was introduced for heart rate [12]. A two degree polynomial equation in this new map was extracted to detect new aspects of HRV dynamics. It is found that this new mapping has a great capability in discrimination of different arrhythmia [12].

In this paper, we have extended this map and introduce new features in this novel extended mapping.

For evaluating these features in new map (*EPPSM*), we try to use them for distinguishing four groups of subjects (Arrhythmia, Congestive Heart Failure (CHF), Atrial Fibrillation (AF) and Normal Sinus Rhythm (NSR)).

## 2. Extended Parabolic Phase Space Mapping (EPPSM)

In this section, first we introduced our novel mapping: Extended Parabolic Phase space Mapping (*EPPSM*).

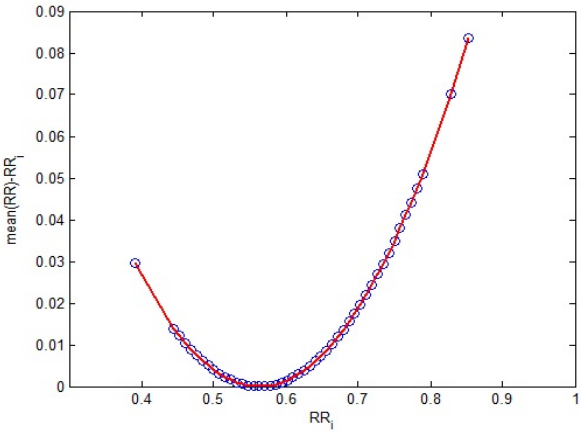


Figure 1. Point distribution in *EPPSM* and the estimation of their quadratic equation.

Then, based on point's distribution in this new space, we extract the second degree polynomial equation that in the following, the theoretical development of it has been given and then it have been compared for distinguishing different groups of subjects which is followed by statistical analysis.

## 2.1. Construction of EPPSM and estimation of second degree polynomial equation

Given a time series RR = {$RR_1$, $RR_2$, …, $RR_n$}, the proposed novel mapping is constructed of the relation between each of these points with the mean of RR intervals which is obtained [5]:

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

So *EPPSM* consists of all the ordered pairs:

$$(RR_i, (\overline{RR} - RR_i)^2) \qquad (2)$$

in which i = 1, 2, 3, …, n.

By evaluating the distribution of points in *EPPSM* which is shown in Fig. 1, we could estimate a two degree polynomial equation in the form of $Y = Ax^2+Bx+C$, in which:

$$Y = (\overline{RR} - y_i)^2 \qquad (3)$$

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 *EPPSM*. The algorithm was implemented in MATLAB 2012.

The most important advantage of this novel extended mapping, is its ability to produce a second order formula for the heart behavior. It would explain more in next section.

## 3. Discrimination of heart arrhythmia

In order to validate the proposed features, *A*, *B* and *C*, we have used them to discriminate 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 [6] 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 [6]. Furthermore, we have also used NHLBI sponsored Cardiac Arrhythmia Suppression Trial (CAST) RR-Interval Sub-study database for the arrhythmia data set from Physionet. Subjects of CAST database had an acute myocardial infarction (MI). The database is divided into three different study groups among which we have used the Encainide (e) group data sets for our study. From that group we have chosen 15 subjects belong to subgroup baseline (no medication) [6]. 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 [6]. The original long term ECG recordings in every four groups were digitized at 128 Hz [6].

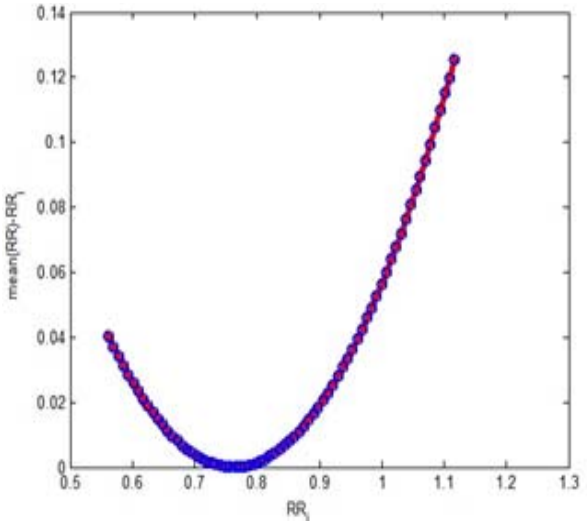


Figure 2. *EPPSM* of the Normal Sinus Rhythm signal

## 4. Results

For comparing the results and evaluating the proposed parameters, we have used statistical analysis, which is explained in details in next section.

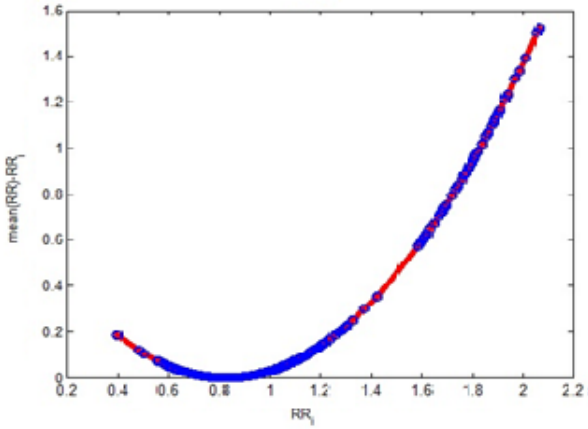


Figure 3. *EPPSM* of the Congestive Heart Failure (CHF) signal

### 4.1. *EPPSM* in different arrhythmia

Sample EPPSM for four groups of subjects have been shown in figures 2 to 5. By comparing these pictures, we can recognize the behaviors of HRV signal in *EPPSM*. We can see the estimated curve have different morphologies in each tested group of subjects. For example, we can see that in Normal Sinus Rhythm signal, the distribution of points is more uniform compared to three other groups.

Furthermore, we can see that the shape of the curve is more different in Figure 3 and 4. It should be noted that in CAST signal, the number of overlapped points is more than others.

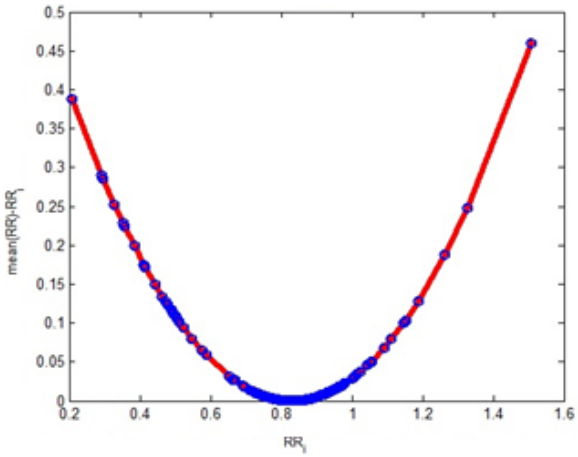


Figure 4. *EPPSM* of the Atrial Fibrillation (AF) signal

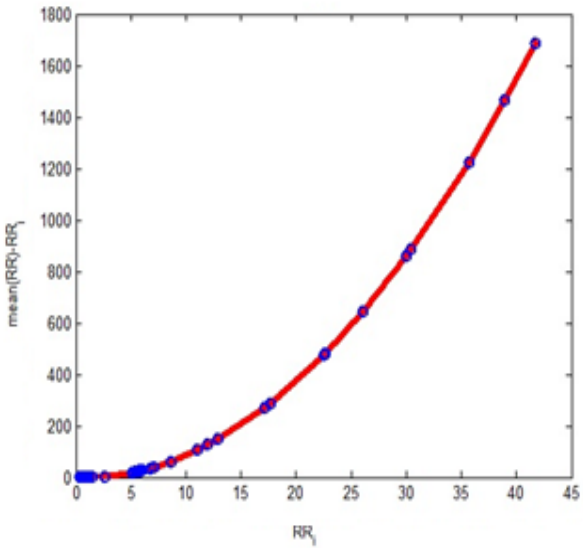


Figure 5. *EPPSM* of the Cardiac Arrhythmia Suppression Trial (CAST) signal

### 4.2. Statistical analysis

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. 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 our study, this test has been used to evaluate the hypothesis for each feature separately. The *p* values obtained from Kruskal-Wallis analysis are shown in Table 1 for coefficients *A*, *B* and *C*.

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

The results show that extracted parameters have very good results and don't depend on the type of arrhythmia (Table 1). They discriminate CHF from NSR by *p<3E-5*; AF from NSR by *p<6E-6*; arrhythmia from NSR by *p<2E-7*, CHF from arrhythmia by p<1E-2; CHF from AF by p<1E-2; and arrhythmia from AF by p<3E-2. Although we can conclude from the results that these kinds of mapping is more useful in discrimination of different arrhythmia from Normal.

Table 1. P-value results for EPPSM features

| Groups | *EPPSM* Features | | |
|---|---|---|---|
| | *A* | *B* | *C* |
| NSR, CHF | 0.0036 | 3E-5 | 0.0308 |
| NSR, CAST | 2E-3 | 0.0057 | 2E-7 |
| NSR, AF | 6E-6 | 0.2148 | 0.2148 |
| CHF, CAST | 0.7128 | 0.0216 | 0.0136 |
| CHF, AF | 0.0380 | 0.0274 | 0.0228 |
| CAST, AF | 0.0345 | 0.9634 | 0.6754 |

## 5. Discussion

In the proposed mapping method, we have used the function between continuous data of time series in relation to the mean of whole data. It was shown that this new mapping was able to differentiate four groups of subjects significantly. In this novel method, we have used the function between current data of time series and their relation with the mean of whole data. Advantage of this mapping is that the points overlapped with each other as a kind of compaction and so this map deletes the extra and useless information and just keeps the useful ones. Moreover, the resulted quadratic equation has the

capability of being used as a prediction method for some kinds of cardiac arrhythmia.

Hence, it seems that this kind of mapping and the resulted quadratic equation would be evaluated in most cases and compared with clinical results to detect its more advantages in cardiac arrhythmia diagnosis.

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