Individual Identification Based on ECG Signal Driven by Multi-layer LSTM and EEMD Algorithm

Xueting Wang(✉) and Xiaohong Zhang

Hangzhou Dianzi University, Hangzhou 300318, China
Wangxue_ting@126.com, xhzhang@hdu.edu.cn

Abstract. As people attach great importance to the field of information security, identification technology based on biometrics has been widely developed and applied. However, biometric identification technology based on face and fingerprint has the disadvantage of weak anti-counterfeiting and easy to prevent. Electrocardiogram (ECG) signals have high anti-counterfeiting properties of living body recognition, which makes the identification technology based on ECG signals have great development potential in the field of information security. This paper proposes an ECG identification algorithm based on Ensemble Empirical Mode Decomposition (EEMD) and Long Short-Term Memory (LSTM). First, the one-dimensional non-stationary and nonlinear ECG signals are decomposed by EEMD, and the Intrinsic Mode Functions (IMFs) of each layer are extracted in the time-frequency domain. The vector is used as the input layer of the multi-layer LSTM to complete the feature classification and output the individual identification result. The recognition accuracy of the proposed model is 95.47% (ECG-ID datasets) and 96.74% (Physionet/Cinc Challenge 2011 datasets), indicating that the proposed model can achieve a high recognition accuracy and capacity for generalization.

Keywords: ECG biometrics · Human identification · Long short-term memory · Ensemble empirical mode decomposition

1 Introduction

The rapid development of Internet of things and artificial intelligence technology provides necessary technical support for the new identity recognition technology with high security and high privacy. However, while the technology is developing, it also provides the possibility for fake fingerprints, dummy faces and other forgery technologies, increases the risk of personal information theft, and causes great damage and attack to the information security system. Therefore, it is particularly important to seek an identity recognition method with high security and high privacy.

With the continuous excavation and exploration of domestic and foreign researchers in the field of biometric technology, a biometric identification technology based on ECG

Y. Chenggang et al. (Eds.): MobiMedia 2022, LNICST 451, pp. 224–237, 2022.
https://doi.org/10.1007/978-3-031-23902-1_17

has rapidly become a research hotspot of biometric technology with the characteristics of high anti-counterfeiting. It is considered to be the biometric technology with the most security potential [1].

However, such a system must still overcome the technical challenges reflected in the following aspects. The first is that it is difficult to extract the detailed features of complex ECG signals, and the second is that the processing speed of the model on the two-dimensional ECG feature map is slow. This paper proposes an identity recognition model based on EEMD-LSTM, uses EEMD to decompose the original ECG signal, and inputs the IMFs component at each time into the multi-layer timing network LSTM for feature learning, so as to complete individual identity recognition and authentication, the detailed structure of the model is shown in Fig. 1.

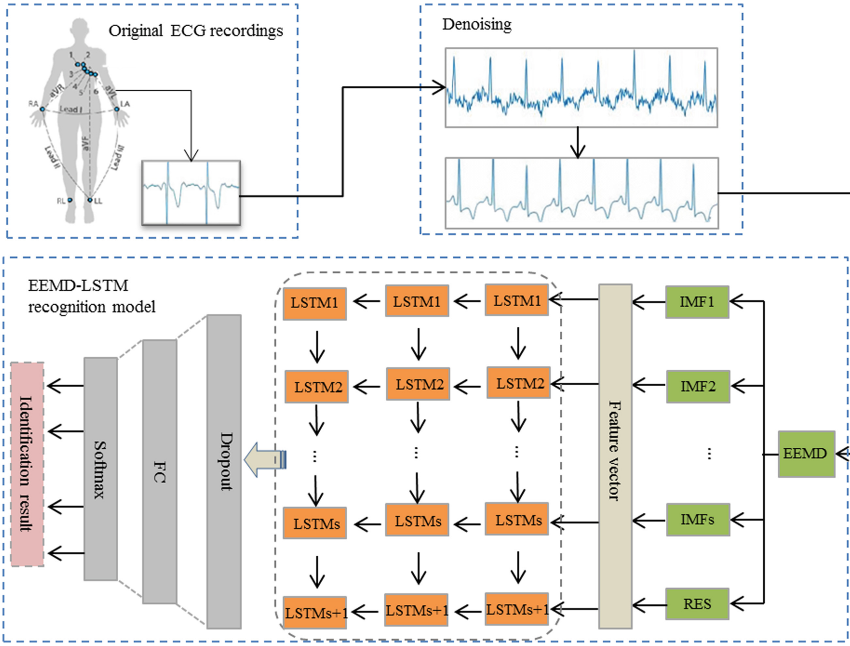


Fig. 1. Structure diagram of ECG recognition model based on EEMD-LSTM

Firstly, the collected individual ECG signal is denoised to obtain a clean ECG signal. Then, the denoised ECG signal is decomposed by n-layer EEMD to obtain the IMFs component of the signal, so as to ensure that each local detail feature of the ECG signal is considered. Secondly, the IMFs component of ECG signal is extracted in time-frequency domain, and the input layer of network model is constructed. Finally, multi-layer LSTM combined with dropout recognition model is designed to capture the change of feature dimension of ECG timing signal in time and space, complete the classification of feature vector and output individual identification results.

2 Related Works

Since L. Biel first proposed the use of ECG signal waveform characteristics as the basis for identification in 2001. ECG biometrics has been widely studied by researchers worldwide using various methods. Semwa [17], Labati [16], X Zhang [18], among others, manually extract the complex time-domain and morphological features of ECG waveform as feature vectors and input them into machine learning or deep learning models for classification training. However, as non-stationary, nonlinear and weak physiological signal, it is difficult to obtain all the detailed features of the ECG signal by manually extracting features, which will eventually affect the recognition accuracy. Zhang Y successively proposed ECG recognition models based on Convolutional Neural Networks (CNN) [19] and Transfer Learning (TL) [20], although the model of deep learning combined with transfer learning speeds up the training speed of the model, the model that uses two-dimensional images as the input layer of the network is slower to process image features.

3 Methods

3.1 Denoising

Since the ECG signal is easily interfered by different noises during the acquisition process, it is necessary to denoise the original ECG signal before the feature extraction of the signal. The traditional wavelet transform denoising algorithm will show the Pseudo-Gibbs phenomenon, resulting in the large oscillation of the reconstructed signal near the singular point. Cyclic shift wavelet threshold denoising algorithm is proposed by improving the traditional wavelet threshold denoising algorithm. Firstly, the original signal is subjected to 8 times of cyclic translation processing to change the position of the singular point in the ECG signal. Secondly, the discrete wavelet transform is used for wavelet decomposition and reconstruction processing, so that the noise components in the processed wavelet detail coefficients are greatly reduced. After 8 times of reverse cyclic translation processing, a clean ECG signal after denoising is obtained after reverse translation, as shown in Fig. 2.

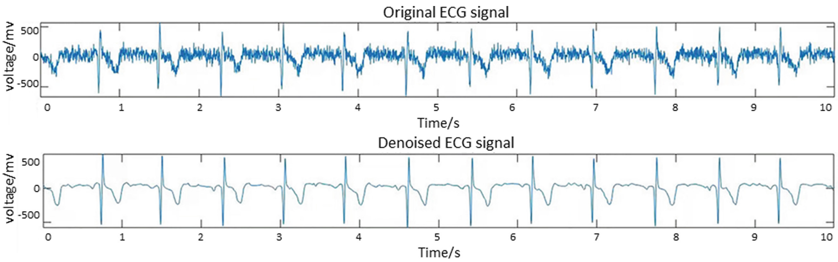


Fig. 2. Comparison of ECG signal before and after denoising

3.2 Ensemble Empirical Mode Decomposition

Norden E. Huang et al. [3] first proposed an analysis method for nonlinear and non-stationary signals empirical mode decomposition (EMD) algorithm, which has been widely used at present. However, EMD algorithm has the problem of mode aliasing when the same IMFs component may contain IMFs of different decomposition scales or the signal of the same scale is decomposed into different IMFs.

In order to avoid the mode aliasing problem of EMD algorithm, this paper adopts the EEMD algorithm proposed by Huang et al. The core idea of the algorithm is to decompose the original signal into several continuous IMFs with different scales by adding Gaussian white noise with normal frequency distribution during the decomposition of the signal to be processed, so as to weaken and even eliminate the phenomenon of mode aliasing. The EEMD algorithm process is similar to the EMD algorithm. The main difference is that Gaussian white noise is introduced into the decomposition process. The detailed steps [4] are as follows:

(1) Determine the decomposition execution times of EEMD algorithm m.

(2) The newly processed signal $f_i(t)$ is the sum of the original signal $f(t)$ and the Gaussian white noise signal $n_i(t)$ whose amplitude follows the standard normal distribution. $f_i(t)$ is defined as:

$$f_i(t) = f(t) + n_i(t) \tag{1}$$

where $i = 1, 2, \ldots, m$.

(3) After EEMD algorithm decomposition, the signal $f_i(t)$ can be decomposed into the superposition of n IMFs components and 1 residual residue.

$$f_i(t) = \sum_{k=1}^{n} C_{j,k}(t) + r_{j,k}(t),\ 1 \le j \le m \tag{2}$$

where j is the number of times the EMD algorithm is performed, and k is the number of layers of IMFs decomposed at the j-th time.

(4) When $j < m$, repeat step (2) until j reaches the number of times m.

(5) To find the mean of each layer of IMFs, the formula is as follows:

$$\overline{C_k}(t) = \frac{1}{m}\left(\sum_{j=1}^{n} C_{j,k}\right), j = 1, 2, \ldots, m, k = 1, 2, \ldots, n \tag{3}$$

(6) The introduced white noise can be offset by the characteristic that the Gaussian white noise amplitude obeys the normal distribution mean value of 0,the average value $\overline{C_k}(t)$ of multiple times is output as the IMFs component of the k-th layer.

Figure 3 shows the ECG signal after EEMD decomposition. It can be shown that EEMD algorithm can not only eliminate the phenomenon of mode aliasing, but also avoid the influence of singular value on the feature matrix, and can better deal with nonlinear and non-stationary ECG signals.

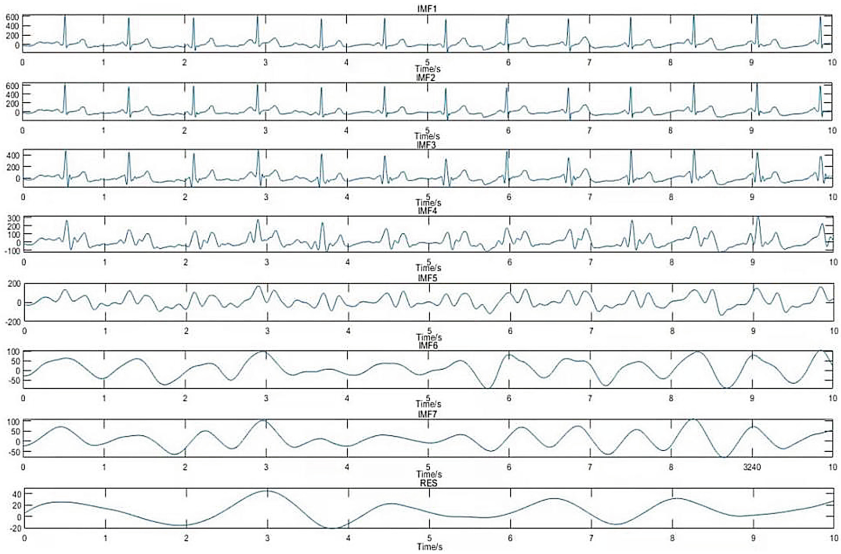


Fig. 3. ECG signal decomposed by EEMD algorithm

3.3 Long Short-Term Memory

Long short-term memory (LSTM) was first proposed by Hochreiter and schmidhuber [5]. It is a unique recurrent neural network (RNN) used for gate units and storage units to overcome the problem of vanishing or exploding gradients in traditional RNNs [6], and can effectively process nonlinear time series data on long time scales [7]. LSTM includes input layer, hidden layer and output layer, a single LSTM neuron [8] is shown in Fig. 4. Among them, f_t, i_t and O_t represent forgetting gate, input gate and output gate, respectively, and long short-term memory network learns long input sequence by using gating mechanism, so as to realize efficient processing of complex time series data.

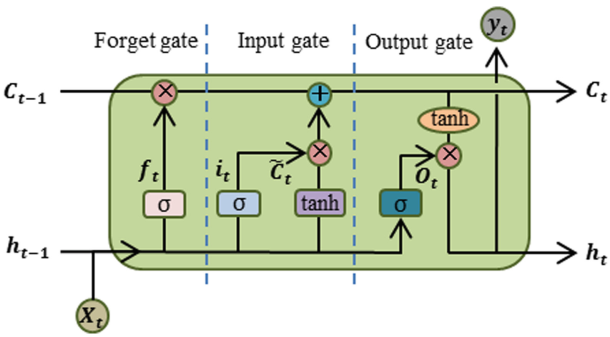


Fig. 4. A single long short-term memory network neuron

(1) Forgetting gate is used to screen memory and determining the amount of information.

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \tag{4}$$

(2) Input gates are used to update the cell state and also store relevant information briefly.

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{5}$$

$$C_t = \tanh\left(W_c \cdot \left[h_{t-1}, x_t\right] + b_c\right) \tag{6}$$

(3) After obtaining the output of the forget gate and the input gate, the current cell state C_t can be known.

$$C_t = f_t C_{t-1} + i_t C_t \tag{7}$$

(4) The output gate is mainly used to control the final output of the cell state.

$$O_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \tag{8}$$

$$h_t = O_t * \tanh(C_t) \tag{9}$$

where W is the weight coefficient and b is the bias term and x_t is the current input state, h_{t-1} is the output state at the previous moment, h_t is the unit output [9].

3.4 EEMD-LSTM ECG Authentication Model

This paper proposed an ECG identification algorithm based on EEMD-LSTM. EEMD has certain advantages for non-stationary and nonlinear signal decomposition, and LSTM model is more suitable for predicting long-term signal data. In order to achieve higher recognition accuracy, the EEMD-LSTM model mainly includes the following steps:

(1) **The input layer of EEMD-LSTM.** As shown in Fig. 5, the denoised ECG signal is decomposed into 8 layers by EEMD algorithm, including 7 IMFs components and one RES component. Then, the time domain and frequency domain features of the ECG signal components of each layer are extracted to construct a feature matrix, which is used as the input sample set of the LSTM layer.

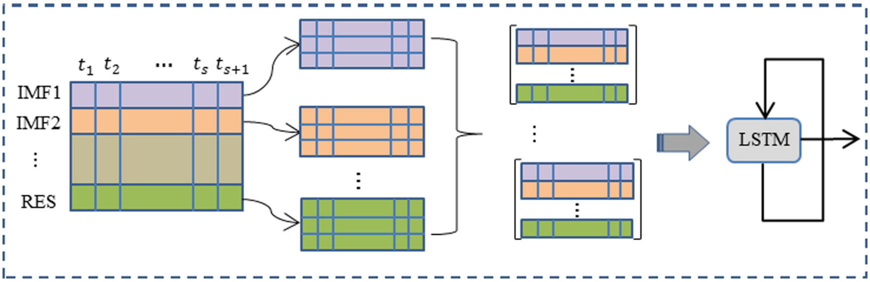


Fig. 5. Construct long and short-term neural network model input feature vector

(2) **The multi-layer LSTM model**. For complex time series ECG signals, it is difficult for a single-layer LSTM to achieve higher accuracy for identity recognition. In order to ensure that the deep detailed features of different time series signals are learned, this paper uses the output of the previous layer of LSTM network as the input of the latter layer of LSTM network, and builds a multi-layer LSTM network model, as shown in Fig. 6. The temporal signal features at each time are input into the multi-layer LSTM model for training.

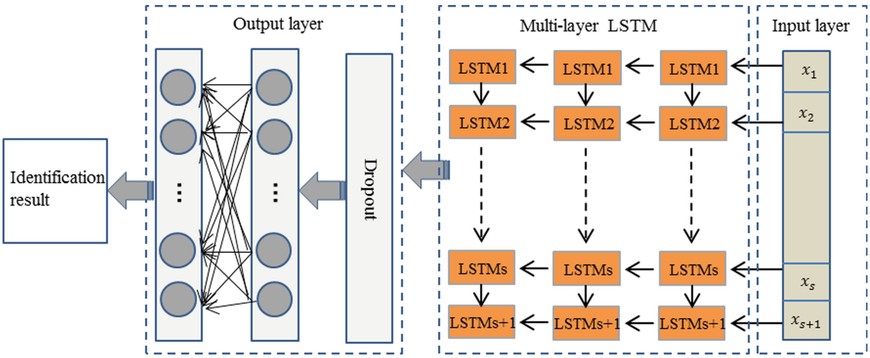


Fig. 6. Building multi-layer LSTM model

(3) **Model optimization**. The multi-layer LSTM is prone to over-fitting in the process of training model parameters, thus reducing the generalization ability of the model. To solve this problem, this paper adopts the method of adding dropout layer to multi-layer LSTM. In the training process, a neuron node is randomly stopped activation with certain probability, so as to reduce the coupling between neurons and the excessive dependence of the model on some features, so as to avoid over fitting and improve the generalization ability of the model. In addition, parameters such as the number of LSTM layers and model training batch size, the learning rate and the number of hidden layer units were determined by the grid optimization

method to determine the optimal values [10], which were set to 3, 50, 0.001 and 150, respectively.

4 Experimental Results and Discussion

4.1 Data Description

To evaluate the performance of the proposed EEMD-LSTM model, we carried out a large number of experiments using the ECG-ID dataset and Physionet/Cinc Challenge 2011 dataset from the Physionet database [11], the specific allocation of data sets is shown in Table 1.

The ECG-ID dataset is specially used to study ECG-based biometrics. It is obtained with ECG lead I from 90 volunteers (44 men and 46 women, of ages 13 to 75 years) in multi-sessions. This database is used to verify whether the ECG data of different collection cycles have an impact on the ECG recognition accuracy. The challenge data is standard multi-lead/single-lead ECG recordings, based on chest collection. Among them, Physionet/Cinc Challenge 2011 dataset is standard 12-lead ECG recordings (leads I, II, II, aVR, aVL, aVF, V1, V2, V3, V4, V5, and V6) with multiple sets of recordings. In this paper, the ECG data sets of lead I and lead II in Physionet/Cinc Challenge 2011 database are used to verify whether different lead acquisition methods have an impact on the ECG recognition accuracy.

Table 1. Characteristics of ECG database.

Protocol	Data source	Data size	Purpose	Characteristic
1	ECG-ID dataset	90×2	Training sample	Two groups are the same session
		90×1	Test sample	Another session
2	Physionet/Cinc Challenge 2011	90×2	Training sample	Lead I-collected
		90×1	Test sample	Different leads (leads I,II)

4.2 Model Evaluation Index

The identification process of the ECG signal determines whether it belongs to the same individual tested by the accuracy threshold set in advance. The performance of the proposed algorithm is evaluated using the most popular benchmark metrics, namely, accuracy (Acc), and equal error rate (EER):

(1) Recognition accuracy (Acc):

$$Acc_{\text{training}} = \frac{TP + TN}{TP + TN + FN + FP} \tag{10}$$

Here, TP and FN are the recognition results where a registered person is accepted correctly and rejected erroneously, respectively. TN and FP are the recognition results where a nonregistered person (illegal intruder) is rejected correctly and accepted erroneously, respectively.

$$Acc_{\text{test}} = \frac{N_{true}}{N_{total}} \tag{11}$$

where N_{true} means the number of true recognitions and N_{total} means the total samples number.

(2) The threshold is adjusted, and when the false rejection rate (FRR) is equal to the false acceptance rate (FAR), the FAR (or FRR) value is called the equal error rate (EER). Here:

$$FAR = \frac{Nunber\ of\ false\ acceptance}{Total\ number\ of\ interclass\ tests} \tag{12}$$

$$FRR = \frac{Nunber\ of\ false\ rejections}{Total\ number\ of\ intraclass\ tests} \tag{13}$$

4.3 Results of the ECG-Based Biometric Algorithm

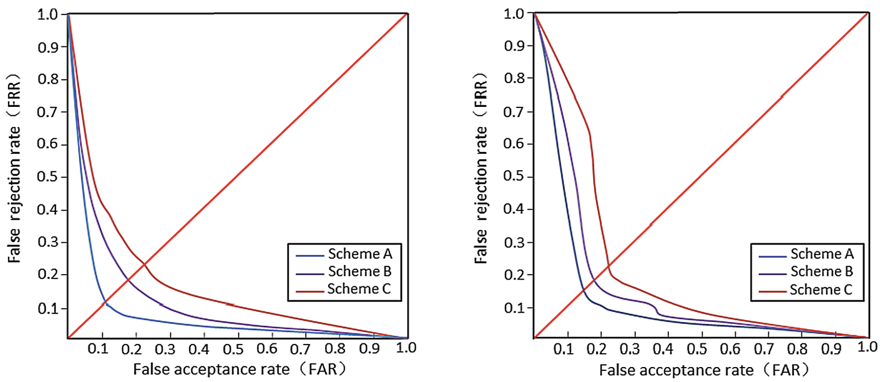
Three recognition models are designed and tested and the detailed design of the models is shown in Table 2. Using the two protocols proposed in Table1 to train the three network models respectively, and compare and analyze the advantages of the network model of EEMD-LSTM combined with Dropout in identity recognition, it reflects the importance of extracting local detail features after decomposing the signal.

Table 2. Overview of the three schemes.

Scheme	Structure	Note	Role
A	EEMD-LSTM	Multi-layer LSTM + Dropout	Performance of the multi-layer LSTM
B	EEMD-LSTM	Multi-layer LSTM	Influence of the dropout
C	Multi-layer LSTM	Without EEMD + Dropout	Influence of the EEMD

The Results of Equal Error Rate. Two ECG-ID datasets in different collection periods in protocol 1 are used as the input of the three model schemes for model training to verify the influence of ECG data of different collection periods on the performance of the recognition model. The samples of the training set are 90 × 2. The sample size of the test set is 90 × 1. The training results of the three models are shown in Fig. 7 (a).

Two ECG data sets with different lead acquisition methods in Protocol 2 were used as the input of the three model schemes for model training to verify the influence of ECG data under different lead acquisition methods on the recognition model performance. The samples in the training set are 90 × 2. The sample size of the test set is 90 × 1. The training results of the three models are shown in Fig. 7 (b).



(a) protocol 1 (b) protocol 2

Fig. 7. EER results of protocol 1and protocol 2 under the training of three network model schemes

It can be seen from Fig. 6 that the EER of scheme A under the two databases is smaller than the performance of EER in Scheme B, indicating that the Dropout layer in the multi-layer LSTM network model plays a key role in avoiding over-fitting. The comparison and analysis of scheme A and It can be seen from scheme C that by using the EEMD algorithm to decompose the ECG signal, some detailed features of the ECG signal can be extracted and the EER in the model training process can be reduced.

The Results of Recognition Accuracy. In view of the recognition accuracy of the network model for ECG signals, this paper uses the training sample sets and test sample sets of protocols 1 and 2 to recognize and train the three designed network models, and the results are shown in Tables 3 and 4, respectively. In addition, in order to more intuitively show the performance advantages and disadvantages of the three models, the experimental data is displayed on the bar chart, the results are shown in Fig. 8.

Table 3. Training set recognition results for different schemes.

Scheme	Structure	Protocol 1 (Training sample)		Protocol 2 (Training sample)	
		Acc (%)	EER (%)	Acc (%)	EER (%)
A	EEMD-LSTM + Dropout	96.58	10.24	94.85	11.12
B	EEMD-LSTM	88.21	16.36	90.78	14.69
C	Multi-layer LSTM	80.62	20.58	82.46	19.54

Table 4. Testing set recognition results for different schemes.

Scheme	Structure	Protocol 1 (Test sample)	Protocol 2 (Test sample)
		Acc (%)	Acc (%)
A	EEMD-LSTM + Dropout	95.47	96.74
B	EEMD-LSTM	90.18	89.10
C	Multi-layer LSTM	79.37	82.59

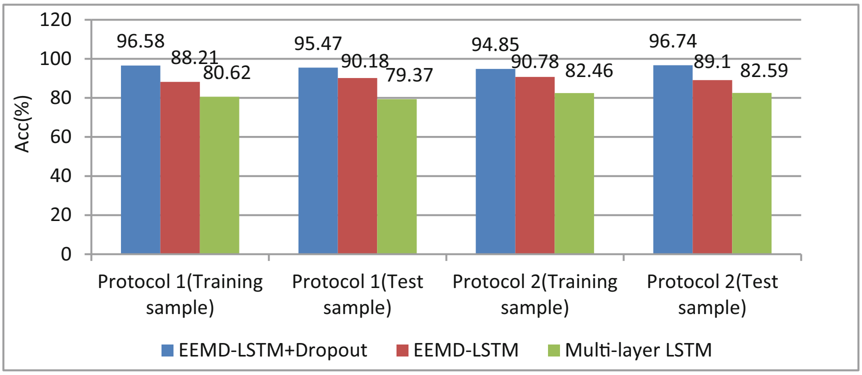


Fig. 8. Column chart of model training results

It can be seen from the recognition accuracy results under the three models that the network model combining EEMD-LSTM with Dropout can show high recognition accuracy for ECG signals with different acquisition periods and different acquisition methods. It shows that the EEMD-LSTM proposed in this paper can achieve highly accurate and robust identification results for non-stationary and nonlinear ECG signals.

Discuss with Other Methods. In order to better prove the pros and cons of the identification algorithm proposed in this paper, we compare and analyze the ECG-based identification algorithm proposed in the paper by other authors, as shown in Table 5.

Table 5. Comparative tabulation of experimental results for different identification algorithms.

Authors	Classifier	Database (Number)	Performance (Acc)
Zhang et al. (2018) [13]	CNN	MIT-Arrh (47)	91.10%
		MIT-NSR (18)	95.10%
Choi et al. (2019) [14]	Linear classifier	CU-ECG (100)	93.00%
Nuno et al. (2020) [15]	DenseNet	ECG-ID (90)	92.22%
Yang et al. (2021) [12]	GoogleNet	ECG-ID (90)	96.58%
Proposed	EEMD + LSTM	ECG-ID (90)	95.47%
		Physionet/Cinc Challenge 2011(90)	96.74%

Nuno uses the ECG signal feature map as the input of the deep learning network recognition model, and obtains a recognition accuracy of 92.22%.The possible reason for the lower than our method is that the training speed of the network model on the two-dimensional feature map is lower than the feature processing speed on the one-dimensional data. The author zhang uses the database MIT-Arrh and MIT-NSR to train the CNN network model, and achieved recognition accuracy of 95.10% and 91.10%, respectively. However, the recognition accuracy is slightly lower due to the small sample set for model training. The author Choi uses a machine learning classifier to identify ECG signals, and obtains a recognition accuracy of 93%, indicating that as long as the feature vector machine learning is processed well, a higher accuracy rate can also be achieved. Yang uses Googlenet with deep network structure as the input of one-dimensional ECG data, and obtains higher recognition accuracy. It is proved that properly increasing the number of network training layers can reflect better model performance.

5 Conclusion

In this paper, we propose an identity recognition model based on EEMD-LSTM for non-stationary and nonlinear time-series ECG signals. Firstly, EEMD algorithm can be well used to process the decomposition of non-stationary and nonlinear ECG signals, so as to extract the local detail features of ECG signals. Secondly, the LSTM method is very suitable for predicting one-dimensional long-time series signal. The recognition model of multi-layer LSTM neural network ensures higher recognition accuracy to a certain extent. In addition, the dropout network layer is introduced to avoid the over fitting phenomenon of multi-layer LSTM relying too much on a feature, so as to improve the generalization ability of the recognition model. During the experiment, the recognition model is trained for two kinds of ECG data under different acquisition cycles and different lead acquisition methods. The experiment shows that the identification model based on EEMD-LSTM proposed in this paper can show high recognition accuracy under two different ECG databases.

In addition, this paper also has some shortcomings. On the one hand, although the recognition model constructed has achieved high recognition accuracy in the process of training. However, the results of only two network data sets are difficult to show that the model has strong generalization ability, and there is still a certain gap compared with the model trained by measured ECG data sets. On the other hand, we should continue to study and optimize the deep learning algorithm, so as to obtain a higher recognition rate.

Acknowledgement. This work was supported by Zhejiang Province Public Welfare Technology Application Research Project (LGG20F010008).

References

1. Silva, H., et al.: ECG Biometrics: Principles and Applications. BIOSIGNALS 2013 (2013)
2. Biel, L., Pettersson, O., Philipson, L., Wide, P.: ECG analysis: a new approach in human identification. IEEE Trans. Instrum. Meas. **50**(3), 808–812 (2001)
3. Li, R., He, D.: Rotational machine health monitoring and fault detection using EMD-based acoustic emission feature quantification. IEEE Trans. Instrum. Meas. **61**(4), 990–1001 (2012)
4. Huang, N.E., et al.: A new view of nonlinear water waves: the Hilbert spectrum1. Annu. Rev. Fluid Mech. **31**, 417–457 (1999)
5. Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural Comput. **9**(8), 1735–1780 (1997)
6. Vu, M.T., Jardani, A., Massei, N., Fournier, M.: Reconstruction of missing groundwater level data by using Long Short-Term Memory (LSTM) deep neural network. J. Hydrol. (2020)
7. Li, et al.: GWO-LSTM deformation prediction model considering the deformation correlation of adjacent points. Railway Investigation and Surveying **47**(06), 26–32 (2021)
8. Jang, Y., et al.: Business failure prediction of construction contractors using a LSTM RNN with accounting, construction market, and macroeconomic variables. J. Manag. Eng. **36**(2) (2020)
9. Wei, X., et al.: Fault diagnosis of high-speed piston pump based on LSTM and CNN. J. Aeronaut. Astronaut. **42**(03), 435–445 (2021)
10. Deshwal, V., Sharma, M.: Breast cancer detection using SVM classifier with grid search technique. Int. J. Comput. Appl. **178**(31), 18–23 (2019)
11. Physionet. https://physionet.org/physiobank/. Last Accessed 1 Mar 2022
12. Yang, S., et al.: Arrhythmia detection based on wavelet decomposition and 1D googlenet. J. Electron. Inf. **43**(10), 3018–3027 (2021)
13. Zhang, Q., Zhou, D., Zeng, X.: HeartID: a multiresolution convolutional neural network for ECG-based biometric human identification in smart health applications. IEEE Access **5**, 11805–11816 (2017)
14. Choi, G.H., Bak, E.-S., Pan, S.B.: User identification system using 2D resized spectrogram features of ECG. IEEE Access **7**, 34862–34873 (2019)
15. Bento, N., Belo, D., Gamboa, H.: ECG biometrics using spectrograms and deep neural networks. Int. J. Mach. Learn. Comput. **10**(2) (2020)
16. Labati, R.D., et al.: Deep-ECG: Convolutional neural networks for ECG biometric recognition. Pattern Recognit. Lett. 78–85 (2018)
17. Semwal, V.B., et al.: An optimized feature selection technique based on incremental feature analysis for bio-metric gait data classification. Multimed. Tools Appl. (2017)
18. Zhang, X.: Research on ECG information acquisition and arrhythmia detection methods. Harbin Institute of Technology (2019). 10.27061

19. Zhao, Z., et al.: ECG authentication system design incorporating a convolutional neural network and generalized S-Transformation. Comput. Biol. Med. (2018)
20. Zhang, Y., et al.: Human identification driven by deep CNN and transfer learning based on multiview feature representations of ECG. Biomed. Signal Process. Control **68**, 102689 (2021)