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

Dechao Wan, Luqiao Zhang, Yunxiang Bai and Hanghang Deng

School of Cyberspace Security, Chengdu University of Information Technology, Chengdu 610225, China
Email: zhanglq@cuit.edu.cn

Abstract. In this paper, an improved convolutional neural network model is proposed, which is used for the identification of ECG signals while PPG signals are rarely used. The PPG data from the mimic database is denoised by wavelet transform, and then directly sent to the model for automatic sign extraction and recognition. This method can achieve the highest recognition rate of 99.39% on PPG data in mimic database. This makes the identification based on PPG signal meet the requirements of high reliability. With the rapid development of sensors and wearable devices, this research can also meet the universality of one of the requirements of identification.

1. Introduction

1.1. Motivation and Background

In today's highly integrated real world and virtual world, the boundary of the world is the boundary of the network. Many aspects of people's daily life are closely related to cyberspace security issues. As a kind of Cyberspace Security Technology, identity recognition technology has been widely studied and applied by academia and industry, such as network system, homeland security, terminal equipment security, access control system. Traditional authentication methods such as physical authentication and password technology are easy to lose, forget and steal. As early as the 1990s, mark Weiser, the former chief scientist of Xerox PARC, has come up with the basic concept of "pervasive computing". He proposed that civil computers will be replaced by a variety of wearable intelligent devices. Nowadays, mobile devices, especially wearable devices, are developing rapidly. In this case, the research and implementation of higher reliability identification technology will be improved to a high position.

At present, the main biometric technologies include DNA recognition, speech recognition, iris, face and fingerprint recognition. The wide application of these technologies can not cover up their shortcomings. For example, photos can easily cheat the face recognition system, fingerprint sleeve can also open the door of fingerprint recognition system, and voice recognition has the same problems. For iris and DNA recognition, the disadvantages of long recognition time and high cost have not been solved.

When people are in the bottleneck period of low reliability and high cost in recognition, two kinds of biometrics, i.e. photoplethysmography (PPG) and electrocardiograms (ECG), have attracted the attention of experts and scholars in the field as biometric methods. At present, the research of identification based on ECG is obviously more than PPG, and even has a high accuracy rate. However, from the universality of biometrics, PPG is undoubtedly more meaningful than ECG.
At present, the research methods of identity recognition based on PPG mainly include: recognition based on P-wave feature points, recognition based on waveform, and feature analysis based on frequency domain.

1.2. Related Work

Compared with the identification technology based on ECG or some other biometric technologies, the research of PPG based signal identification technology is relatively late, and it is still in its infancy. At present, there are two main methods of identity recognition based on PPG signals:

(1) Recognition based on P-wave feature points

This method selects some characteristic points of PPG signal and uses some time-domain characteristics as characteristic values, such as amplitude, slope, time interval, etc., to realize identity recognition. The following are typical algorithms of this type:

Samik Chakraborty et al. [1] used the first and second derivative to extract PPG signals from 15 healthy individuals 12 features of amplitude and time are obtained. The recognition rate is 100% by calculating the Euclidean distance of statistical parameters of 15 individual PPG signals. Anthony Lee et al. [2] took 708 datasets from 10 healthy individuals, took the turning point data, area and waveform angle of PPG signal as the eigenvalue, used feed forward neural network for recognition, trained the data and test data according to the proportion of 7:3, and compared the different situations of sports and resting state, finally the error rejection rate was 3.7% and the error acceptance rate was 3.7% in resting state. Chen Yuyan et al. [3] took PV wave time interval, VV wave time interval, PV wave amplitude value difference, PP wave time interval as the benchmark, and collected PPG data of 30 subjects independently, and used KNN classifier to complete classification and recognition, reaching 87.22% recognition rate. Gu. Y. y et al. [4] used the four characteristic points of the number of wave peaks of PPG signal in a single period, the slope of P-wave and the previous V-wave, the time interval between adjacent P-waves, the falling peak and the slope of the next V-wave as the characteristic values, and weighted each characteristic point to increase the ratio of the difference between the classes and the difference within the classes. He selected 17 healthy individuals as samples, and took multiple periods of PPG for each individual Four feature points of the signal are used to calculate the matching score of Gaussian curve between different individuals by using the Gaussian function of fuzzy logic. The score from 1 to 0 indicates the matching degree. When the data comes from the same sample, the recognition rate is 94%; when the data comes from different samples, the recognition rate is 82.3%. The advantage of P-wave feature point based identification method is that it is easy to get the feature value, and the calculation complexity is low. But for small sample data, the recognition rate is low.

(2) Recognition based on waveform

This method generally uses the P wave as the reference point to segment the single period PPG signal waveform, and then through the data dimension reduction processing, the processed data is taken as the eigenvalue. The following literature respectively analyzes the waveform characteristics and experimental results of PPG signal. N.S. Girish Rao salanke et al. [5] Based on the P-wave of PPG signal, segmented the single period of PPG signal waveform. Through the principal component analysis method, the single period waveform of PPG signal is characterized, and the recognition performance under tension condition is analyzed. The results show that the signal obtained under tension condition is specific Sex is more obvious, so the effect of recognition is more significant than that of relaxation. Petros spachos et al. [6] used the P-wave dimension reference point of PPG signal to segment the single period waveform of the signal. After normalization, the linear discriminant analysis (LDA) was used to reduce the dimension of the data, and the coefficient table of the PPG signal waveform in the LDA subspace was obtained. These coefficients were taken as the eigenvalues, and then k-nearest neighbor (k-nearest neighbor) algorithm was used NN) takes 14 healthy individuals as the test objects, and the error rejection rate and error acceptance rate are both lower than 0.5%. This method has the advantages of strong anti noise and good stability. Under the condition of small samples, its recognition rate is relatively ideal compared with P-wave feature point method. However, due to the large amount of feature data, the recognition speed will be reduced.
2. Approach

2.1. Mimic Database
Mimic Database is an evaluation database of multiple physiological signal parameters established by various intelligent patient monitoring systems jointly developed by Philips Medical Systems, MIT and Beth Israel Deaconess Medical Center. The database is collected from some patients in the intermediate ward. The authenticity of the data has been verified by authoritative experts. At present, it is open on PhysioNet [7], which can be used by scientific researchers for free. Each record in the database contains a sampling data file (.dat), a header file (.hea), and a comment file (.txt). The header file defines the type of physiological data collected by the individual (pleth is the PPG signal required in the paper, ABP is the arterial blood pressure signal, resp is the respiratory signal, III is the ECG signal as shown in Figure 1), sampling frequency (125Hz), sampling time and other information; the sampling data file contains the sampling data of various physiological signals specified in the header file; the annotation file contains the physiological signal Results of measurement records and data analysis. In this paper, 30 individuals are selected as the research objects, and their individual information is shown in Table 1. In the individual information column, M represents male, f represents female, and M/70 represents male age of 70.

![Figure 1. Schematic Diagram of No. 039 Individual Header File](image)

| Database number | Individual information | Line number of pleth in .hea | Database number | Individual information | Line number of pleth in .hea |
|-----------------|------------------------|-------------------------------|-----------------|------------------------|-------------------------------|
| 1               | 039                    | M/70                          | 4               | 16                     | 403                          | F/64                         | 5                           |
| 2               | 055                    | M/38                          | 7               | 17                     | 408                          | M/45                         | 6                           |
| 3               | 210                    | M/80                          | 6               | 18                     | 410                          | M/57                         | 6                           |
| 4               | 211                    | F/67                          | 5               | 19                     | 411                          | F/82                         | 6                           |
| 5               | 212                    | M/84                          | 7               | 20                     | 437                          | M/75                         | 6                           |
| 6               | 218                    | M/67                          | 6               | 21                     | 439                          | F/75                         | 6                           |
| 7               | 221                    | F/68                          | 5               | 22                     | 444                          | M/75                         | 6                           |
| 8               | 224                    | M/21                          | 5               | 23                     | 449                          | M/75                         | 6                           |
| 9               | 225                    | M/73                          | 6               | 24                     | 451                          | F/76                         | 7                           |
| 10              | 230                    | F/75                          | 6               | 25                     | 466                          | M/70                         | 5                           |
| 11              | 240                    | M/68                          | 6               | 26                     | 471                          | F/78                         | 6                           |
| 12              | 253                    | M/52                          | 7               | 27                     | 472                          | M/79                         | 6                           |
| 13              | 276                    | F/66                          | 7               | 28                     | 474                          | M/75                         | 7                           |
| 14              | 281                    | M/61                          | 8               | 29                     | 476                          | F/72                         | 7                           |
| 15              | 284                    | F/59                          | 6               | 30                     | 484                          | M/60                         | 8                           |

2.2. Data Preprocessing
The amplitude of PPG signal is generally in millivolt level, which belongs to a kind of non-stationary quasi periodic random signal. Compared with the strong interference environment in the acquisition process, it is inevitable to be interfered by noise. In order to avoid the influence of signal noise on the experimental results, it is necessary to denoise the original PPG signal. At present, it has been proved...
that there are three kinds of common noise in PPG signal: baseline drift, high frequency random interference and motion pseudo difference noise.

As an upgrade technology of Fourier transform, wavelet transform can get the spectrum of time-domain signal. In wavelet transform, signal can be expressed as a linear combination of shift and expansion form of "mother wavelet". By converting the time-domain signal whose waveform changes with time into frequency spectrum, we can observe the change of different frequencies with time [8]. Eight kinds of wavelet basis functions are provided in MATLAB. There are three bases for researchers to choose mother wavelet function: 1. Visual observation 2. Correlation between interested signal and original signal 3. According to accumulated energy [9], mother wavelet and threshold selection based on genetic algorithm are also considered to denoise signal. It is a complex mother wavelet selection algorithm, which may require more computation [10]. The layer data decomposed by wavelet transform needs to be appropriate. The excessive layer number will lead to too many children, too obvious displacement, and serious image expansion, resulting in serious image boundary distortion.

The PPG waveforms before and after denoising are shown in Figure 2 and Figure 3 respectively:

**Figure 2.** Original PPG Signal Waveform

**Figure 3.** PPG Signal Waveform after Denoising
2.3. Methods
Convolutional neural network has achieved great success in image recognition and other fields. It is also one of the most important basic algorithms of deep learning. As shown in formula 1, the core of the convolution neural network is similar to the artificial neural network, in which $\theta(x)$ is the activation function corresponding to the rectifier linear unit (Relu), $w_n$ is the weight vector, and $b_n$ is the bias term of the filter $h_n$. After the convolution filter, the maximum pool layer performs the local time maximum operation on the input sequence, and selects the maximum value in a fixed size window.

$$h_n = \theta(w_n x^T + b_n)$$  \hspace{1cm} (1)

Our research is based on this efficient and simple deep learning algorithm: convolutional neural network. Convolution layer helps us to automatically extract more abstract features, which is not possible before using the algorithm of artificial feature extraction. The pooling layer reduces the dimension of the features extracted from the convolution layer, which effectively avoids the occurrence of over fitting and improves the fault tolerance of our model. The model of this study is shown in Figure 1. The original PPG signal uses a one second window, and slides the data in the window into the parallel $N \times L_n$ convolution layer conv1d. After each convolution network, there is a linked maximum pooling layer, and then the parallel output results are concatenated to get the intermediate layer data with a length of 2n. The output results are input into the parallel convolution plus pooling layer again to get to the data with a length of 4N, and then calculate the validation score by the dense layer. It should be noted that the convolution layer in the model is one-dimensional convolution, just like the method used in paper [11]. Suppose that the PPG signal input to CNN is a vector $x$, and its element is the sampling $x = [X_1, X_{k+1}, ..., X_{k+k}]$ of the original PPG, where is the PPG sampling of each step of the sliding window. In our experiment, we used a time offset of 1 second and a fixed size $X_{k+k}$ sample to collect 200 samples per second from 1 second. The activation of the first volume of integrators consists of $N = 6$ filters, which we represent as $h_n = [H_1, H_2, ..., H_n]$. Therefore, the convolution layer operation can be regarded as the convolution operation of each filter input on the original PPG. In our model, we divide 30 records into training set, test set and verification set according to the proportion of 6:5:4.

![Figure 4. Improved Convolution Neural Network Model](image)

3. Experimental Results and Analysis
In the classification problem, the model divides the test samples into positive and negative categories, and the following four categories appear:

A. True positive (TP). The sample is positive and the model recognizes the sample as a positive class.

B. False positive (FP). The sample is false and the model recognizes the sample as a positive class.
C. True negative (TN). The sample is false and the model recognizes the sample as a negative class.
D. False negative (FN). The sample is positive and the model recognizes the sample as a negative class.

According to the four categories of the classification model, I have designed an evaluation index suitable for the problem. The evaluation index and its description are shown in Table 2:

| Name of evaluation index | Index description |
|--------------------------|-------------------|
| Accuracy rate (Acc)      | \( \frac{TP + TN}{TP + FP + TN + FN} \) |
| Cross entropy cost function | \( C = -\frac{1}{n} \sum_{i=1}^{n} [y \ln a + (1-y) \ln(1-a)] \) |
| Training time            | Time consumed in network model training process |

The in-depth learning part of this study is based on tensorflow architecture. Matlab r2018b is used for signal denoising. The platform used is Windows operating system and Intel Core i5 CPU. The video card is configured with NVIDIA GTX 1080ti, 32g DDR3 1600MHZ memory and 6GB video memory.

The improved convolutional neural network used in the experiment is designed to be 512 in size, 150 iterations and 0.0001 in learning rate. It can be seen from the experimental results that after 60 iterations, the accuracy of the verification set is almost 100%. The change of training accuracy of improved convolution neural network algorithm is shown in Figure 5, and the change of cross entropy cost function of improved convolution neural network algorithm is shown in Figure 6:

**Figure 5.** Change of Training Accuracy of Improved Convolutional Neural Network Algorithm

**Figure 6.** Change of Cross Entropy Cost Function in Training Process of Improved Convolution Neural Network Algorithm
We compare the methods used in this study with some traditional methods in the past, our method does not need to extract features manually in feature extraction, feature extraction and classification are completed in the improved convolution neural network, and the accuracy is up to 99.39%. Linear discriminant analysis adopts the method of datum feature to extract features, and the final highest accuracy is only 75.21%. The standardized Euclidean distance method adopts autocorrelation estimation to extract features, and the highest accuracy can reach 92.88%. It can be seen that our method can finally beat some traditional algorithms and achieve the highest accuracy.

Table 3. Comparison of Several Recognition Algorithms

| Feature extraction method         | Classification algorithm             | Highest accuracy |
|----------------------------------|--------------------------------------|------------------|
| Convolutional neural network     | Convolutional neural network          | 99.39%           |
| Benchmark characteristics        | Linear discriminant analysis         | 75.21%           |
| Autocorrelation estimation       | Standardized Euclidean distance      | 92.88%           |

4. Summary
In this paper, an improved convolutional neural network model is proposed to be used as the identification technology. Compared with the traditional identification algorithm based on PPG signal, this model can automatically extract features from the original PPG signal, and in the 30 records of the mimic database, after denoising with wavelet transform, the highest recognition rate is 99.39%. However, there are still some deficiencies in the research described in this paper, for example, there is no distinction between PPG signals in different motion states, and the number of data sets is not particularly large, in addition, there is no real life data detection. This also points out the direction for future research.

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