Efficient Localization of Origins of PVC based on Random Signal Segmentation

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***Abstract*—Localization of origins of premature ventricular contraction (PVC) is significant in the treatment of ventricular arrhythmia. Existing localization methods usually adopt a heartbeat localization algorithm in which R-peak localization and wavelet transform processes are rather time-consuming. Considering the fact that ECG is usually long and the overall quantity of ECG is large, efficient localization of origins of PVC is desired. In this paper, we propose to use random signal segmentation to process ECG so that the R-peak localization and wavelet transform processes are discarded with improved efficiency. The study included the dataset from 843 patients with spontaneous PVCs, which were clustered and labeled corresponding to 4 regions in the entire ventricle. The dataset contains a total number of 76221 groups, each incorporating 250 sampling points in 12 leads. To obtain the optimal classification model, 75% (sample group = 57166) of the whole dataset is randomly selected for training, while the remaining 25% (sample group = 19055) are selected for testing. The deep residual network (ResNet) is used to estimate the performance of classification methods. Experimental results show that the proposed scheme achieves a speedup of 2.86x while with limited accuracy loss.**

***Index Terms*—ECG, PVC origins localization, Random signal segmentation, Deep residual network**

I. Introduction

Premature ventricular contraction (PVC) is one of the most common ventricular arrhythmias with a prevalence of 1-4% in the general population [1]. In contrast to the normal excitation by the atria, PVCs are autonomous excitation of the ventricles. Meanwhile, frequent seizures may lead to heart enlargement or cardiac insufficiency, which impose an underlying threat as the disease progresses [2]. Radio-frequency catheter ablation is one of the treatments by delivering energy to the heart [3], and the key of Radio-frequency catheter ablation is the localization of the origin of PVC.

In clinic, electrocardiogram (ECG) is widely used to determine the origin of PVC according to its characteristics. ECG records the electrical activity of the heart through 12 electrodes placing on different tissues of the human body. The standard ECG can be characterized by different features including PR, QT, RR intervals, PR and ST segments, P, T, U waves, and QRS complex waves, respectively. Each of these features contains distinct information about the heart. For example, QRS complex waves demonstrate the depolarization process in the left and right ventricle. The early appearance of distorted QRS waves without preceding P waves indicates the presence of PVC. This indicator poses an effective way of diagnosing PVCs. Therefore, how to efficiently localize the origin of PVCs from ECG features has become one of the most critical issues.

For decades, a variety of works have been proposed for localization of origins of PVC. The identification of 12-lead ECG was first demonstrated by Josephson et al. in the 1980s to help focus areas of PVC [2]. Since then, several methods have been developed for localizing the origins of PVCs. The fuzzy neural network proposed by Miller et al. successfully realized the PVC localization of anterior and inferior myocardial infarction [3]. After that, Segal et al. realized a multi-classes localization based on fast Fourier transform (FFT) and artificial neural network [4]. However, most of the above algorithms only try to locate the PVC origin of the left ventricle. Although they have significant advantages in improving the classification accuracy and enhancing the generalization ability of classifiers, there are still some problems such as complicated classifier structure, and heavy manual amendments, etc.

Recently, deep neural networks have boosted the performance of a variety of tasks [5-10]. Yokokawa et al. first verified the feasibility of automatic algorithm in PVC origin localization [11], in which the utilization of arithmetic features of deep neural networks (DNN) effectively replaces the morphological ones, by this means, the efficiency of localization is greatly improved. Yang et al. mentioned one kind of optimized convolutional neural networks (CNN), which leads to good classification results, however, a large amount of data for training are required [12]. He et al. constructed a machine learning based approach that reduces the dependence on manual design and the classification error [13]. However, the arithmetic features learned from these networks are still dependent on the heartbeat localization algorithm, but the heartbeat localization algorithm takes assumptions on signal morphology and this does not include all the features of the ECG [14]. As a result, the signal diagnosis is not comprehensive and the network can only recognize signals of a specific morphology. Most importantly, existing localization methods usually need R-peak localization and wavelet transform processes which are rather time-consuming.

To tackle the above problems, in this paper, we propose a random signal segmentation method that does not rely on the heartbeat localization algorithm. This study aims to verify the feasibility of localization of PVC origins based on random signal segmentation, furthermore, an automatic localization

algorithm based on 12-lead ECG is explored.

II. Method

A. Dataset

We collected a dataset consisting of PVC beats of 843 patients from the Guangdong Provincial People's Hospital under Research Ethics Committee (REC) approval with Protocol No. *20140316*. Each patient has a single category of abnormal beats, diagnosed by the physician and marked in one of four regions: tricuspid valve (TV), right ventricular outflow tract (RVOT), left ventricular outflow tract (LVOT), and left ventricular papillary muscle (LVPM). The segmentation of the ventricles and pie chart of PVC distribution is shown in Fig. 1, where the left figure is the visualization of the whole ventricular segmentation, and the right one shows the pie chart of the percentage of types. In Fig. 1, the criterion for elaborating the site of origin was a minimum of 30 sample groups in each segment, which were combined into four classifications because some samples were too small.

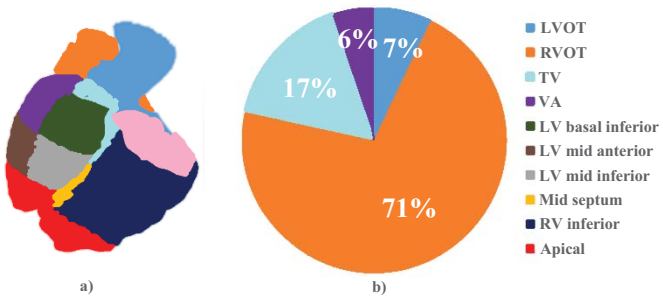

Fig. 1. Segmentation of the ventricles and pie chart of PVC distribution,(a) ventricular visualization, (b) categorical occupancy pie chart

With the collected data, we further prepared two databases. The distribution of PVC origin in the first database (DB1) is shown in Table I. In Table I, all samples were randomly selected by the random signal segmentation method. In order to match the samples with the structure of ResNet, a randomly segmented signal of 3000 points length is used as input using a frequency resampling of 500 Hz. The PVC origins dataset is categorized according to the aforementioned ratio of 75% for training and 25% for testing, including 53 cases of TV, 592 cases of RVOT, 148 cases of LVOT, and 45 cases of LVPM. In the second database (DB2), the data of 843 patients were segmented by the Pan-Tompkin algorithm for heartbeat localization, with the same sampling frequency as DB1 [9]. One sample corresponds to a combination of 12 lead heartbeats, with a beat length of 250 sampling points. Table II shows the distribution of PVC origin in DB2, including 5146 cases of TV, 53,056 cases of RVOT, 13,301 cases of LVOT, and 4,718 cases of LVPM.

B. Data processing

Here the random signal segmentation and heartbeat localization methods are described in detail. For DB1, unlike the heartbeat localization method, signals are randomly segmented and labeled with the following classification criteria:

- If all heartbeats in a segment are normal, the segment is normal;
- If both normal and abnormal heartbeats exist in a segment, the segment is abnormal;
- If multiple types of abnormal heartbeats exist in a segment, the largest number of abnormal heartbeats in the segment dominates the segment type;
- If multiple types of abnormal heartbeats in a segment share the same number of abnormal heartbeats, the first one is the segment type.

As described in the Dataset subsection, DB2 is derived from the heartbeat localization method and consists of heartbeats with QRS morphology. For the patient with tricuspid valve, its example of segment heartbeats with QRS morphology features is shown in Fig. 2. In Fig.2, the data processing of DB2 using the heartbeat localization method is described as follows:

- **RMS filtering**: The root mean square (RMS) of 12-lead ECG is calculated as Equation (1) and smoothed by 10ms mean filter [16].
- **R-peak localization**: The filtered signal is localized by Pan-Tompkin algorithm to obtain the R-peaks.
- **Resampling**: Depending on the positions of the R-peaks, the signal is resampled and segmented.
- **Wavelet transform (WT)**: The segmented signal are wavelet transformed by Daubechies-based algorithm to obtain a single heartbeat without baseline interference.
- **Normalization**: The heartbeats are normalized to reduce the dimension of the network.

$$RMS = \sqrt{\frac{1}{12}\sum_{j=1}^{12} ECG_i^2} \tag{1}$$

According to the above data processing, all data have been heartbeat localized. The 12-lead localization results for a patient with TV are shown in Fig. 3. In Figure 3, there are apparently positive waves in leads I and aVF, which are unique features of PVC that originated from TV. Thanks to this

TABLE I
Distribution of PVC Origin in DB1

PVC types	TV	RVOT	LVOT	LVPM	Total
Train	40	444	111	36	631
Test	15	148	37	12	212
Total	53	592	148	48	843

TABLE II
Distribution of PVC Origin in DB2

PVC types	TV	RVOT	LVOT	LVPM	Total
Train	3860	39792	9975	3539	57166
Test	1286	13264	3326	1179	19055
Total	5146	53056	13301	4718	76221

attribute, the rest abnormal heartbeats can be segmented from leads I and aVL. In order to form the samples of DB2, here the abnormal heartbeats from leads I and aVL are segmented and combined with normal heartbeats from other leads.

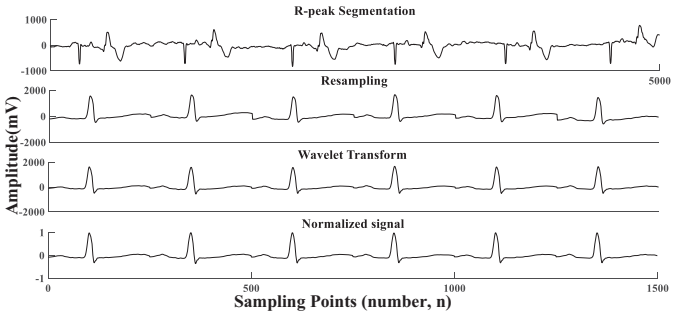

Fig. 2. Example of segment heartbeats with QRS morphology features (from the patient with TV)

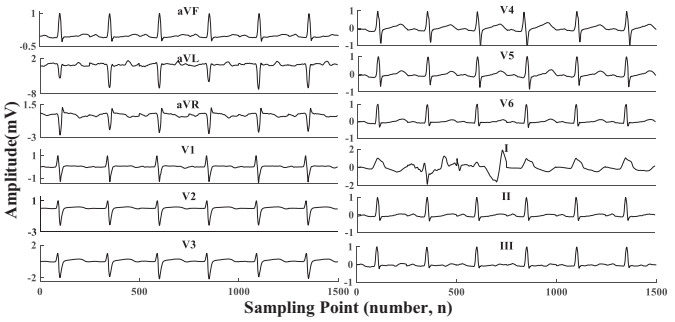

Fig. 3. Example of 12-lead ECG heartbeat localization (from the patient with TV)

C. Sample Classification

The classifier in this paper adopts an optimized ResNet-18 network structure, as shown in Fig. 4. In Fig. 4, the first samples of length 3000 are used as network input. Then the network learns the features by 17 convolutional layers. After a series of sequential steps, the network finally outputs 4 classifications through the fully connected layers. In contrast to the conventional structure using 3 × 3 arrayed convolution kernels which are suitable for two dimensional (2D) image classification, this paper utilizes one dimensional (1D) convolution kernels directly with a length of 16 [17]. The main reason comes from that the mapping result is just 3 correspond to the 2D 3 × 3 array, the critical information in a 3 × 3 size may be lost. Moreover, the sampling points are susceptible to noise and can be easily deteriorated which may lead to non-convergence. Therefore, L2 regularization was enhanced in the network to reduce parameter number, and the dropout probability was adjusted from 0.2 to 0.5 to speed up the network convergence.

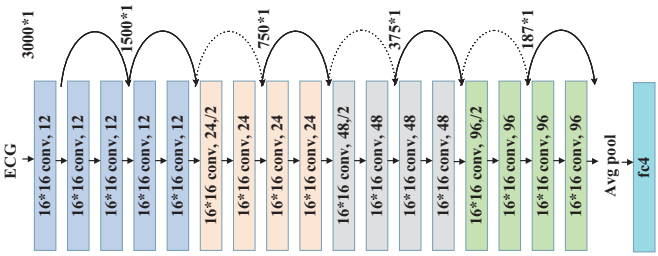

Fig. 4. The optimized ResNet-18 network structure

III. Experiments and Results

A. Experimental Results

The current classification of ECG signal can be divided into inter-patient and intra-patient models, while the inter-patient model represents the test-set independent of the training-set, and the intra-patient model indicates the test-set distinct from the training-set. To better fit practical applications, we adopted the inter-patient model for effect evaluation. Meanwhile, the prediction results are shown in a confusion matrix. In addition, the operation time of the random signal segmentation and heartbeat localization methods is measured repeatedly for all patients, and the average time of 100 times is used as the results.

The accuracy comparison of the random signal segmentation method and the heartbeat localization method is shown in Table III, where the overall test accuracy of ResNet for the two data processing methods reaches 71.35% and 77.83%, respectively. The confusion matrices of two different data processing methods are shown in Fig. 5, where (a) represents the random signal segmentation method, and (b) represents the heartbeat localization method. In Fig. 5, the diagonal line of the confusion matrix shows the number of correct predictions in each category, and the rest are the number of incorrect predictions. As the results show, the predicted results of both data processing methods are biased towards RVOT, which is caused by dataset imbalance. In addition, the random signal segmentation method achieves better balance and has higher accuracy than the heartbeat localization method in other categories.

The comparison of the operation times of the two methods is shown in Table IV. The data processing operation time of the heartbeat localization method is 1.8175 ms, while the random signal segmentation method takes only 0.0215 ms. The efficiency improvement comes from that the random signal segmentation method discards the R-peak localization and wavelet transform processes, which makes the operation time greatly reduced. Meanwhile, the difference between the operation times of the two methods in the classification operation is not significant. In addition, the proposed method has two advantages. Firstly, the proposed method avoids errors in the heartbeat localization process, and it will achieve higher accuracy with sufficient amount of data. Secondly, the classification

TABLE III
PERFORMANCE COMPARISON BETWEEN THE PROPOSED METHOD AND RELATED WORKS

Work	Patients number	PVC samples	Class	Feature	Classifier	Train Acc(%)	Test Acc(%)
[4]	171	292	10	Manually	Manually	93	None
[11]	62	138	10	Manually	Manually	93	None
[12]	/	3887	11	Heartbeat localization	CNN	None	77.7
[13]	247	374	11	Heartbeat localization	SVM	85.6	74
					RF	99.9	71.9
					GBDT	95.4	72.5
					GNB	78.1	71.2
Our Method	833	4170	4	Random segmentation	ResNet	90.74	71.35
				Heartbeat localization		83	77.83

TABLE IV
COMPARISON OF THE OPERATION TIME IN MILLISECOND OF RANDOM SIGNAL SEGMENTATION AND HEARTBEAT LOCALIZATION METHODS FOR A SINGLE SAMPLE

Operation	Time for one sample (ms)	Random signal segmentation	Heartbeat location algorithm
Segmentation	**RMS filtering**	0.0132	0.0075
	R-peak localization		1.3178
	Resamping		0.0084
	WT		0.4754
	Normalize	0.0083	0.0084
	Total	0.0215	1.8175
Classification	**Preprocess**	0.084	0.06
	Predict	0.8324	0.7932
	Total	0.8783	0.8654
	Total	0.9379	2.6829

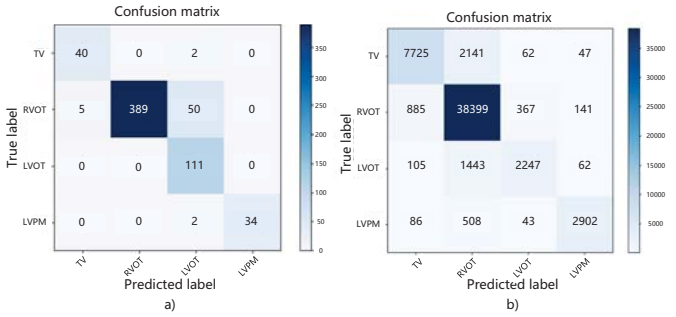

Fig. 5. The confusion matrices between two different segmentation methods, (a) the random signal segmentation method, (b) the heartbeat localization method

network based on the heartbeat localization method can only learn specific ECG features such as QRS waves, while other ECG features will be removed. However, the proposed method can classify all ECG features, which can theoretically diagnose more diseases without missing any information.

B. Comparison with existing works

Table III shows the results between the state-of-the-art methods and the proposed method. It can be seen that the accuracy of the traditional machine learning methods may reach 90%, but they are no longer practical due to their complex feature design, and high labor cost. In addition, the automatic classification works in Table III achieves an accuracy of about 70%, and the random signal segmentation method has an accuracy of 71.35%, which reaches the mainstream level. Ultimately, the proposed method outperforms previous methods in terms of efficiency. Moreover, it achieves automatic localization of PVC origins, which may facilitate the mining and utilization of large amount of clinical data and lay the foundation for further big data processing.

IV. CONCLUSION

In this paper, we propose an efficient data processing method based on random signal segmentation for localization of origins of PVC. We collected a dataset from 843 patients with spontaneous PVCs, which were clustered and labeled corresponding to 4 regions in the entire ventricle for evaluation. Experimental results show that our method achieves a speedup of 2.86x over existing methods while an comparable accuracy of 71.35%. In addition, our method is especially suitable for localization of origins of PVC and is also promising for real-time monitoring of ventricular arrhythmias on 12-lead ECG, which is expected to guide Radio-frequency ablation surgery.

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