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Original Research Article

# Cardiac arrhythmia classification using the phase space sorted by Poincare sections

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ABSTRACT

Many methods for automatic heartbeat classification have been applied and reported in literature, but methods, which used the basin geometry of quasi-periodic oscillations of electrocardiogram (ECG) signal in the phase space for classifying cardiac arrhythmias, frequently extracted a limited amount of information of this geometry. Therefore, in this study, we proposed a novel technique based on Poincare section to quantify the basin of quasi-periodic oscillations, which can fill the mentioned gap to some extent. For this purpose, we first reconstructed the two-dimensional phase space of ECG signal. Then, we sorted this space using the Poincare sections in different angles. Finally, we evaluated the geometric features extracted from the sorted spaces of five heartbeat groups recommend by the association for the advancement of medical instrumentation (AAMI) by using the sequential forward selection (SFS) algorithm. The results of this algorithm indicated that a combination of nine features extracted from the sorted phase space along with per and post instantaneous heart rate could significantly separate the five heartbeat groups (99.23% and 96.07% for training and testing sets, respectively). Comparing these results with the results of earlier work also indicated that our proposed method had a figure of merit (FOM) about 32.12%. Therefore, this new technique not only can quantify the basin geometry of quasi-periodic oscillations of ECG signal in the phase space, but also its output can improve the performance of detection systems developed for the cardiac arrhythmias, especially in the five heartbeat groups recommend by the AAMI.





## 1. Introduction

Cardiac arrhythmia is an irregular in the electrical activity of the heart [1–3] that does not usually appear at all the times [2–4]. Hence, cardiologists often monitor the long-term electrocardiogram (ECG) recordings for diagnosing the cardiac arrhythmias [3,4]. Due to large number of patients in intensive care units and the need for continuous observation of such conditions, this approach is very tedious and time consuming

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[3,5,6] for cardiologists, because the human eye is poorly suited to detect the morphological changes of ECG signal [7]. Therefore, the development of computer-based analyzers can be very helpful in diagnosing the cardiac arrhythmias.

Currently, a wide range of linear signal processing techniques have been used for the computer-aided diagnosis (CAD) of cardiac disorders, which include: simple-based methods [35], morphology-based methods [35], spectral analysis [8,9], time-frequency distribution [10,11], wavelet analysis [12–19], higher order spectra [20–24] and the coefficients of parametric models [25]. There are also works that relied on principal component analysis (PCA), linear discriminant analysis (LDA) and independent component analysis (ICA) for extracting the optimal feature and improving the classification results [12,26–30]. Even though fairly good results have been obtained using such techniques, they seem to provide only a limited amount of information about the ECG signal, because they ignore the underlying nonlinear signal dynamics [3]. Therefore, a remarkable number of researchers have applied techniques from the domains of nonlinear analysis and chaos theory such as lyapunov exponents, entropy, correlation dimension, detrended fluctuation analysis and fractal dimension for studying the nonlinear dynamics of ECG signals in recent years [36–46]. These nonlinear techniques as a different representation of the ECG signals could improve the classification accuracy of arrhythmias. In addition, some of them such as the phase space could perform much better in situations of noise contamination and waveform deformation [42,43].

The phase space as one of these nonlinear techniques is a qualitative and quantitative tool [38,47,48], which can recognize the hidden correlation patterns of ECG signal in addition to describing the evolution of trajectories obtained from ECG signal. These properties have currently caused that different geometrical and statistical methods have been provided to quantify the phase space reconstructed from ECG signal and detect the cardiac abnormalities. For example, Malgina and et al. [49] separated abnormal heartbeats by using the length and angle of R vector extracted from the phase space of ECG signals. Chan and et al. [42,43] used the area of triangles formed by two successive states in two-dimensional phase space of ECG signal to distinguish the premature ventricular contraction (PVC) from normal heartbeats. Srinivasan and et al. [46] classified five heartbeat types using the density of states appeared in the phase space of ECG signals. Povinelli and et al. [45] and also Nejadgholi and et al. [44] distinguished different arrhythmias by estimating the parameters of Gaussian mixture model defined on the density of states appeared in the phase space. Roopaei and et al. [50] used the box counting of images obtained from the phase space of ECG signals for classifying the ventricular tachycardia, ventricular fibrillation and normal ECG signals. They also indicated that superiority of their proposed method relative to the traditional schemes based on the correlation dimension, the largest Lyapunov exponent and approximate entropy.

Although, some of these studies [42,43,49] quantify the amount of stretching and folding of ECG oscillating basin in the phase space for the diagnosis of cardiac arrhythmias, they only gathered the limited information of ECG oscillating basin such as the length and angle of R vector or the area of triangles formed by two successive states. Some other of these studies [44–46,50], which often used the density of states appeared in the phase space of ECG signals, considered the reconstructed phase space of ECG signal as a Poincare map. Therefore, according the Poincare recurrence theorem [51–53] they only quantify the complexity of cardiac processes (ECG signals).

In this work, we sort the phase space of ECG segments obtained from the long-term ECG recordings of MIT-BIH arrhythmia database by a set of Poincare sections and then, classify the ECG segments into five heartbeat groups recommend by the AAMI. This sorted space has a unique advantage; it can provide the coordinates of recurrence points at each point of the phase space. This advantage helps that we can estimate the basin geometry of quasi-periodic oscillations captured in the reconstructed phase space of ECG signals, in addition to evaluating the status of recurrence points recorded on the linear Poincare sections.

The remainder of this paper is organized as follows. Section 2.1 presents the data selection and noise removal processes. Sections 2.2–2.4 describe how to sort the phase space by the Poincare section. Section 2.5 represents the evaluation of the geometric features extracted from the sorted space of five heartbeat groups recommend by the AAMI using the SFS algorithm founded based on the accuracy of decision tree, and finally, Section 3 presents the discussion.

## 2. Materials and methods

### 2.1. Data selection

We selected the ECG signals from the MIT-BIH arrhythmia database [54]. This database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects in the BIH arrhythmia laboratory between 1975 and 1979. The sampling frequency was 360 samples per second per channel with 11-bit resolution over a 10 mV range and the band pass filter of ECG recorder was set to 0.1–100 Hz.

In agreement with the AAMI (association for the advancement of medical instrumentation) recommended practice, we divided the twenty-two records of this database into two datasets: DS1 and DS2 [31] and used these two datasets to train and test classifiers, respectively. In addition, we grouped the heartbeat stored in the ECG records of these datasets according to the AAMI recommended practice into five heartbeat classes, i.e. Non-ectopic beat (N), Supra-ventricular ectopic beat (S), Ventricular ectopic beat (V), Fusion beat (F) and Unknown beat (U) [27,31]. Table 1 provides the details of these five heartbeat classes used in this research.

In preprocessing phase, we filtered the ECG signals of lead MLII (modified-lead II) by a notch filter set to 60 Hz and a band-pass filter set to 1–100 Hz. Then, we extracted the cardiac cycles based on the RR intervals. Fig. 1 shows our segmentation approach based on the R-points of three QRS complexes. In fact, each segment includes one third of the per-RR interval and two-third of post-RR interval ($t_{Seg} = T_1/3 + 2T_2/3$).

### 2.2. Phase space

State space represents the status of state variables in a system [55,56]. Therefore, this space is not suitable for systems that