International Journal of Social Science and Education Research Volume 3 Issue 4, 2020
ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202004_3(4).0014

# Research on Finger Vein Recognition Based on Improved Convolutional Neural Network

Renze Luo[1, a], Ke Zhang[1, b]

[1]School of Southwest Petroleum University, Chengdu 610500, China.

[a]lrzsmith@126.com, [b]zkswpu@163.com

## Abstract

**Aiming at the problems of low recognition accuracy and poor generalization performance of finger vein recognition method, a finger vein recognition method based on the combination of deep convolutional network and extreme learning machine was proposed. Use deep convolutional networks to automatically extract feature from finger veins to reduce the large amount of effective information lost in traditional method feature extraction. At the same time, in order to enhance generalization, the deep convolutional network has been improved to remove the original fully connected layer Add extreme learning machine layers to identify the extracted feature vectors. An experimental analysis of the proposed method was performed on a common finger vein dataset. Experimental results show that, compared with other finger vein recognition methods, this method has higher accuracy and stronger generalization performance in finger vein recognition.**

## Keywords

**Finger vein; Deep learning; Deep Convolutional Network; Extreme learning machine.**

## 1. Introduction

Nowadays, the biometric identification technology is more and more closely related to our daily life, and is more and more widely used in electronic payment, security protection and other fields. Commonly used biometric recognition technologies include face recognition, fingerprint recognition, iris recognition, and vein recognition. Because the finger vein has characteristics such as stability and uniqueness, and is an internal feature of the human body, it is not easy to be stolen by others. So, finger vein recognition technology has attracted more and more attention.

Finger vein recognition is usually divided into two stages. The first stage is to extract the ROI image of the finger vein from the original finger vein image containing irrelevant background regions, and remove the irrelevant background regions to prevent the influence of irrelevant background regions on recognition. This stage is the feature extraction and recognition of finger vein ROI image. The focus of research has been on the latter feature extraction of vein ROI images, such as texture-based feature extraction methods[1], texture-based feature extraction methods[2], and local invariant feature extraction methods[3], but these methods usually require artificial design extraction steps.

In the context of current big data, the advantages of deep convolutional neural networks (DCNN) in feature extraction and data dimensionality reduction have been widely used in image processing, speech recognition and other fields. In particular, it has a good recognition effect in the field of image recognition such as image classification and face recognition[4]. DCNN has the feature of automatically extracting feature information from data. Compared with traditional artificial feature selection, it is more conducive to extracting intrinsic feature information of data[5]. More and more experiments show that separating the traditional DCNN

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202004_3(4).0014

feature extractor from the classifier and integrating the DCNN feature extractor into a classifier such as a support vector machine also have very good classification performance[6, 7].

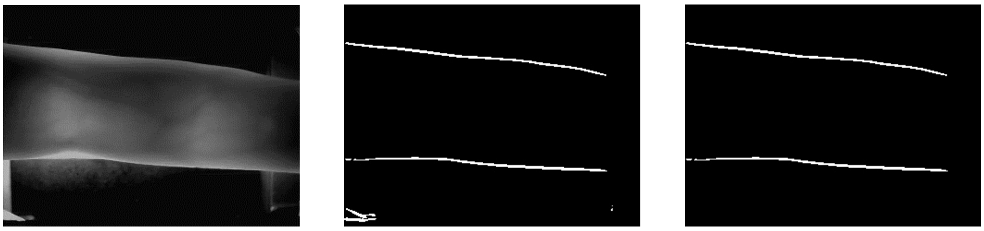
ELM is a learning algorithm based on single hidden layer feedforward neural networks (SLFNs). A powerful learning algorithm proposed by Huang Guangbin and others[8, 9, 10] . Compared with the traditional BP neural network using the error gradient descent learning strategy, ELM has the advantages of fast convergence, good generalization performance, does not fall into a local minimum, and can use a variety of excitation functions[11] . Therefore, this paper proposes a finger vein recognition method based on the combination of a deep convolutional network and an over-limit learning machine. This method uses deep convolutional network to extract the deep feature vector of the finger vein ROI and input the extracted deep feature vector into the over-limit learning Compared with conventional methods, not only the recognition accuracy is higher, but also the generalization ability is stronger.

## 2. Finger Vein ROI Image Extraction

Generally, the finger vein image collected contains not only the finger vein image, but also some irrelevant information such as the device, so it is necessary to extract the finger vein ROI. The extraction of finger vein ROI images by traditional methods is mainly divided into the following parts.

### 2.1. Finger Edge Detection

By detecting the edge of the finger, the position of the finger is obtained initially. The common edge detection operators are Sobel operator, Prewitt operator and Canny operator. The experiment performed edge detection on the finger vein image of Fig. 1 (a) by Prewitt operator, and obtained Fig. 1 (b). Remove the irrelevant edge area in Fig. 1 (b) to get Fig. 1 (c)



(a) Original finger vein image (b) Finger vein edge detection image (c) Irrelevant edge area removed

**Fig 1.** Finger edge detection process

### 2.2. Finger Rotation Correction

In the process of collecting finger vein images, it is very likely that the fingers will rotate in a plane. In order to ensure the effectiveness of extracting ROI, it is usually necessary to correct the rotation of the fingers. Use the upper and lower finger edge curves obtained in Section 2.1 to traverse the upper and lower edge pixels along the x-axis from left to right, and add the y-axis coordinates to average the point set of the central axis, which is fitted by the least square method the axis of the finger. The midline fitting formula is as follows:

$$k = \sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y}) / \sum_{i=1}^{n}(x_i - \bar{x})^2 \tag{1}$$

$$b = \bar{y} - k\bar{x} \tag{2}$$

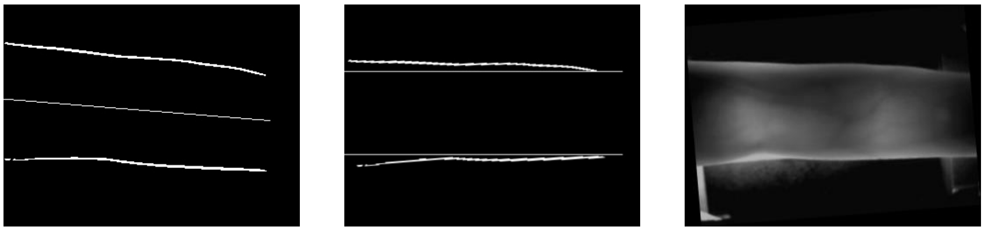
ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202004_3(4).0014

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3}$$

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{4}$$

In the formula, $k$ is the slope of the fitted midline, $b$ is a constant, $\bar{x}$ is the x-axis average of all points, and $\bar{y}$ is the y-axis average of all points, $i = 1, 2 \cdots n$.

Fig. 2 (a) is the image of the edge of the finger after the midline fitting, and rotated counterclockwise to obtain the image of the edge of the finger after rotation correction in Fig. 2 (b).

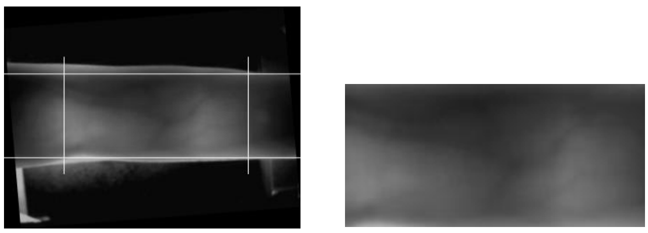


(a) Centerline fit image (b) Finger edge corrected image (c) Original image corrected image

**Fig 2.** Finger rotation correction process

### 2.3. Finger Vein ROI Capture

By observing the finger vein image, it can be found that the average brightness of the knuckle area is greater than other positions, so the positioning is relatively simple. Therefore, when the ROI of the knuckle is generally cut, the knuckle is often used as the benchmark. As shown in Fig. 3 (a), the ROI image is positioned with the knuckle as a reference. Fig. 3 (b) is the final extracted ROI image of the finger vein.



(a) Positioning ROI by knuckle (b) ROI image of finger vein

**Fig 3.** Finger Vein ROI Extraction Process

## 3. Improved Convolutional Neural Network Finger Vein Recognition Method

The network structure of a convolutional neural network includes an input layer, a convolutional layer, a pooling layer, a fully connected layer, and an output layer. A deep convolutional network has a deeper network structure. A deep convolutional network can generally be considered to consist of two major parts. The first part is a feature extractor consisting of alternating convolutional layers and pooling layers. The second part consists of

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202004_3(4).0014

one or more fully connected layers plus an output layer. Composed classifier. As shown in Fig. 4.

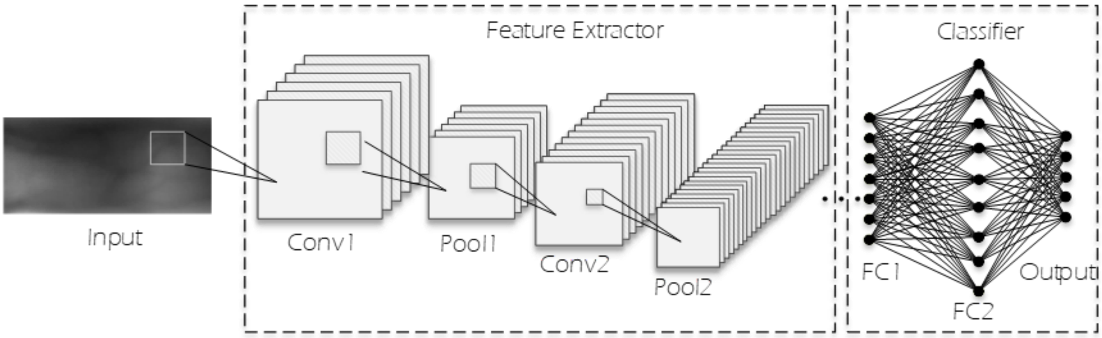



**Fig 4.** Convolutional neural network structure

Unlike other deep learning models, DCNN can use backpropagation for parameter optimization training. Due to its three structural features (i.e. local receptive fields, shared weights and subsampling), the number of hyperparameters is greatly reduced, but due to the fully connected layer the composed classifier is trained by gradient descent, so the generalization ability is limited. Aiming at the problem of insufficient generalization ability of the classifier composed of fully connected layers, this paper proposes a finger vein recognition method based on the combination of deep convolutional network and extreme learning machine.

The specific implementation steps are as follows:

(1) Preprocessing the finger vein training set data to obtain the finger vein training set samples.

(2) Construct a convolutional autoencoder model, and use the finger vein training set data to perform unsupervised training on the convolutional autoencoder to obtain the coding layer parameters.

(3) Build a deep convolutional network model and initialize the convolutional layer parameters of the deep convolutional network using the encoding layer parameters obtained from the convolutional self-encoder.

(4) Use the training set samples to train the deep convolutional network. The output results and the sample labels are used to calculate the error. The back-propagation algorithm and gradient descent method are used to iteratively update the parameters of the deep convolution network to obtain the optimal parameters.

(5) Remove the fully connected layer of the trained deep convolutional network, add the limit learning machine layer, train this layer, and get the trained parameters.

(6) Preprocessing the finger vein test set data to obtain finger vein test set samples, and input them into the parameter-trained network model to obtain the recognition type.

Among them, the activation function used is LeakyReLU:

$$f(x)=\begin{cases} x & x>0 \\ \gamma x & x<0 \end{cases} \tag{5}$$

In the formula, $\gamma$ is a small constant.

Among them, the cross-entropy loss function is used to calculate the error:

$$E=-\sum_k t_k \log(y_k) \tag{6}$$

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202004_3(4).0014

In the formula, $y_k$ is the prediction type and $t_k$ is the true type.

Compared with the conventional method, the method in this paper uses deep convolutional network to automatically extract the finger veins to reduce the large amount of effective information lost during the traditional extraction of finger veins. At the same time, it introduces a limit learning machine layer to increase generalization.

In training, in order to improve the training efficiency of deep convolutional networks, this paper uses a deep convolutional encoder to perform unsupervised pre-training on the samples, obtain the preliminary characteristics of the finger vein samples, and use the parameters trained by the deep convolutional encoder to detect the depth of the convolutional network. The convolutional layer parameters of the convolutional network are initialized. Figure 3 shows the initialization process of the finger vein recognition model parameters.

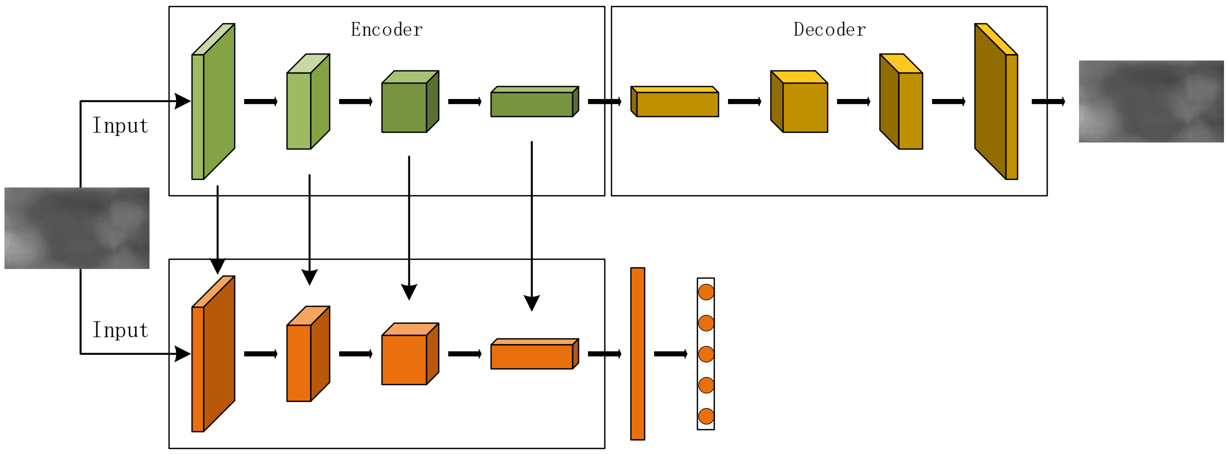



**Fig 5.** Parameter initialization process of finger vein recognition model

## 4. Experimental Results and Comparative Analysis

### 4.1. Finger Edge Detection

The effectiveness of the proposed network model was evaluated through two publicly available finger vein databases, namely the FV-USM database of the University of Malaysia and the SDUMLA database of the Shandong University[12], [13] . The following is an introduction to the two databases.

(1) The FV-USM database is from the Malaysian Polytechnic University. The database collected the index and middle fingers of the left and right hands of 123 subjects, including 83 males and 40 females, aged between 20 and 52 years old. Each finger was collected in two stages. Six finger vein images were collected at each stage, and a total of 12 finger vein images were collected.

(2) The SDUMLA database was collected by Shandong University. The database collected the index, middle and ring fingers of the left and right hands of 106 subjects, including 61 males and 45 females, aged between 17 and 31 years old. Six fingers vein images were collected with one finger at a time.

Using the finger vein ROI extraction method, ROI image extraction was performed on the finger vein data collected from the two finger vein databases, and the training and test sets of each finger ROI image in the extracted database were divided into 4: 2 ratios.

### 4.2. Construction of Convolutional Neural Network Feature Extraction Model

This paper builds a deep convolution model through experiments. The network model consists of 21 layers, including 1 input layer, 16 convolutional layers, 1 maximum pooling layer, 2 fully connected layers, and 1 output classification layer. Table 1 is Detailed network structure

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202004_3(4).0014

settings. To prevent the network from overfitting, Dropout is added after each fully connected layer.

**Table 1.** Deep Convolutional Network Structure Settings

| Layer | Size of Feature Map | Size of Kernel | Stride | Padding |
|---|---|---|---|---|
| Conv1 | 128*160*64 | 5*5 | 2 | 2 |
| Maxpool | 64*80*64 | 3*3 | 2 | 1 |
| Conv2-Conv5 | 64*80*64 | 3*3 | 1 | 1 |
| Conv6 | 32*40*128 | 3*3 | 2 | 1 |
| Conv7-Conv9 | 32*40*128 | 3*3 | 1 | 1 |
| Conv10 | 16*20*256 | 3*3 | 2 | 1 |
| Conv11-Conv113 | 16*20*256 | 3*3 | 1 | 1 |
| Conv114 | 8*10*512 | 3*3 | 2 | 1 |
| Conv15-Conv17 | 8*10*512 | 3*3 | 1 | 1 |
| FC18 | 1024 | - | - | - |
| FC19 | 512 | - | - | - |
| Output | classes | - | - | - |

## 4.3. Experimental Results and Analysis

The proposed model is used to train the finger vein ROI datasets extracted from the SDUMLA and FV-USM datasets respectively. The training set recognition accuracy curve and loss curve are shown in Fig. 6, where the vertical axis represents the recognition accuracy rate and loss value. The horizontal axis represents the number of iterations of the model, and all the training set data is trained once for one iteration.

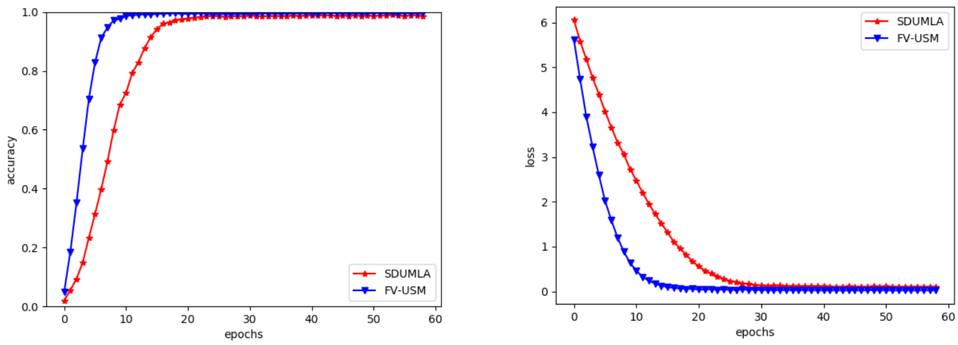



**Figure 6.** The recognition accuracy curve and loss curve of training set recognition in SDUMLA and FV-USM data sets

The convolutional layer parameters of the trained deep convolutional model are kept unchanged, the fully connected layer is replaced with the extreme learning machine layer, and then the extreme learning machine layer is trained. The retrained model is imported into the test set data and tested to obtain recognition results. Table 2 compares the recognition accuracy of the methods mentioned in the literature and the method in this paper in two common data sets.

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202004_3(4).0014

**Table 2.** Comparison of recognition rates of two public data sets

| Comparison methods | Database | |
|---|---|---|
| | FV-USM | SDUMLA |
| CNN(based on LeNet)[1]. | 97.53% | 97.48% |
| CNN with CLAH[1]. | 97.05% | 95.13% |
| ARTeM[14]. | - | 90.72% |
| Pseudo-elliptical transformer[15]. | 97.02% | 97.61% |
| Proposed CNN | 98.02% | 97.86% |
| Proposed CNN+ELM | 98.88% | 98.58% |

As can be seen from Table 2, compared with the other methods in the table, the method in this paper has achieved the best recognition accuracy on both public data sets. Compared with other methods, the recognition accuracy on FV-USM dataset is improved by 1.35% to 1.86%. Compared with other methods, the recognition accuracy on the SDUMLA dataset is improved by 0.97% to 7.86%. Comparing the fully connected layer as a classifier and ELM as a classifier, it can be obtained that when ELM is used as a classifier, it has better generalization performance, and the test set recognition accuracy is higher.

## 5. Summary

Aiming at the problems of traditional finger vein recognition methods with low recognition accuracy and weak generalization performance, this paper proposes a finger vein recognition method based on the combination of deep convolutional network and over-limit learning machine, and carried out through two public data sets. Experimentally, the method proposed in this paper is compared with the recognition methods in[1] , [14] and[15].

1) Compared with the traditional finger vein recognition model that requires manual extraction of geometric feature vectors as input, this method automatically extracts the finger vein image features, simplifies the feature extraction steps in traditional finger vein recognition, and improves the finger vein recognition efficiency.

2) The method in this paper uses deep convolutional networks to perform automatic feature extraction on the finger veins to reduce the large amount of effective information lost in the traditional method feature extraction. At the same time, in order to enhance generalization, the original fully connected layer is removed from the deep convolutional network. The limit learning machine layer is added to identify the extracted feature vectors. Compared with other methods, the proposed method achieves better recognition results.

## References

[1] T. Liu, J. B. Xie and W. Yan, et al. An algorithm for finger-vein segmentation based on modified repeated line tracking, The Imaging Science Journal. Vol. 61(2013) No. 6, p. 491-502.

[2] X. Meng, G. Yang and Y. Yin, et al. Finger Vein Recognition Based on Local Directional Code, SENSORS. Vol. 12(2012) No. 11, p. 14937-14952.

[3] H. Qin, L. Qin and L. Xue, et al. Finger-Vein Verification Based on Multi-Features Fusion, SENSORS. Vol. 13(2013) No. 11, p. 15048-15067.

[4] A. Krizhevsky, I. Sutskever and G. Hinton, et al. ImageNet Classification with Deep Convolutional Neural Networks, COMMUNICATIONS OF THE ACM. Vol. 60(2017) No. 6, p. 84-90.

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202004_3(4).0014

[5] P. Li, Z. Chen and L. T. Yang, et al. Deep Convolutional Computation Model for Feature Learning on Big Data in Internet of Things, IEEE Transactions on Industrial Informatics. Vol. 14(2018) No. 2, p. 790-798.

[6] J. Kang, Y. Park and J. Lee, et al. Novel Leakage Detection by Ensemble CNN-SVM and Graph-Based Localization in Water Distribution Systems, IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS. Vol. 65(2018) No. 5, p. 4279-4289.

[7] L. H. S. Vogado, R. M. S. Veras and F. H. D. Araujo, et al. Leukemia diagnosis in blood slides using transfer learning in CNNs and SVM for classification, ENGINEERING APPLICATIONS OF ARTIFICIAL INTELLIGENCE. Vol. 72(2018) No. 6, p. 415-422.

[8] G. Huang, Q. Zhu and C. Siew, et al. Extreme learning machine: Theory and applications, NEUROCOMPUTING. Vol. 70(2006) No. 1, p. 489-501.

[9] J. Tang, C. Deng and G. Huang Extreme Learning Machine for Multilayer Perceptron, IEEE Transactions on Neural Networks and Learning Systems. Vol. 27(2016) No. 4, p. 809-821.

[10] Z. Huang, Y. Yu and J. Gu, et al. An Efficient Method for Traffic Sign Recognition Based on Extreme Learning Machine, IEEE Transactions on Cybernetics. Vol. 47(2017) No. 4, p. 920-933.

[11] G. Huang, H. Zhou and X. Ding, et al. Extreme Learning Machine for Regression and Multiclass Classification, IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics). Vol. 42; 42(2012) No. 2; 2, p. 513-529.

[12] Y. Yin, L. Liu and X. Sun, SDUMLA-HMT: A Multimodal Biometric Database, Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 260-268.

[13] M. S. Mohd Asaari, S. A. Suandi and B. A. Rosdi Fusion of Band Limited Phase Only Correlation and Width Centroid Contour Distance for finger based biometrics, EXPERT SYSTEMS WITH APPLICATIONS. Vol. 41(2014) No. 7, p. 3367-3382.

[14] A. Banerjee, A. Banerjee and S. Basu, et al. ARTeM: a new system for human authentication using finger vein images, MULTIMEDIA TOOLS AND APPLICATIONS. Vol. 77(2018) No. 5, p. 5857-5884.

[15] S. Qiu, Y. Liu and Y. Zhou, et al. Finger-vein recognition based on dual-sliding window localization and pseudo-elli.