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Chaotic based reconstructed phase space features for detecting ventricular fibrillation

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ABSTRACT

Among the variety of cardiac arrhythmias, ventricular fibrillation (VF) and ventricular tachycardia (VT) are life-threatening; thus, accurate classification of these arrhythmias is a crucial task for cardiologists. Nevertheless, VT and VF signals are very similar in the time domain and accurate distinguishing these signals with naked eyes in some cases is impossible. In this paper, a novel self-similarity image-based scheme is introduced to classify the underlying information of VT, VF and normal electrocardiogram (ECG) signals. In this study, VT, VF and normal ECG signals are selected from CCU of the Royal Infirmary of Edinburgh and MIT-BIH datasets. According to the time delay method, signal samples can be assigned to state variables and a trajectory can be achieved. To extract the proposed self-similarity feature, first, two different trajectories from each signal trial are drawn according to two different delay time values. The two-dimensional state space of each trial trajectory is considered as an image. Therefore, two trajectory images are produced for each signal. Number of visited pixels in the first image is determined and is subtracted from that of the second image as the self-similarity feature of that signal. Moreover, another scheme is proposed to have a better estimation of self-similarity in which the logical AND operator is applied to both images (matrices) of each ECG trial. The third proposed criterion is similar to box counting method by this difference that each pixel is assigned a weight according to the trajectory density at that point and finally visited weighted pixels are counted. To classify VF from VT and normal ECG, a threshold is determined through the cross validation phase under the Receiver Operating Characteristic (ROC) criterion. To assess the proposed methods, the mentioned signals are classified using the-state-of-art chaotic features such as correlation dimension, the largest Lyapunov exponent and Approximate Entropy (ApEn). Experimental results indicate superiority of the proposed method in classifying the VT, VF and normal ECG signals compared to present traditional schemes. In addition, computational complexity of the introduced methods is very low and can be implemented in real-time applications.

1. Introduction

Reliable detection and classification of cardiac arrhythmias is crucial for cardiologists. ECG signal is an efficient non-invasive diagnosis tool which can reveal many cardiac arrhythmias [1,7,17]. Among the threatening arrhythmias, VF is the most dangerous one as thousands of deaths occur daily due to VF [11,12]. VF signal is a disorganized, irregular heart rhythm that renders the heart incapable of pumping blood. It is fatal within minutes unless externally terminated by the passage of a large electrical current through the heart muscle. Ventricular tachycardia (VT) signal is very similar to VF signals in the time domain and there is an urgent need to classify these two patterns in cardiac care units (CCU). Accurate and automatic detection and classification of VF is of interest in this research. Here, three novel schemes are presented to improve the classification accuracy between the VT, VF, and normal ECG signals.

Background: When an arrhythmia occurs, normal ECG signal becomes irregular and complex, consequently its frequency content changes dramatically. Various studies have shown that spectral and chaotic feature values of cardiac signals vary from one arrhythmia to another one. Therefore, different spectral features and several complexity measures are selected as informative features to classify different arrhythmias [3,10,11,13,15,16–18]. In this section we report state-of-the-art researches carried out to classify the VT from VF signals. The main informative features reported in these researches include: spectral features, Heart Rate Variability (HRV) [31], Auto-Regressive (AR) model coefficients, Approximation Entropy (ApEn) [31], chaotic dimension, nonlinear measures [2,15], sequential detection algorithm [9], Fourier transform [11], time-frequency analysis [6], correlation analysis [4], complexity

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measures [12], and a total least squares-based Prony modelling algorithm [15]. Castiglioni and Rienzo [31] employed HRV feature as an effective index to classify different heart arrhythmias. Moreover, chaotic-based features such as correlation dimension [29], largest Lyapunov exponent [30] and ApEn [31,40] were used to classify VT from VF signals. In another approach to differentiate various types of cardiac arrhythmias, signals were characterized in the state space and were classified regarding to their trajectory behaviour. Roberts et al. [32] obtained the Reconstructed Phase Space (RPS) from leads II and VI of cardiac signal by drawing them versus each other for four different types of arrhythmias. The authors extracted 100 features from the RPS and applied them as input to a neural network in order to classify cardiac arrhythmias by discriminating the signals based on their spectral features [9] in which signals are filtered into four sub-bands: 0.5–5, 5–10, 10–20 and 20–32 Hz. Povinelli et al. [33] extracted 101 features from the reconstructed phase space by using leads II and VI for different segment time intervals from 0.5 to 3.0 s to classify different cardiac arrhythmias. In another effort Povinelli et al. [34] modelled the RPS of irregular cardiac signals by both parametric and non-parametric methods to classify VT from VF signals according to their model coefficients. The authors [34] have also used the phase space features to classify four different ECG rhythms by using the global false nearest-neighbor technique to calculate RPS dimension. They trained a Gaussian Mixture Model (GMM) for each specific arrhythmia based on its RPS in order to classify the arrhythmias via their GMMs. Amann et al. [20] mapped the normal ECG and VT signals in the state space and then partitioned the state space into small boxes (pixels) in order to classify them by counting the number of visited boxes (pixels) for each signal trajectory. They considered signal samples as state variables and in which each signal trial $x(t+\tau)$ is plotted versus $x(t)$ where τ is estimated by mutual information. Then RPS of each trial signal is partitioned and the visited cells by its trajectory are counted. The achieved number presents as a feature to classify normal from VF arrhythmias. Sarvestani et al. [23] designed some masks to be applied to the partitioned RPS and their results showed that applying efficient masks can enhance the classification accuracy of VT signals from normal ECG.

In this article, the scheme presented in [20] is improved and a new chaotic based RPS feature is introduced to enhance the classification rate between normal–VF and VT–VF signals. Although the proposed scheme maps each signal to the state space, the novelty of this method is its construction of two different RPS from each signal by considering delay time method using two different delay time values τ_1 and τ_2. Then these two RPSs are considered as two images and the similarity of these images measures the self-similarity of that signal. At last, signals are classified according to their self-similarity value.

In this study, three novel schemes are introduced to determine the self-similarity of two images and the challenges of each method are discussed comprehensively. The novelty of these indexes is that the proposed self-similarity values are not determined directly from the signal. In contrast, two RPS are drawn for each signal trial and self-similarity of these trajectory images is considered as a novel index. To determine the self-similarity of two generated images for each signal, three indexes are introduced in terms of difference method, weighted box counting method, and similarity method. Thus, a simple threshold can distinguish the signals according to their index values. The achieved results by applying the proposed methods compare to that of the present state-of-the-art methods shows the effectiveness of our approaches. The rest of this paper is structured as follows. In Section 2, the nature and underlying information of VF, VT and normal ECG are presented in detail. In Section 3, the datasets used in this study are described. In Section 4, the box counting method which maps a signal into the phase portrait and the visited boxes (pixels) are numerated is briefly described. In Section 5, the three proposed schemes are introduced. Experimental results are shown in Section 6 and the results are discussed and interpreted in Section 7. Finally, Section 8 presents the conclusion and future works.

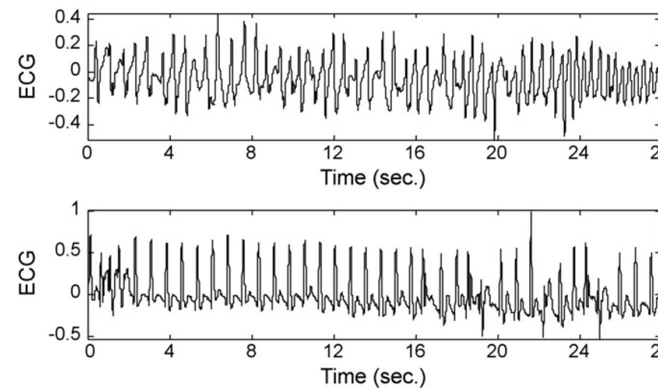

Fig. 1. A typical VF signal depicted above is very similar to a VT signal trial shown below.

2. Cardiac arrhythmias

Cardiac arrhythmia (also called dysrhythmia) is a term for any of a large and heterogeneous group of conditions in which there is abnormal electrical activity in the heart. Some arrhythmias are life-threatening medical emergencies that can result in cardiac arrest and sudden death [1]. Some arrhythmias are very minor and can be regarded as normal variants. Among various kinds of arrhythmias, VF and VT signals look similar in the time domain but their underlying information is totally different. VF is a lethal arrhythmia and mostly followed by death while VT is an arrhythmia which can happen for patients with heart disease. Fibrillation happens when an entire chamber of the heart is involved in multiple micro-reentry circuits, and therefore quivering with chaotic electrical impulses. Fibrillation can affect the atrium (atrial-fibrillation) or the ventricle (ventricular fibrillation). In VF the ventricles (lower chambers) of the heart are dysfunctional, thus preventing the effective pumping of the blood [1]. VF is considered a form of cardiac arrest, and an individual suffering from it will not survive unless Cardiopulmonary Resuscitation (CPR) and defibrillation are provided immediately [1]. Ventricular tachycardia (VT) is a tachycardia, or fast heart rhythm that originates in one of the ventricles of the heart. This is a potentially life-threatening arrhythmia because it may lead to ventricular fibrillation and sudden death. Less commonly, however, some forms of this arrhythmia appear benign, especially among young individuals. VT is associated with no effective cardiac output, hence, no significance pulse is generated; thus it may lead to cardiac arrest. In this situation, it is best treated the same way as VF is processed and recognized as one of the shockable rhythms on the cardiac arrest protocol. Some VTs are associated with reasonable cardiac output and may even be asymptomatic [1]. Hence, it is important to detect the heart arrhythmia and classify its type [5,8]. To show the similarity of VT and VF signals, a signal trial of VT along with a signal trial of VF are selected from the MIT-BIH [27] database and sketched in Fig. 1.

3. Database

A part of our experimental data is from the MIT-BIH arrhythmia database [27] and the other part is recorded in Coronary Care Unit (CCU) of the Royal Infirmary of Edinburgh [28]. The first dataset contains ECG of 49 subjects, classified as 19 normal, 20 VT, and 20 VF subjects. The second dataset contains ECG of 81 subjects of 31