PATIENT-SPECIFIC ECG CLASSIFICATION BASED ON RECURRENT NEURAL NETWORKS AND CLUSTERING TECHNIQUE

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ABSTRACT

In this paper, we propose a novel patient-specific electrocardiogram (ECG) classification algorithm based on the recurrent neural networks (RNN) and density based clustering technique. We use RNN to learn time correlation among ECG signal points and to classify ECG beats with different heart rates. Morphology information including the present beat and the T wave of former beat is fed into RNN to learn underlying features automatically. Clustering method is employed to find representative beats as the training data. Evaluated on the MIT-BIH Arrhythmia Database, the experimental results show that proposed algorithm achieves the state-of-the-art classification performance.

KEY WORDS

ECG Classification, Deep Learning, Recurrent Neural Networks, Density Based Clustering Algorithm.

1 Introduction

2 Introduction

Electrocardiogram (ECG) plays a significant role in disease diagnosis. Many fully automatic ECG classification methods have been proposed, including support vector machines [1], linear discriminant analysis [2], optimum-path forest [3], fully-connected neural networks [4]–[6] and probabilistic neural networks [6] [7]. Due to enormous differences among patients, these fully automatic algorithms perform not very well. Thus, it is widely used to train a patient-adaptable model to improve classification performance as in [8]–[11].

Although various algorithms have been widely studied, the classification performance can be further improved by considering the following two aspects.

First, it is recommendable to learn feature representation of ECG signals automatically instead of using handcrafted features. A variety of handcrafted features are reported by investigators, including higher order statistics [1], the independent component analysis (ICA) based features [6], hermite transform coefficients [1] [3] [9], wavelet transform features [4] [5] [10] and temporal features [3] [4] [6] [9] [10]. However, handcrafted features may not represent the underlying difference among classes, thereby limiting the classification performance.

Second, a training data set with more typical patterns can improve the classification performance. In [9]–[11], since the randomly selected common data and the first several minutes of each record are used to train the classifiers, the distribution of the whole data pool cannot be captured. This greatly limits the improvement of performance. Recently, deep learning has been applied to many fields, including ECG classification. In [11], convolutional neural networks (CNN) are used to find out ectopic beats, which achieve a superior performance over most of other algorithms. However, CNN cuts ECG beats to pieces of fixed length, which may restrict the performance enhancement due to enormous variability of heart rates. In addiction, recurrent neural networks (RNN) are used in [12] [13], which can be improved in three aspects. First, handcrafted features (power spectral density [12] and lyapunouv exponents [13]) are fed into RNN to classify beats. Second, both researches do not follow the AAMI recommendation [14] which classifies beats into five specific classes. Third, it is unpersuasive about the generalization capability of handcrafted features and method since the algorithm is only tested on 360 beats in each paper.

To improve classification performance, we propose a novel patient-specific classifier based on recurrent neural networks and clustering technique. Morphology information including present beat and the T wave of former beat is fed into RNN to learn the underlying features of ECG beats automatically. We use RNN to learn the strong correlation among ECG signal points and to address ECG beats with various lengths. A density based clustering method is then

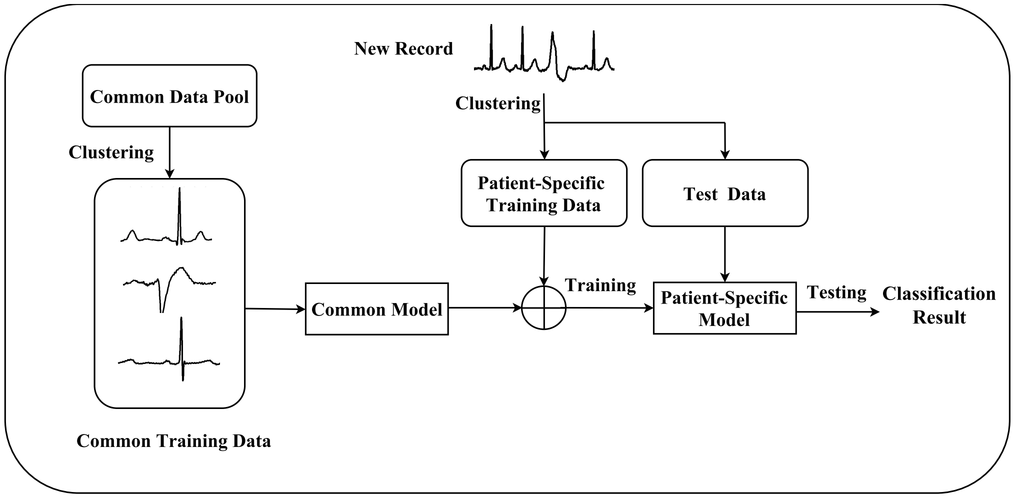

Figure 1. Overview of system framework

applied to obtain a representative training data set. Proposed algorithm achieves the state-of-the-art performance with a relatively small number of labeled beats per record.

3 System Framework

The framework of our proposed algorithm is shown in Figure 1. Firstly, common training data is selected from a large data pool according to the clustering result. A common model is then trained. Secondly, when a new record comes, we use clustering method to find representative patterns in that record as patient-specific data. A patient-specific model is trained based on common model with the patient-specific data, which improves the classification performance to a large extent.

Details of the algorithm are as follows.

3.1 Data Processing

In this paper, we use RNN to learn the underlying features automatically based on beat morphology information. Annotations of R peaks are used to locate beats. The present beat and the T wave of the former beat are included as morphology vector, as shown in Figure 1. There are two considerations for choosing the vector length. First, relative position between the present beat and the former beat is of vital importance when finding out premature beats or escape beats. Second, we do not include P wave and QRS complex of former beat due to the possible significant amplitude difference between adjacent beats.

In this work, we utilize a denoising method combining wavelet-based denosing and median filtering. ECG signals are decomposed into 11 scales using Dual-Tree Complex Wavelet Transform(DTCWT). Information in scale 2 to 9 is retained to reconstruct the signals, while the others are regarded as noise and removed. In order to remove the baseline wander effectively, as in [2], a 200ms width median filter removing P wave and QRS complex, then a 600ms width median filter removing T waves are used to fit the baselines. The fitted baseline would be subtracted from the denoised signal by DTCWT. Moreover, we downsample the denoised signal by a factor of three to reduce dimensions.

3.2 ECG Classifier Based on Recurrent Neural Networks

In the recurrent neural network, a new memory module is introduced to take history information into consideration in the classifying process. In order to have a long access to the past context, Long Short Term Memory (LSTM) network was proposed and has been the most widely used recurrent structure so far. The structure of the LSTM memory block

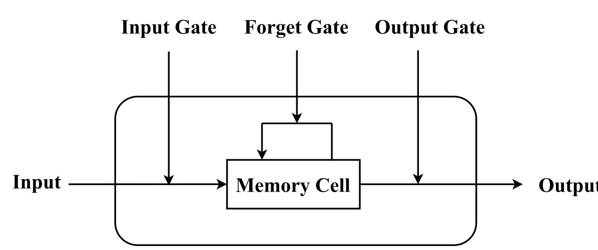

Figure 2. Internal structure of LSTM memory block

is shown in Figure 2. Based on the input at time t and the output of memory blocks at time $t-1$, the input gate and the output gate take control of when to send the data into or to read the data from the memory block. Meanwhile, the forget gate provides a way for the memory cells to reset

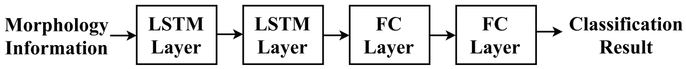

Figure 3. Proposed RNN

themselves. The weights of the three gates and the memory cell are learned during the training process [15].

Considering the network simplicity and the classification performance, we propose a four-layer RNN to classify ECG beats, as shown in Figure 3. The first two layers are LSTM layers, including 50 and 150 memory blocks, respectively. The last two layers are fully-connected (FC) layers. In particular, the third layer includes 20 neurons, while the fourth layer (the output layer) has 4 neurons according to the number of classes. We implement RNN based on a deep learning library named Keras [16].

In the training stage of RNN, the training accuracy and training epochs are used as stopping flags. Training process of common model consists of five iterations. In each iteration, one fold of common training data is used as validation data and the other four folds are used as training data. The model in each iteration is trained based on the final model in former iteration. The training stage in each iteration stops when the training accuracy reaches 0.98 for five times or the training epochs achieve 200. Each patient-specific model is trained based on the common model. Training stage stops when the training accuracy achieves 0.99 for five times or the training epochs achieve 400.

In the testing stage of RNN, we use the prediction of the patient-specific model in the last trained epoch as the final result.

3.3 Selection of Training Data with Clustering Algorithm

In order to obtain a representative training data set, we implement a density based clustering algorithm [17] before selecting training data from the large data pool.

According to [17], the cluster centers are samples which have a higher density than their neighbors and a relatively large distance from points with higher densities. After the cluster centers have been found, the remaining sample is assigned to the same cluster as its nearest neighbor of higher density. This clustering method produces superior performance in the clustering of ECG beats over other clustering algorithms, such as K-means clustering algorithm.

For the common training data, we cluster beats in each class separately. For the patient-specific data, we cluster all beats in one record. After the clustering stage, samples from each cluster are chosen at random to represent the whole cluster. The number of selected samples from each cluster depends on the total number of beats in that cluster.

4 Experimental Results

4.1 Experimental Setups

As recommended by AAMI [14], all beats should be classified into five classes: normal (N), ventricular (V, VEB), supraventricular (S, SVEB), fusion of normal and ventricular (F) and unclassified (Q). In this paper, we do not consider the class Q since it is marginally represented in the available database and the key mission is to distinguish VEBs and SVEBs from others.

We train our model and evaluate its performance on MIT-BIH Arrhythmia database (MITDB), which is the most widely used database in researches on ECG classification [1]–[4], [6]–[13]. MITDB contains 48 records from 47 patients. Each record has two-lead signals slightly longer than 30 minutes, which are band-pass filtered at 0.1-100 Hz and sampled at 360 Hz. According to the AAMI convention, 4 paced records (102,104,107,217) are excluded from the training and test data sets. We use ECG signal of modified limb lead II in this paper.

For the building of common training set, we choose typical beats from the following 22 records of MITDB grouped in DS1= (101, 106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203, 205, 207, 208, 209, 215, 220, 223, 230) as in [2]. In order to train a patient-specific model, we choose several representative beats as patient-specific data from each record. The remaining beats in MITDB are used as test data. We performed our experiment independently for ten times. As a result, an average of 457 beats are selected as common training data, including 124 type-N, 116 type-V, 106 type-S and 111 type-F. An average of 198 beats per record are selected as patient-oriented training data. The exact number varies with the record. There are 91370 beats in the test data set (82201 type-N, 6044 type-V , 2492 type-S and 633 type-F).

Four standard metrics are used to evaluate the classification performance: classification accuracy (Acc), sensitivity (Se), specificity (Sp) and positive predictivity (Pp). Using true positive (TP), false positive (FP), true negative (TN), false positive (FN), Acc, Se, Sp, Pp are defined as follows. Acc is the ratio between the number of correctly classified patterns and the total number of patterns, i.e., $Acc = (TP + TN)/(TP + TN + FP + FN)$. Se is the proportion of the number of correctly detected events in all events, i.e., $Se = TP/(TP + FN)$. Sp is the ratio of correctly classified nonevents among nonevents, i.e., $Sp = TN/(TN + FP)$. Pp is the proportion of correctly detected events in all detected events, i.e., $Pp = TP/(TP + FP)$.

4.2 Results on MIT-BIH Arrhythmia Database

As in the evaluation of several state-of-the-art algorithms [9]–[11], experimental results of the proposed algorithm on MITDB are presented in three evaluation data sets. Evaluation data set 1 contains different records for different class

Table 1. Classification results of the proposed method on MITDB and comparison with the state-of-the-art algorithms

Evaluation Data Set	Method	Labeled Beats Per Record	VEB				SVEB			
			Acc	Se	Sp	Pp	Acc	Se	Sp	Pp
Evaluation Data Set 1	Jiang and Kong [9]	408*	98.8	94.3	99.4	95.8	97.5	74.9	98.8	78.8
	Ince *et al.* [10]	408*	97.9	90.3	98.8	92.2	96.1	81.8	98.5	63.4
	Kiranyaz *et al.* [11]	408*	98.9	95.9	99.4	96.2	96.4	68.8	**99.5**	79.2
	Proposed	**201**	**99.4**	**97.6**	**99.7**	**97.6**	**98.7**	**87.4**	99.4	**89.4**
Evaluation Data Set 2	Jiang and Kong [9]	419*	98.1	86.6	99.3	93.3	96.6	50.6	98.8	67.9
	Ince *et al.* [10]	419*	97.6	83.4	98.1	87.4	96.1	62.1	98.5	56.7
	Kiranyaz *et al.* [11]	419*	98.6	95	98.1	89.5	96.4	64.6	98.6	62.1
	Proposed	**204**	**99.6**	**97.5**	**99.8**	**97.9**	**98.9**	**86.7**	**99.5**	**89.0**
Evaluation Data Set 3	Ince *et al.* [10]	382*	98.3	84.6	98.7	87.4	97.4	63.5	99.0	53.7
	Kiranyaz *et al.* [11]	382*	99	93.9	98.9	90.6	97.6	60.3	99.2	63.5
	Proposed	**198**	**99.7**	**97.1**	**99.9**	**98.1**	**99.3**	**85.9**	**99.7**	**88.7**

[1]* The average number of heartbeats in the first 5 minutes of each record (without paced beats).

detections. For VEB detection, the data set contains 11 records (200, 202, 210, 213, 214, 219, 221, 228, 231, 233, 234). For SVEB detection, another three records (212, 222, 232) are added. Evaluation data set 2 is composed of 24 records (200 and onward). Evaluation data set 3 contains all of 44 records (without paced records) in MITDB.

The average classification results of ten independent experiments and comparison with the state-of-the-art algorithms are shown in Table 1, from which we have the following observations. First, compared with [9]–[11], our method achieves a superior performance in both VEB and SVEB detection. Second, with a common model trained as the basis of patient-specific classifier, we use a relatively small number of training data from each record while achieving satisfying performance. Third, results for SVEB detection are inferior to VEB detection results in all algorithms. One reason for this phenomenon is that the SVEBs are under-represented due to the small number of training data. Despite this limitation, our algorithm obtains large improvement in SVEB detection.

5 Conclusions

In this paper, we propose a patient-specific ECG classifier based on recurrent neural networks and clustering technique. We use RNN to find the underlying features of ECG beats automatically. The original characteristics of ECG beats are well preserved since the beats with different lengths are fed into RNN without being truncated to a fixed length. The application of clustering method ensures that representative beats can be selected from a large data pool. Our algorithm is especially suitable for the classification of long term records, since we need a relatively small number of labeled training data per record compared to other state-of-the-art algorithms. Evaluation results on MIT-BIH Arrhythmia Database demonstrates that our algorithm achieves the state-of-the-art classification performance.

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