Research on Identification Algorithm Based on ECG Signal and Improved Convolutional Neural Network

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Abstract. In the research of ECG signal identity recognition, most of them adopt the method of feature extraction and recognition model separation, extract the time domain features, transform domain features of the original signal, or combine the features with the cross domain. Then the model is used to complete the recognition and classification. In this paper, an advanced improved convolutional neural network model is proposed, which integrates feature extraction and classification to complete identity recognition. ECG data selected from the ecg-id database and MIT-BIH arrhythmia database are directly sent to the model for automatic sign extraction after hierarchical denoising with wavelet tools and then identified. This method achieves the highest recognition rate of 98.49% on ecg-id database and 99.35% on ECG data of MIT-BIH arrhythmia database. The high reliability of the algorithm and the universality of wireless sensors in mobile devices make this research has high commercial value.

Keywords: Intelligent Agent; University Education; New Infrastructure, Man-machine Integration

1. Introduction

With the rapid development of mobile Internet and wireless sensor network, a large number of industrial systems and personal application systems require more and more system security and data security. As a reliable means of system security and data information security in cyberspace, identity recognition technology has been widely studied in academic circles and widely used in the industry. At the end of the last century, mark Weiser, a scientist, put forward the concept of "pervasive computing". He believed that a variety of wearable intelligent devices would replace civilian
computers. Today, the use of small mobile devices, especially wearable devices, has increased dramatically. In this case, it is imperative to find high-reliability identification technology.

Traditional identification technology, such as password technology, access token, fingerprint recognition, iris recognition, face recognition, and so on, has its own limitations. These technologies are either easy to be forged or have low universality. For high security and universality, the method proposed in this paper has been studied.

When people are in the bottleneck period of low reliability and high cost, the biological characteristics of ECG signal as a biometric method have attracted the attention of experts and scholars. At present, the identification method based on ECG has been widely studied and has obtained a relatively high accuracy rate. However, most of the research methods are relatively cumbersome and not suitable for the built-in algorithm of small mobile devices. At present, ECG based identification algorithms mainly start with feature extraction in the time domain, transform domain, and fusion, and then combine with classification algorithm to identify. The algorithm proposed in this study simplifies the complexity, combines feature extraction and classification recognition, and the process is automatically completed by deep learning method. The comparison between the traditional research methods. In terms of the source of experimental data, most of the current studies use 12 lead ECG data collected by strict medical equipment, and a few use short-term single lead signal. In this paper, we use the ECG data of MIT-BIH arrhythmia database[1] and ecg-id database to do comparative experiments on two different data sets and get good experimental results.

2. Related work

Identification based on ECG signal has been widely studied since its feasibility was proved in 2001, and has produced excellent results. Up to now, the research in this field can be roughly divided into four categories as follows:

2.1. Recognition based on time domain features

The time domain feature is the most obvious feature but also has a complex waveform. From this aspect, many scholars take different methods to extract diverse features for experimental and theoretical research.

Masaki Kyoso[2] mainly analyzed the interval characteristics of ECG signals, such as S-T interval, QRS complex interval, etc., and used a simple Euclidean distance criterion as a recognition method. The test set samples used the time domain characteristics of ECG signals of 9 normal individuals and then combined different time-domain features to check the recognition effect. The study found that the combination of QT interval and QS interval can obtain a high recognition Rate.

Palaniappan et al.[3] Extracted six time-domain features including amplitude and interval from ECG signals of 10 normal individuals, and extracted the FF feature of waveform factor for the first time. The recognition rate reached 97.6% by using the neural network clustering analysis method.

The test data and samples used by Silva and others[4] are V2 lead sub-signals that are decomposed from 25 normal ECG signals. The weighted average processing of five time-domain interval features
is carried out, and then each feature is extracted for 10 cycles. Finally, a 100% recognition rate is achieved.

2.2. Recognition based on transform domain features

In view of the limitations of time-domain features, many researchers turn their minds to the frequency domain or other transform domain, with the help of powerful mathematical tools, extract the information that is not obvious, and then use efficient algorithms to achieve a higher recognition rate.

Zhao Zhidong et al. [5] normalized the ECG signal through the zero mean unit variance method, performed a fast Fourier transform, and then extracted the time-frequency parameters and projection values of the first three atoms through the analysis of matching pursuit (MP), compared the SVM algorithms of different kernel functions, and finally adopted the SVM of linear kernel function. The recognition rate reaches 97.1%.

Chiu et al. [6] respectively extracted wavelet coefficient features from ECG signals of 35 healthy individuals and 10 patients with heart disease by wavelet transform, and then separately identified them with Euclidean distance criterion. Finally, the recognition rate of healthy individuals was 100%, and that of patients with heart diseases was 81%.

2.3. Recognition based on fusion features

After considerable achievements have been made in the study of time domain and transform domain features, experts consider to combine the features in time domain and transform domain for recognition. This method of feature fusion has achieved good results in the recognition of some algorithms.

Shen Jun et al. [7] used the multi period waveform of ECG signal. After normalization, the average waveform was taken as the time domain feature of ECG signal, and then wavelet coefficients of ECG signal in the wavelet domain were obtained by using wavelet tools. The extracted wavelet coefficients were taken as transform domain features, and the features were fused into feature vectors by linear combination method. The recognition rate of patients with heart rate irregularity is 88.21%, and that of healthy individuals is 99%.

3. Approach

The data sets are from two databases: the first is the ecg-id database, which contains 310 ECG records from 90 people. This study mainly uses the single lead ECG record of the database. As shown in Fig 1, the single lead ECG signals are all short-term signals of 30 seconds. Compared with the data extracted by professional ECG measuring equipment, this kind of data will lack some information. However, its lightweight and easy to process characteristics are closer to ECG data extracted by small personal terminals, so it has been widely studied.
The second database is the MIT-BIH arrhythmia database, which contains 47 subjects. Thirty individuals were used in the classification. In this database, the 30 subjects were classified according to their heart rate. Six types of ECG and cardiogram were selected. 1 case was normal (normal), 5 cases were ECG arrhythmia, such as ventricular premature beat (PVC), pacing (PACE), right bundle branch block (RBBB), left bundle branch block (LBBB), atrial premature beat (APC).

ECG signal is subject to a lot of noise interference, among which the main noise to be removed is the following two kinds [8]:

1. The effect of EMG interference is relatively slight, which belongs to the least of the three main noise interference. It comes from the biological noise of the human body and has a wide frequency distribution, ranging from 5 to 2000 Hz.

2. Baseline drift is common in ECG signals and is difficult to avoid, which is caused by the breathing of the subjects. The frequency of this interference is very low. The direct effect on ECG signal is that ECG signal deviates from the horizontal line on the whole.

Wavelet transform is a signal transform domain conversion technology based on Fourier transform, which can obtain the spectrum of the signal. In the transformation, the signal can be expressed as a linear combination of the shift and expansion of the "mother wavelet". By converting the time domain signal into the frequency domain signal, we can observe the frequency time relationship of the signal.

\[
CWT_x^\psi(\tau, s) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t) \psi^*(\frac{t}{s} - \tau) dt
\]

Eight wavelet base methods are built in MATLAB. Researchers must first determine the mother wavelet function, and then choose the appropriate decomposition level of the wavelet transform. An excessive number of layers will make the generation of children too much, the displacement becomes too obvious, leading to serious image boundary distortion. The PPG waveforms before and after denoising are shown in Fig. 2.
As one of the basic algorithms of deep learning, a convolutional neural network is widely used in the field of image recognition, which has been widely studied and achieved excellent results. In this study, we configure and adjust the basic convolution as the recognition model. Now I'll give a brief introduction to convolution and the models we use.

In our model, the training set and test set of ECG data are sent to the preprocessing module for denoising. The processed data will be taken over by CNN network. The number of CNN layers can be set according to the needs of the experiment and the specific performance. In our experiment, the number of CNN layers is set to eight. From the macro level, we can see that our model is composed of three parts: feature extraction, classification, and output function. The feature extraction is completed by the convolution layer, relu activation function, and maximum pooling layer.

Convolution layer is just like the filter in signal processing. A type of filter is selected to scan the input data according to the set rules and extract the specified information. The information level of each convolution extraction is different, and the granularity of features is not consistent. Of course, the details of these features are hard for us to understand.

\[ y(n) = \sum_{i=-\infty}^{\infty} x(i) h(n - i) = x(n) * h(n) \]  

\[ f(\tau) g(x - \tau)d\tau \]  

**Fig. 2** ECG signal denoising
In order to simulate more subtle changes, the input and output values can go to any value between 0 and 1. We use activation functions to add nonlinear factors. Here we use the relu function as below.

$$f(x) = \max(0, x)$$

(4)

Our model, shown in Fig 3, uses full connection and softmax to implement the classification task. Full connection layer exists as "Classifier" in CNN. Convolution layer, pooling layer and activation function layer convert the initial data to the hidden layer feature space, while the full connection layer maps the learned "distributed feature representation" to the labeled sample space to realize the classification function.

![Improved convolution neural network model](image1)

**Fig.3** improved convolution neural network model

In the experiment, the improved convolution neural network is used to set the size of 512, the learning rate is set to 0.0001, and the iterations are 150 times. From the results, it is easy to see that after 40 iterations, the accuracy of the test set is close to 100%. The changes of training accuracy rate of our model in the process of training are shown in Fig 4:

![Training accuracy](image2)

**Fig.4** training accuracy
In this study, our method perfectly integrates feature extraction and classification recognition. In the experiment based on multi lead ECG data, linear discriminant analysis (LDA) uses benchmark features to extract features first and then classify them. The highest accuracy rate is only 77.21%. In addition, our study also compared the experimental results of different data. On the short-term single lead data of ecg-id database, the accuracy rate of our model reached 98.49%, and on the multi lead long-term data of MIT-BIH arrhythmia database, our model had an accuracy rate of 99.35%.

4. Conclusion
In this paper, a deep learning-based identity recognition algorithm is proposed. Compared with the previous identification algorithm based on ECG signal, the algorithm can combine feature extraction with identity recognition, and the whole process does not need to extract features separately. In the experimental aspect, the algorithm proposed in this study can achieve a high recognition rate whether on the 12 leads long-term signal collected by professional medical equipment or on the single lead short-term ECG signal. However, there are some research bottlenecks in this study, such as the number of data sets used in the experiment is not too large, and the experimental data are relatively old, and the experimental data are collected under a static state, and so on. Our team's future research will focus on solving these problems.

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