

Study on a New Deep Bidirectional GRU Network for Electrocardiogram Signals Classification

Yun Ju ^a, Min Zhang ^b, Huixian Zhu ^c

School of Control and Computer Engineering, North China Electric Power University, Beijing 102206, China.

^a50501482@ncepu.edu.cn, ^b1172227038@ncepu.edu.cn, ^czhuhuixian@ncepu.edu.cn

Abstract. The classification of electrocardiogram (ECG) signals has become a major issue in the medical field. And the timing characteristics of RNN are superior in the diagnosis. To cope with this problem more effectively, this paper described a new deep bidirectional gated recurrent unit (DBGRU) network. The raw input data was processed by principal component analysis (PCA) and sent to the classification model to improve performance where PCA is used for data denoising and dimensionality reduction. Several other models include unidirectional long short-term memory (ULSTM), unidirectional gated recurrent unit (UGRU), convolutional neural network (CNN) and neural network (NN) are used for comparisons. The experiment has been performed for all 23 categories of arrhythmia data obtained from the MIT-BIH arrhythmia database. The deep bidirectional GRU network was trained using the processed data and achieved a high overall accuracy of 99.51% which greatly exceeds the other four models.

Keywords: ECG signals classification; Gated recurrent unit; Recurrent neural networks.

1. Introduction

Biomedical data, which include video, image and signal data, are widely used in the medical field. Electrocardiogram (ECG) signals, coming from a noninvasive test, are one of the most frequently studied data. However, the extremely low doctor-patient ratio and the huge data analysis workload, leading to the prevention and diagnosis of arrhythmia is a long-term problem. With the development of machine learning and artificial intelligence technology, computer-aided arrhythmia diagnostic tools have emerged. Therefore, the arrhythmia classification technology is developing towards intelligent, rapid, high-precision and diversified detection parameters [1].

The research on ECG signals can be divided into two aspects: QRS wave detection and data classification. QRS wave detection is based on ECG raw data acquired over a period of time. And arrhythmia classification includes data preprocessing, feature extraction and classification model construction. The models used for classification are basically be divided into two broad categories: traditional shallow machine learning model [2],[3] and deep learning methods [4],[5].

2. Bidirectional GRU Network

2.1 Gated Recurrent Unit

GRU is a type of recurrent neural network. Like LSTM, it is also proposed to solve problems such as long-term memory and gradients in backpropagation [6]. Compared to LSTM, the forget gate and the input gate are combined into a single update gate, the hidden state, and cell state are also mixed. All these changes lead to a simpler structure. Fig 1 shows this structure.

2.2 Deep Bidirectional GRU

The proposed bidirectional RNN is used to solve the problem that the output of the previous moment is not only related to the previous state but also related to the state afterward. For a BRNN, it can learn the positive law of the data as well as its reverse law. Such a combination of forwarding and reverse networks will have a higher degree of fit than a unidirectional RNN.

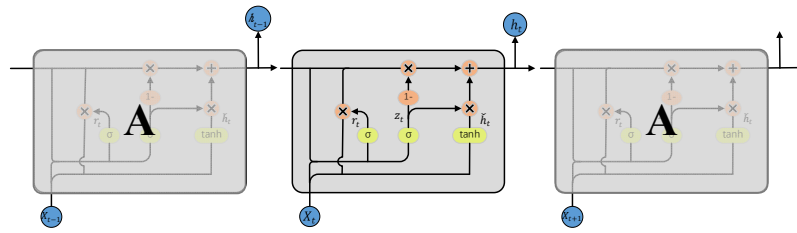


Fig. 1 the internal structure of the GRU unit.

The bidirectional GRU is a special form of the bidirectional RNN which splits the ordinary GRU into two directions, one forward, associated with historical data; and one reverse, associated with future data, so that the input historical data and future data can be used at the same time. This structure can effectively improve the classification performance of the unidirectional GRU. And deep bidirectional GRU provides more powerful expression and learning ability. The structure of a bidirectional GRU is shown in Fig 2.

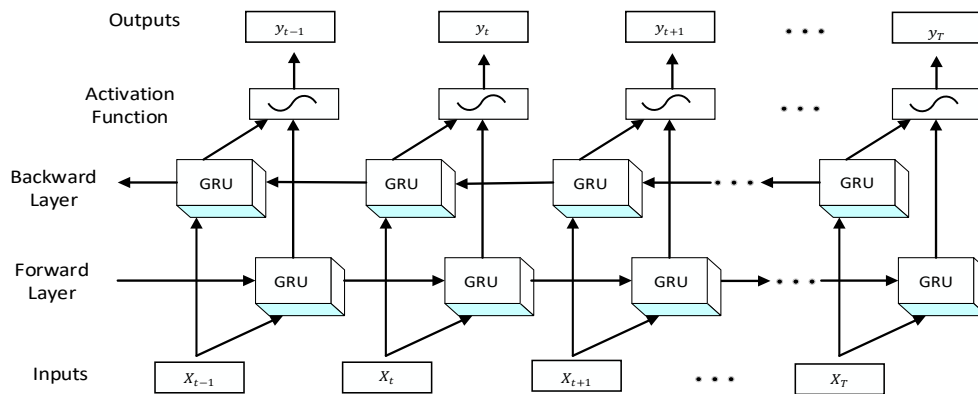


Fig. 2 the structure of a bidirectional GRU.

The GRUs in both directions have their own states and there is no direct connection between them. The forward state propagates from time 1 \rightarrow T and the reverse propagates from T \rightarrow 1. The forward state is unknown at $t=1$, and the reverse state is unknown at $t=T$, both of which need to be manually set. The bidirectional GRU training process is as follows:

- (1) First, calculate the forward state along the direction of 1 \rightarrow T, then calculate the reverse state along T \rightarrow 1, and finally calculate the output.
- (2) Calculate the forward gradient along T \rightarrow 1 and calculate the inverse gradient along 1 \rightarrow T.
- (3) Update model parameters based on the gradient values calculated above.

3. Datasets and Experiments

In this section, we proposed a deep bidirectional GRU (DBGRU) model to classify ECG signals. Before DBGRU the PCA is used to perform noise reduction and dimensionality reduction on ECG data. To verify the performance of the model, the ECG data for all 23 categories were classified from the MIT-BIH arrhythmia database and five-fold cross-validation is used to divide the training set and the verification set to ensure the randomness of the training data, also we compare the performance of DBGRU structure with several other structures. Performance metrics like precision, recall rate, F1 score and the overall accuracy are used to measure the models.

3.1 Data Preprocessing

The ECG data used in this paper is from the publicly available MIT-BIH arrhythmia database, which is widely used in the detection and classification of arrhythmic heartbeats. In this paper, we collected all 23 categories of MIT-BIH data where the signals were sampled at 300Hz. For the data

got from the MIT-BIH arrhythmia database may contain noise and baseline wander, they were denoised using PCA and then was sent to the classification model. The use of PCA in this paper is not only to reduce dimensionality of high-dimensional data, but more importantly, it removes noise through dimensionality reduction and discovers patterns in the data.

3.2 Model

In this paper, a deep bidirectional GRU network is proposed to classify the ECG data, Fig 3 shows the structure of the network. The proposed network consists of three bidirectional GRU layers with 256 hidden units, three bidirectional GRU layers with 128 hidden units, dropout layers, and fully-connected layers. The detailed information of the architecture is summarized in Table 1.

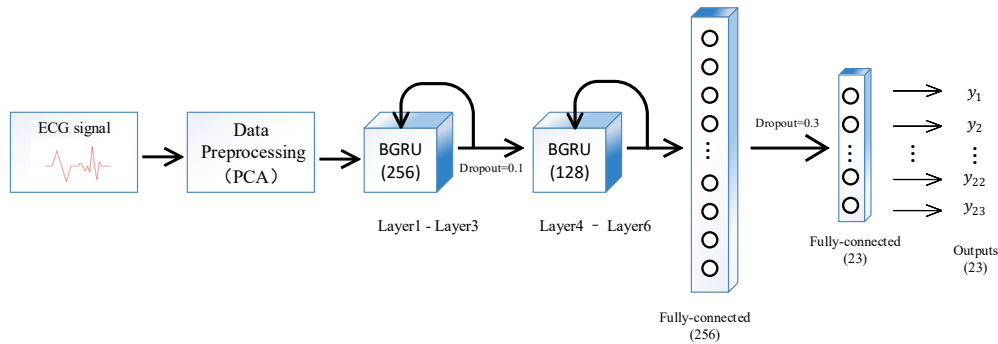


Fig. 3 the architecture of the deep bidirectional GRU network.

In addition, five-fold cross-validation is used for experimental data, that is, the whole ECG data is randomly divided into five equal parts. Four-fifths of data is used for training and the rest of the data is used in the model testing process. And the final model performance is reflected by five average performance. This method can effectively achieve the randomness of the data and make the experimental results more credible.

Table 1. The detailed information of the proposed deep bidirectional GRU network

Layers	Layer names	Parameters of Layers	Other Parameters
Layer 1-3	Bidirectional GRU	256 Unit	Dropout :0.1
Layer 4-6	Bidirectional GRU	128 Unit	Dropout :0.1
Layer 7	Fully-connected	256 Unit	Activation : Relu
Layer 8	Dropout	-	Rate :0.3
Layer 9	Fully-connected	23 Unit	Activation : softmax

3.3 Experiment

The experimental data of this paper consist of 112358 raw ECG signals which are selected from the MIT-BIH arrhythmia database. After data processing and sampling, we get the input data has a sequence size of 112358×300 . Then the total experimental data is divided into a training set and test set using five-fold cross-validation. After experimental comparison, the following parameters were selected in the final GRU network. The bidirectional GRU's hidden unit selected 256 and 128 unit, the batch size of the mini batches was determined as 128, we chose Adam optimizer as the model optimizer and cross-entropy was applied to the loss function. And the experiment was performed during 30 epochs to get the results.

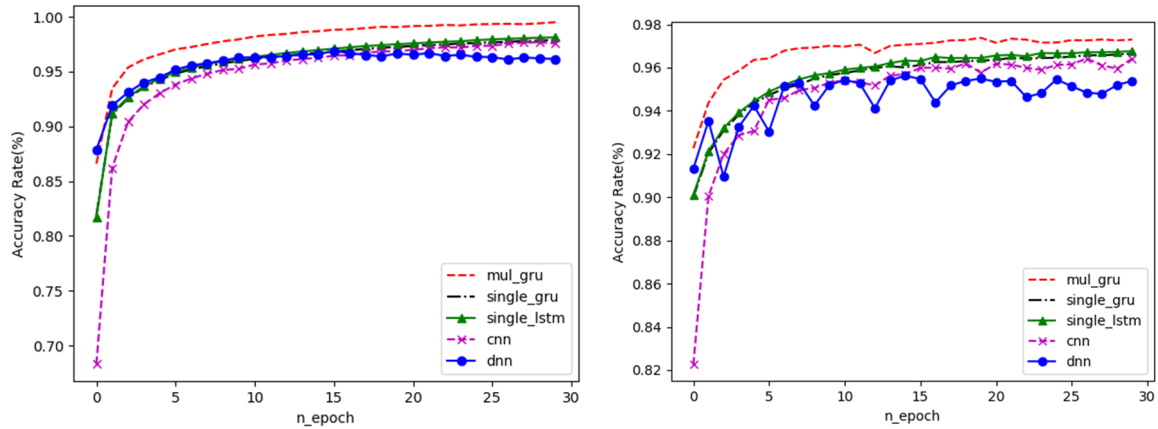


Fig. 4 The accuracy rate of the five models on training set (left) and test set (right).

The input of the training set has a sequence size of 89886×31 for the original input data is processed by a PCA that retains 99.5% of the variance ratio, similarly, the input sequence size of the test set is 22472×31 . And to evaluate the performance of the DBGRU model, we compare it to a unidirectional GRU network, a unidirectional LSTM network, a CNN and a DNN. The experimental results of the five classification models are as follows.

Fig 4 shows the accuracy rate curves of the five models proposed above on the training set and the test set. As we can see from this Figure, the DBGRU network had a high accuracy rate at the beginning of the training phase. And it also performed remarkable success on the ECG data both in the training phase and test phase. In addition, we can also see that the bidirectional network performed a much better accuracy than the unidirectional network.

Table 2. The classification performance of the DBGRU model

DBGRU network						
Epoch	Training set			Test set		
	Precision	Recall	F1-score	Precision	Recall	F1-score
0	0.62	0.68	0.66	0.93	0.94	0.93
10	0.88	0.90	0.88	0.96	0.97	0.96
20	0.97	0.97	0.97	0.97	0.97	0.97
30	0.98	0.99	0.98	0.97	0.97	0.97
Classification Accuracy Rate of training set (30th epoch) =99.51%						
Classification Accuracy Rate of test set (30th epoch) =97.86%						

Table 3. The classification performance comparison of the DUGRU, DULSTM, CNN and NN model

Models	Training set				Test set			
	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score	Accuracy
DUGRU	0.97	0.97	0.97	97.90%	0.96	0.96	0.96	96.65%
DULSTM	0.97	0.97	0.97	97.92%	0.96	0.96	0.96	96.41%
CNN	0.96	0.96	0.97	97.57%	0.95	0.96	0.95	96.42%
NN	0.95	0.96	0.96	96.15%	0.94	0.95	0.95	95.39%

The detailed information for the classification performance of the DBGRU is described in Table 2. And the performance of the other four models is summarized in Table 3. The whole training and test procedure are divided into 30 epoch (0th, 10th, 20th and 30th) and the classification metrics including precision, recall rate, F1 score as well as the accuracy rate are recorded in the two tables. From the two tables, we can see that the DBGRU model (0.98, 0.98, 0.99) performed better than

DUGRU (0.97,0.97,0.97), DULSTM (0.97, 0.97, 0.97), CNN (0.96 ,0.96 ,0.97) and NN (0.95 ,0.96 ,0.96) in terms of precision, recall rate as well as the F1 score. As for accuracy score, the overall accuracy of the DBGRU network on training set was up to 99.51%, and the test accuracy was up to 97.86%. And the accuracy score on the training set and test set for DUGRU were equal to 97.90% and 96.65% respectively, for DULSTM were equal to 97.92% and 96.41%. As for CNN, its accuracy on training set and test set can reach 97.57% and 96.42%. And for NN, its accuracy can reach 96.15% and 95.39%. Summarizing the above two tables, what can be seen is that the overall performance of the DBGRU network is superior to the other four classification models.

4. Conclusion

In this paper, we had proposed an end-to-end learning architecture for the classification of ECG data. A deep bidirectional GRU network was employed to the input data which was obtained from the MIT-BIH arrhythmia database. Also, there were other four models designed for comparison. All 23 categories of arrhythmia data were classified in these models. The experiment results prove that the bidirectional GRU network proposed in this study is better than the other models in terms of the comprehensive consideration of the classification accuracy and the time cost.

Acknowledgements

I would like to express my gratitude to all those who have helped me during the writing of this paper. I gratefully acknowledge the help of my supervisor Professor Yun Ju. I do appreciate his patience and professional instructions during my paper writing. Also, my gratitude also extends to my partner who helped me with my paper correction.

This work was supported by the Fundamental Research Funds for the Central Universities under Grant 2018MS030,2016MS35.

References

- [1]. S. Min, B. Lee and S. Yoon. "Deep learning in bioinformatics". Briefings in Bioinformatics. p. bbw068, 2016.
- [2]. I. Saini, D. Singh and A. Khosla. "QRS detection using K-Nearest Neighbor algorithm (KNN) and evaluation on standard ECG databases". Journal of Advanced Research. Vol. 4, no. 4, pp. 331-344, 2013.
- [3]. Can Ye, B. Kumar and M. Coimbra. "Heartbeat Classification Using Morphological and Dynamic Features of ECG Signals". IEEE Transactions on Biomedical Engineering. Vol. 59, no. 10, pp. 2930-2941, 2012.
- [4]. U. Acharya, S. Oh, Y. Hagiwara, et, al. "A deep convolutional neural network model to classify heartbeats". Computers in Biology and Medicine. Vol. 89, pp. 389-396, 2017.
- [5]. Rajpurkar P, Hannun A Y, Haghpanahi M, et al. Cardiologist-Level Arrhythmia Detection with Convolutional Neural Networks[J]. 2017.
- [6]. Cho K, Merriënboer B V, Gulcehre C, et al. Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation[J]. Computer Science, 2014.