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Automatic diagnosis of premature ventricular contraction based on Lyapunov exponents and LVQ neural network

Xiuling Liu [a,*], *Haiman Du* [a], *Guanglei Wang* [a], *Suiping Zhou* [b], *Hong Zhang* [c]

[a] *Key Laboratory of Digital Medical Engineering of Hebei Province, College of Electronic and Information Engineering, Hebei University, Baoding, China*
[b] *School of Science and Technology, Middlesex University, UK*
[c] *Affiliated Hospital of Hebei University, Baoding, China*

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ABSTRACT

Premature ventricular contraction (PVC) is a common type of abnormal heartbeat. Without early diagnosis and proper treatment, PVC may result in serious harms. Diagnosis of PVC is of great importance in goal-directed treatment and preoperation prognosis. This paper proposes a novel diagnostic method for PVC based on Lyapunov exponents of electrocardiogram (ECG) beats. The methodology consists of preprocessing, feature extraction and classification integrated into the system. PVC beats can be classified and differentiated from other types of abnormal heartbeats by analyzing Lyapunov exponents and training a learning vector quantization (LVQ) neural network. Our algorithm can obtain a good diagnostic result with little features by using single lead ECG data. The sensitivity, positive predictability, and the overall accuracy of the automatic diagnosis of PVC is 90.26%, 92.31%, and 98.90%, respectively. The effectiveness of the new method is validated through extensive tests using data from MIT-BIH database. The experimental results show that the proposed method is efficient and robust.

1. Introduction

Premature ventricular contraction (PVC) can be observed in both normal people and patients with coronary heart disease, rheumatic heart disease, and hypertensive heart disease. PVC has caused extensive concern as a common, frequent arrhythmia. Frequent PVC is often associated with complications like syncope, angina, cardiomyopathy and heart failure [1]. The prevalence of PVCs varies greatly, with estimates of less than 3% to more than 60% in asymptomatic individuals [2]. Diagnosis of PVCs plays an important role in the early warning of cardiovascular diseases, which can help patients get timely and active treatment. Because of the randomness and uncertainty in the occurrence of PVC, the diagnosis of PVC needs observation of dynamic ECG during a long period, which may overload physicians with large amount of ECG data. To reduce the workload on physicians and to improve the efficiency of PVC diagnosis, computerized automatic identification techniques [3–5] have been developed for many years.

* *Corresponding author*. Tel.: +86 13722296965.
E-mail address: liuxiuling121@hotmail.com (X. Liu).

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Martis et al. used Gaussian mixture model to classify ECG signals [6], and later they used higher order spectra for cardiac decision making [7]. In [8], Hickey et al. proposed to discern PVC and premature atrial contraction (PAC) beats using morphological indices such as the width, amplitude, and the area of the QRS complexes. However, one major concern of the proposed method is that its effect can be easily affected by noise. An automated diagnostic system is proposed in [9] using type-2 fuzzy clustering neural network. This system effectively combined type-2 fuzzy c-means clustering (T2FCM) algorithm with neural network. ECG signals can be classified by the cluster centers that may converge to a more desirable location. The system performs well on the classification of fuzzy boundary data. In [10], an arrhythmia classification scheme is developed which uses principal component analysis (PCA) with linear discriminant analysis (LDA) for feature reduction, and a probabilistic neural network (PNN) classifier to differentiate eight types of ECG beats. In [11], discrete wavelet transforms is proposed to classify ECG signals, where linear discriminant analysis and a multi-layer perceptron are used as classifiers. The neural network is trained by the back-propagation and a genetic algorithm. The results indicate that wavelet optimization may improve the classification capability of a neural network. In [12], a new supervised noise-artifact-robust heart arrhythmia fusion classification method is introduced. This method consists of structurally diverse classifiers with a new QRS complex geometrical feature extraction technique.

An interesting development is the application of the chaos theory in the processing of biomedical signals, particularly ECG analysis. As human heart is a complex system, the heartbeat signal naturally exhibits some chaotic characteristics [13,16]. It is noteworthy that methods for the study and classification of nonlinear system through the analysis of one observable are increasingly used in ECG analysis [15]. In [16], 14 features (time domain, frequency domain, nonlinear and chaotic features) are carefully selected and used to train MLP neural networks in order to classify 7 arrhythmias. In [17], the nonlinear dynamics tools are used to differentiate four types of ECG beats. The research demonstrates that the Lyapunov exponents are important features for representing the ECG signals, and the recurrent neural network (RNN) trained on these features is able to achieve high classification accuracies.

In general, existing methods need to extract multiple features from the ECG signal to deal with the influence of noise. In this paper, we present a novel method for PVC diagnosis with few features based on Lyapunov exponents of the ECG signal. The proposed method is simple and easy to implement. It can also achieve more accurate and robust results in PVC diagnosis as shown in our experimental study.

The remainder of this paper is organized as follows. Section 2 describes details of the proposed method. Experimental results and discussion are described in Section 3. Conclusions and future work are described in Section 4.

2. Material and methods

2.1. *The overall structure*

Fig. 1 shows the block diagram of our method which includes three stages: preprocessing (R-peak detection), feature extraction (premature beat recognition, and feature extraction of Lyapunov exponent curve), and classification (training and testing using LVQ neural network). QRS complex is first extracted from ECG signal by energy analysis. Since R wave in ECG signal is more apparent than the other waves, the peak of R wave is determined by an optimized thresholding method. Next, premature beat is classified based on the non-uniformity of RR interval. The features can be extracted based on the Lyapunov exponent curve. Lastly, PVCs are identified by a LVQ neural network. The key steps and algorithms will be described in the following subsections.

2.2. *ECG database*

The ECG recordings from the MIT-BIH arrhythmia database (mitdb) [18] are used in this paper. The database is well recognized as the standard ECG record which contains 48 recordings each of which has a duration of 30 min and includes two leads, the modified-lead II in 46 recordings, V1 in 40 recordings, and V2, V4 and V5 distributed among 10 recordings. The data of the limb lead II is chosen in our experiments except in two recordings (102 and 104), where lead V5 is substituted since modified-lead II is not available. The sampling frequency is 360 Hz and the resolution is 200 samples per mV. It provides a variety of standard data of arrhythmia with artificial markers and annotation, including normal beat (N), PVC, PAC, right bundle branch block (R), junctional premature beat (J), auricular escape (e), atrial ectopic beat, and nodal ectopic beat, etc, which can be used as a reference for the scientific research of ECG signal.

2.3. *The proposed method*

2.3.1. *R-peak detection*

ECG signals are often contaminated by various noise in real applications. To simulate the noisy condition, Gaussian white noise is added into the original ECG signal. We use wavelet transform [19,20] to remove the noise in ECG signals. DB6 is selected as the wavelet basis in wavelet decomposition. DB6 is chosen by a rule of thumb and its prototype has the same morphology as the original signal. A self-adaptive threshold method is used to isolate the original noise of ECG signal in threshold processing. QRS complex has the main energy of ECG whereas P-waves and T-waves have less energy. Meanwhile the frequency range of QRS complex and P, T waves are different. Therefore, P-waves and T-waves can be removed through wavelet reconstruction based on the analysis of energy and frequency range. Each QRS complex can be identified by a R-wave with energy peak [21]. In addition, R-waves can be associated with the maximum value of filtered ECG signal which is searched with a variable length window. The method of R-peak detection was validated by the MIT-BIH Arrhythmia database. The sensitivity and positive predictive accuracy are 98.74% and 99.46%, respectively. Fig. 2(a) shows the original ECG signal and Fig. 2(b) shows the detected R-peaks that are marked by dots.

2.3.2. *Feature extraction*

2.3.2.1. *Premature beat recognition*. Premature heartbeat is the most common arrhythmia that is caused by the stimulus