Finger Vein Recognition Based on Deep Learning

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Abstract----As a new biometric technology, finger vein recognition has received much attention in recent years. Since deep learning is an end-to-end system, and has achieved very good results in such fields as face recognition and target detection, we try to apply it to finger vein recognition. In this paper, we adopt seven layers of CNN which include 5 convolution layers and 2 fully-connected layers. This network obtains a recognition rate of 99.53%, which proves to be better performing than traditional algorithm.

Key words： biometrics, finger vein recognition, deep learning, convolutional neural network, traditional algorithm

I. Introduction

Biometric technology is playing an increasingly significant role in modern society. Main research fields of biometrics include: face recognition, fingerprint recognition, iris recognition, voice recognition and so on. In recent years, research on finger vein recognition has received much more attention. Medical research shows: (1) finger veins for different people are not the same; (2) for the same person, his/her finger veins vary among different fingers; (3) for adults, patterns of finger vein will not change over time.[1-2] Hence, finger vein offers a safe and feasible approach for biometric recognition.

Traditional finger vein recognition process mainly includes four steps(Figure 1): finger vein image acquisition, image preprocessing, feature extraction and image matching recognition. However, by using an end-to-end mechanism in training and learning, deep learning has changed the recognition process above. In 2006, Professor Hiton put forward the model of deep learning.[3]Deep convolution neural network (ConvNet/CNN) proves to work more quickly and accurately than traditional algorithm. [4] Since it won in the ImageNet competition of 2012, deep learning has developped rapidly. This method has been widely applied in fields of recognition, detection and so on. [5-10] The process of CNN is showed in Figure 2.

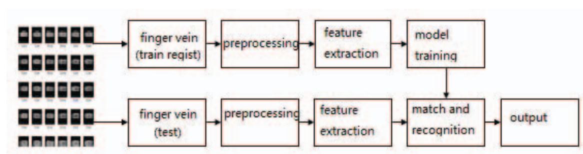

Figure 1: traditional finger vein recognition process

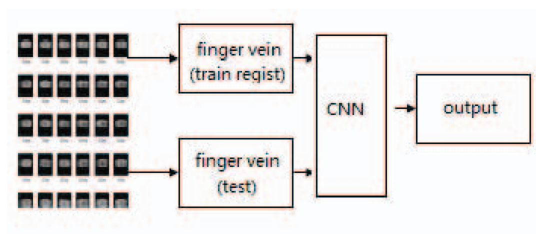

Figure 2: finger vein recognition process based on CNN

So far, a large number of articles have expounded on finger vein recognition using traditional algorithm, but few explored finger vein recognition based on deep learning. In this paper, we try to utilize the method of deep learning in finger vein recognition. Through a large number of experiments, we find that CNN can be effectively used in finger vein recognition, and the recognition rate can reach

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99.90%.

The rest of the paper is organized as follows: the second section introduces related work on finger vein recognition; the third part proposes our approach for finger vein recognition; the fourth part is a brief description of our experiment and analysis of experimental results; the fifth part summarizes the paper.

II. Related work

In this section, we will make a short description on traditional algorithms used for finger vein recognition, as well as modern methods based on deep learning.

Naoto Miura et al. put forward the repeated line tracking method and maximum curvature method to extract finger-vein patterns, and achieved very good results.[11-12] Lee et al. adopted the method of LBP and LDP extracting finger vein patterns.[13] Peng et al. and Pang et al. proposed using SIFT operator to extract finger-vein features.[14-15] In the work of Wu et al., PCA was used for finger-vein identification.[16] Xin et al. extracted finger-vein features using sparse representation.[17] Munalih Ahmad Syarif et al. applied maximum curvature method, HOG and SVM to finger vein verification. [18]

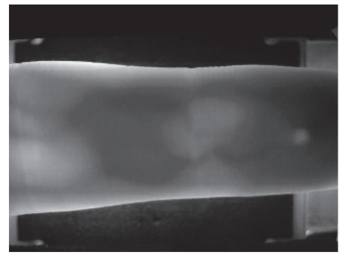
The above methods have used traditional algorithms for finger vein recognition. Instead of using LRN or dropout, Ahmad Radzi Syafeeza et al. applied CNN which is based on LeNet-5 to finger vein recognition, his net did not adopt a full connection scheme either. [19]

III. Proposed Method

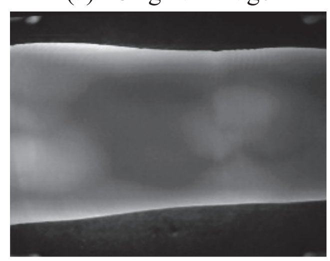
Our approach for finger vein recognition consists of two steps: first to extract regions of interest (ROI), second to train CNN for recognition. CNN mentioned in this article is based on AlexNet, while its network structure and parameters are adjusted because of different experimental subjects.

A. ROI extraction

Whatever type of finger vein apparatus is used to collect finger vein images, there inevitably exist redundant part of body and noise. To acquire effective information of finger vein for subsequent experiments, we first remove instrument section, then use a compass operator to extract edge data of finger images, determine their width and length, and finally extract the ROI region. Examples are showed in Figure3 :

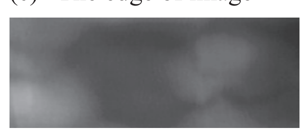


(a) Original image



(b) After removing instrument section

(c) The edge of image



(d) ROI

Figure 3: ROI extraction examples

B. Network Architecture

Network in this paper consists of 5 convolution layers and 2 fully-connected layers. Input images are grey with a fixed-size of 60*175 pixels. Convolution layer C1 is the first layer of the net, in which we first do convolution of the image followed by ReLU, max pooling and LRN. The second, third, fourth and fifth layer of the net are called convolution layer C2,

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C3, C4 and C5, each layer containing convolution, ReLU and max pooling. These convolutional layers consist of 64 kernels in total, which have same size of 5*5. Size of pooling is 2*2 and we take the maximum. There are two fully connected layers (the sixth and the seventh layer, namely F1 and F2) after convolution C5 in this network. F1 that has 150 dimensional vectors is used for extracting features of input images. And F2 computes the class posterior probabilities of each feature through a softmax function, and projects it to corresponding 198 classes. Details of the network's architecture and parameters are showed in table 1:

Model	C1	C2	C3	C4	C5	F1	F2
Five convolution layers and two fully-connected layers	64*5*5 ReLU LRN Pooling 2*2	64*5*5 ReLU Pooling 2*2	64*5*5 ReLU Pooling 2*2	64*5*5 ReLU Pooling 2*2	64*5*5 ReLU Pooling 2*2	150 Dropout 0.5	198 Softmax

Table 1：Network model's architecture and parameters

IV. Experiments and results

A. Finger vein database

Until now, there are few public finger vein databases that can be used for finger vein test. Therefore, we established a database in our laboratory for further research. This database contains 198 identities with 2970 images, each identity containing 15 images. In our database, the ratio of male to female is about 1:1. Majority of the objects are young students aging between 20 and 30. The database contains four types of fingers: index finger, middle finger, ring finger and little finger. In addition, we also adopt SDUMLA-FV database[21] constructed by Shandong University. This database contains 636 identities with 3816 finger vein images, each identity containing 6 images.

B. Experiment 1

In this part, experimental data of each object in our established database is divided to a training set with 13 images and a testing set with 2 images. We will evaluate the performances of our CNN model, in comparison with experimental results by several traditional methods for finger vein recognition including Gabor filter[19], LBP[13], HOG[20].

As for process designing, experiment operation by CNN is much simpler. When we use traditional algorithms in our experiment, images are preprocessed by normalization, contrast limited adaptive histogram equalization (CLAHE), and contrast stretch. Whereas, images input in convolutional neural network are not preprocessed, as CNN is an end-to-end system, we only need to tune parameters of the net. Original images and preprocessed images are showed in Figure 4. Evaluation criterion is EER (Equal Error Rate), when the FRR(False Rejection Rate) is equivalent to the FAR (False Acceptance Rate) in this experimental results. Results by different methods are listed in table 2:

Feature extraction algorithm	**EER (%)**
Gabor	1.667
LBP	4.200
HOG	0.804
CNN	0.079

Table 2: Comparison between CNN and traditional algorithms in established database

Results from table 2 show that the EER of CNN is obviously lower than traditional algorithms, even though images input in CNN are not preprocessed. It implies that the performance of CNN is obviously superior to traditional algorithms.

(a) (b)

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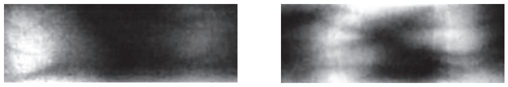

(c) (d)

Figure 4: Original images(a)(b) of finger vein and preprocessed images(c)(d)

C. Experiment 2

In this experiment, we use SDUMLA-FV database, in which first three images are used as training samples and the other three as testing samples. Three-fold cross-validation is adopted in the experiment.[25] We will compare CNN with some state-of-the-art finger vein recognition methods including LBP[13], LLBP[23], LDC[22], Mean Curvature (MeanC)[24], Maximum Curvature (MaxiC) [13]and SPCF[25]. Tabel 3 shows the EER by different methods. Figure 5 shows ROC curve of different methods in SDUMLA-FV database.

Feature extraction algorithm	EER (%)
LBP	10.27
LLBP	10.96
LDC	8.87
MeanC	11.54
Maxic	3.51
SPCF	1.94
CNN	0.80

Table 3: Comparison between CNN and other algorithms in SDUMLA-FV database

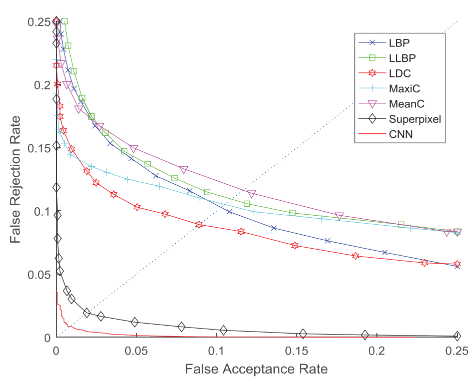

Figure 5: ROC curve of different methods

From Table 3, we can easily know that the EER of CNN is 0.80%, better than performances of other methods used in SDUMLA-FV database. As CNN can learn a great quantity of data, it can be trained to a robust feature extractor which has better generalization ability.

D. Experiment 3

In this experiment, we use CNN in SDUMLA-FV database to test the correct recognition rate, compared with SPF[26] and SPCF[25]. As we can see from table 4, the correct recognition rate of our proposed method is 99.53%, which is far better than SPF and SPCF in SDUMLA-FV database.

Feature extraction algorithm	AccRate (%)
SPF	87.00
SPCF	92.71
CNN	99.53

Table 4: The correct recognition rate compared between CNN and other algorithms in SDUMLA-FV database

V. Conclusion and future work

This paper applies a deep learning method in finger vein recognition. The correct recognition rate of our proposed method can reach 99.53%. It shows that the performance of using CNN is better than using traditional algorithms. Besides, CNN is an end-to-end system which is simple for finger-vein recognition and has high robustness. Considering the superior performance of CNN, we will do more research with deep learning method on finger vein recognition in the future. One important thing about finger vein recognition is to build a public database with a large quantity of data.

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