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ECGID: a human identification method based on adaptive particle swarm optimization and the bidirectional LSTM model

Key words: ECG biometrics; Human identification; Long short-term memory (LSTM); Adaptive particle swarm optimization (APSO)

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Motivation

1. Traditional identification methods such as passwords and smart cards are now outdated because they can be lost, stolen, or shared.

2. Expert and intelligent biometric based identification technologies (e.g., fingerprints and voiceprints) are attracting more and more interest in many areas, ranging from national security to daily life (e.g., criminal investigations, healthcare applications, and smartphone access).

3. However, IoT and AI technologies can facilitate the development of pseudo-fingerprint and pseudo-face technologies, increasing the risk of forgery and hacking of personal information.

Tendency and challenges

1. Difficulties in optimizing hyperparameters in the network model's training phase. A common problem in training pattern recognition or classification models with deep neural networks (DNNs) is that a large number of parameters need to be manually set during the training phase.

2. Low identification speed. The more network layers there are, the lower the recognition speed will be.

3. Influence of different acquisition statuses on the ECG signal's waveform characteristics.

Method

Design a deep bidirectional LSTM with adaptive particle swarm optimization (BLSTM-APSO) model network supplemented by a denoised one-dimensional (1D) ECG signal as the input vector.

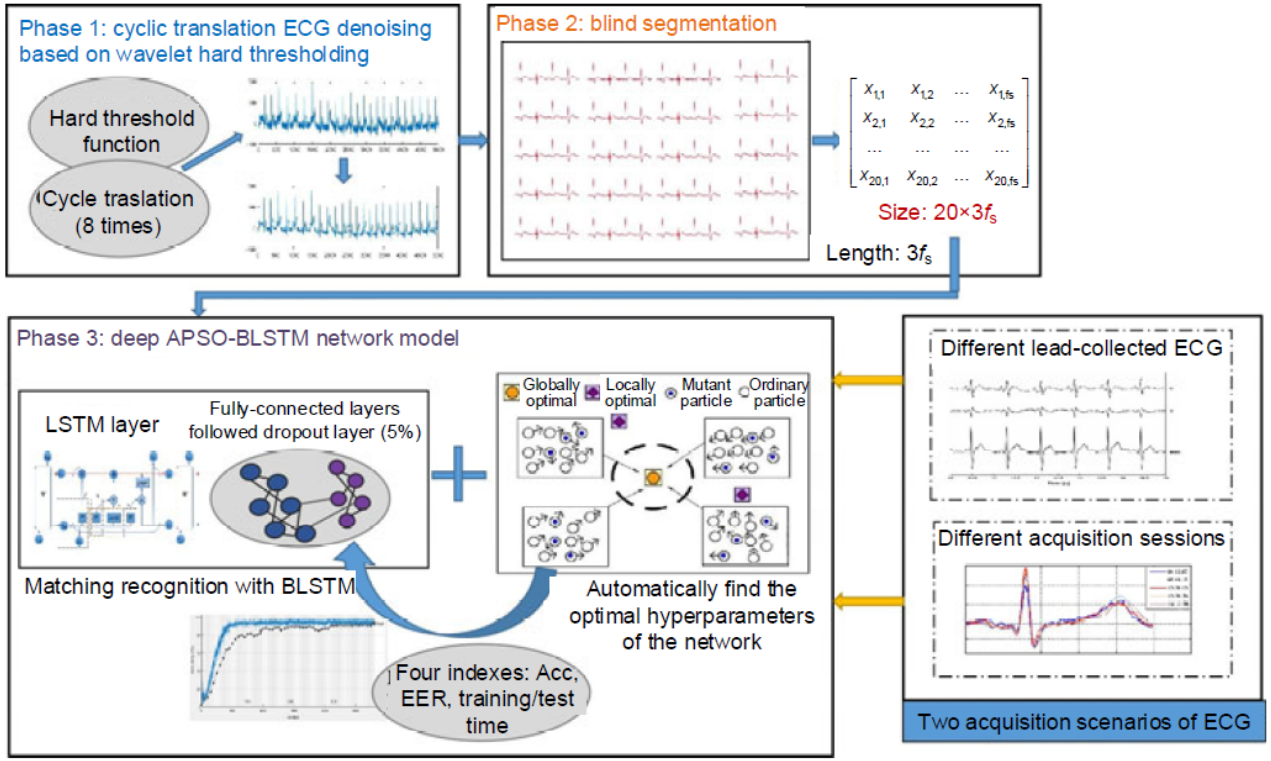

Fig. 1 Architecture of the deep learning driven ECG identification system

Highlighting the denoising section: considering real-life scenarios and applications, ECG signals are highly susceptible to noise. Thus, the cyclic translation ECG denoising based on wavelet hard thresholding is first used to remove noise. Then the denoised ECG is blindly segmented into signal segments with an equal length of $3f_s$ (f_s: sampling frequency), without leveraging any heartbeat location information. For this part, the detailed instructions are referred to Zhao et al. (2018)

Method

Deep BLSTM-APSO biometric model

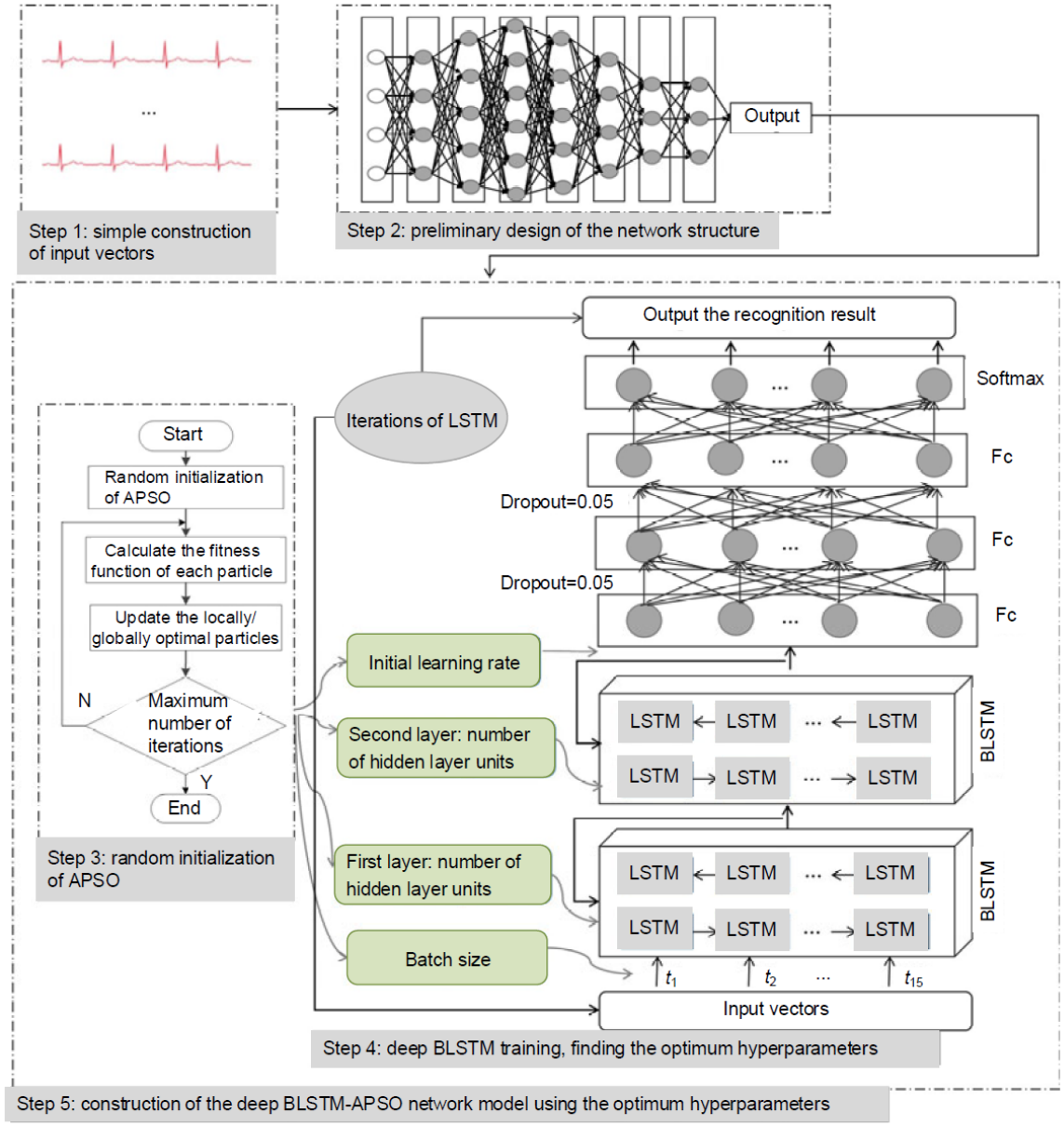

Fig. 3 Detailed structure of the deep APSO-BLSTM network used for identification

Method

Step 1: simple construction of input vectors. The denoised 1D ECG signal is blindly segmented into equal-length segments using a fixed window. The window length is regulated as $3f_s$ to ensure that there is at least one complete heartbeat. Thereafter, the divided ECG signal is directly used as the input vector of the model.

Step 2: preliminary design of the deep BLSTM network structure. A DNN structure is constructed with several BLSTM structures. Overfitting is a considerable obstacle for this type of network. In this study, we introduce dropout at different layers to prevent overfitting. Randomly dropping out part of the network during the training process at the specified rates prevents the neurons from adapting overly well to the training data.

Method

Step 3: random initialization of APSO. Three hyperparameters (batch size, initial learning rate, and number of hidden layer units) are optimized by APSO, and the position information of each particle is randomly initialized according to the range of the hyperparameters.

Step 4: deep BLSTM training to find the optimum hyperparameters. The deep BLSTM network model is established according to the value of the hyperparameter corresponding to the particle position.

Step 5: construction of the deep BLSTM-APSO network model using the optimal hyperparameters. Through ECG data training, the trained model is saved for identification.

Major results

1. Data description

Table 1 Characteristics of ECGs obtained from the Physionet ECG database

Protocol	Dataset	Data source	Characteristics and role	Acquisition method	Number of subjects
1	D1	PhysioNet/Cinc Challenge 2011	Lead I-collected	Standard 12-lead	Training+validation: 90 Test: 90
	D2	ECG-ID Database	Collected from the same session	Lead I	
2	D1	PhysioNet/Cinc Challenge 2011	Different leads (leads I, II)	Standard 12-lead	
	D2	ECG-ID Database	Collected from different sessions, ranging from 1 d to 2 months	Lead I	

2. Network structure

Table 2 Overview of the four schemes proposed

Scheme	Number of layers	Type/Action	Note	Role
A	10	In-LSTM-LSTM-Fc-Dropout, 5%-Fc-Dropout, 5%-Fc-Sm-O	LSTM, dropout B	Performance of the BLSTM and LSTM layers
B	7	In-BLSTM-BLSTM-Fc-Fc-Sm-O	BLSTM, without dropout	Role of the dropout layer
C	9	In-BLSTM-Dropout, 5%-BLSTM-Dropout, 5%-Fc-Fc-Sm-O	BLSTM, dropout A	Influence of the dropout layer position
D	10	In-BLSTM-BLSTM-Fc-Dropout, 5%-Fc-Dropout, 5%-Fc-Sm-O	BLSTM, dropout B	–

Scheme D was selected as the best network structure based on our experiments. In: input; Fc: fully-connected; Sm: softmax; O: output

Major results

3. Optimization of the deep BLSTM-APSO model

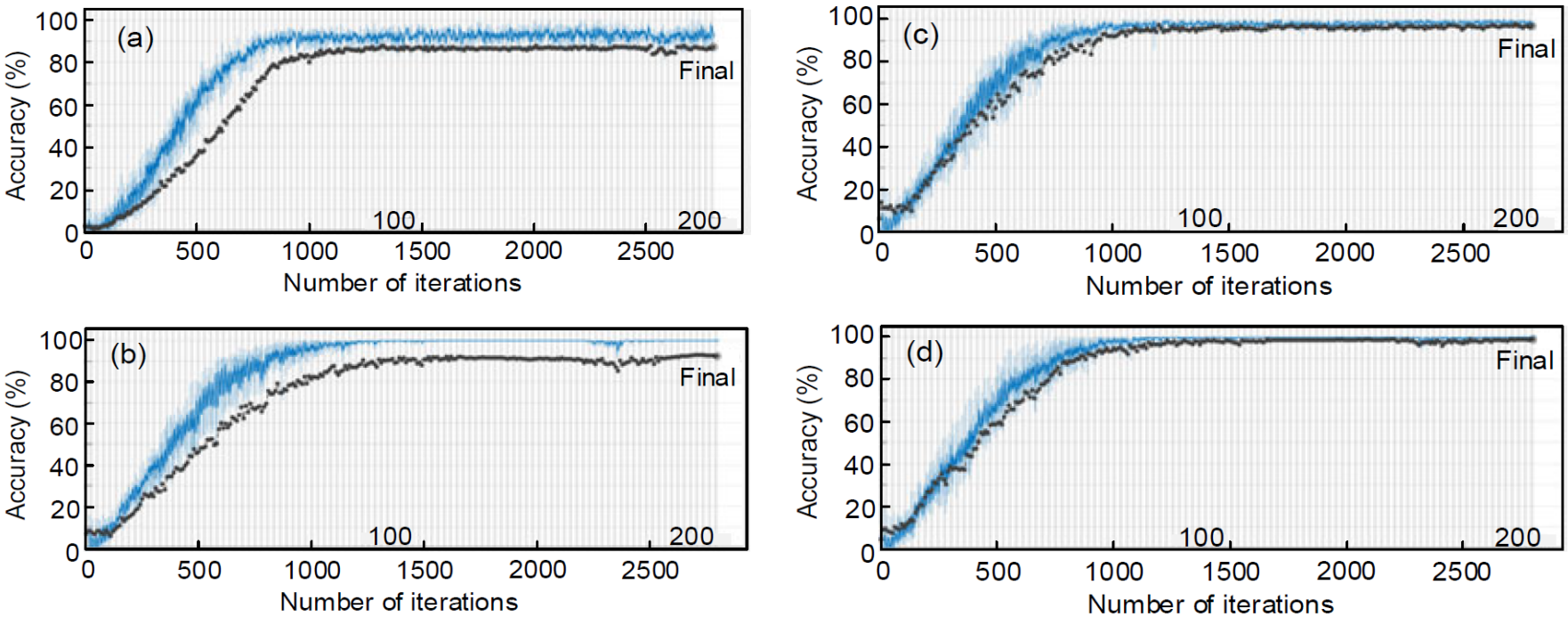

Fig. 5 Accuracy plots for the four schemes during model training (database D2 in protocol 2): (a) scheme A; (b) scheme B; (c) scheme C; (d) scheme D

Conclusions

1. This paper introduces a novel DNN framework that integrates deep BLSTM and APSO, supplemented by original denoised ECG time series.

2. Most previous research has used ECG as a whole to extract features or average the features of different windows after partitioning windows, ignoring the changes of ECG signals in the time dimension and the memory characteristics of recognition algorithms to key features. BLSTM performs forward and backward synchronization training on long-period signals, effectively identifying key features in the time series.

3. The PSO algorithm of the adaptive learning strategy is used to match ECG signal features with deep BLSTM network topology, achieving fast and effective parameter optimization and the best recognition performance under the existing conditions.

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