Dorsal Hand Vein Recognition Based On Convolutional Neural Networks

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***Abstract*—In this paper, we proposed a dorsal hand vein recognition method based on Convolutional Neural Network (CNN), compared the recognition rate of different depth CNN models and analyzed the influence of dataset size on dorsal hand vein recognition rate. Firstly, the region of interest (ROI) of dorsal hand vein images was extracted, and contrast limited adaptive histogram equalization (CLAHE) and Gaussian smoothing filter algorithm were used to preprocess the images. Then Reference-CaffeNet AlexNet and VGG depth CNN were trained to extract image feature. Finally, logistic regression was applied for identification. The experimental results on two different size of dataset shown that the depth of network and size of data set size have different degree effect on recognition rate, the dorsal hand vein recognition rate based on VGG-19 reaches 99.7%. In this paper, we also explored the feasibility of ensemble learning on SqueezeNet. The recognition rate declined slightly with 99.52%, but the model size has been decreased sharply.**

Keywords—dorsal hand vein recognition; deep learning; convolutional neural network; ensemble learning

I. INTRODUCTION

Dorsal hand vein recognition technology is a kind of biometric recognition based on the characteristics of the dorsal hand vein. Compared with traditional biological features, the dorsal hand vein characteristics have more following advantages: The first one is uniqueness, even between the twins, there is still some difference in the dorsal hand veins; the second one is invariance, the dorsal hand vein of human is basically constant; the third one is difficult to forge, the dorsal vein is a kind of biological characteristic; the last one is the detection method is friendly, as the dorsal vein characteristics belong to the internal features, it is difficult to be damaged. Therefore, the technique of dorsal hand vein recognition has great research value and wide application prospect.

Owing to the characteristic of deep learning that can automatically select the target feature, it performs well in solving the problem like visual recognition, speech recognition and natural language processing. Afterwards, among the common model of deep learning, CNN (Convolution Neural Network) which is inspired by the mechanism of natural visual cognition, gets the most thorough research. Its modern structure was established in the paper published by LeCun et al in the 1990s [1]. CNN can obtain the effective representation of the original image, and can recognize its visual regularity directly from the image pixels with very little pretreatment.

The main contributions of this paper are as follows:

- Proposed a method of dorsal hand vein recognition based on CNN, which use the depth feature of the dorsal hand vein is to identify;
- The feature extraction method of CNN avoids cumbersome manual selection process and simplifies the preprocessing;
- Analyzing the influence of the depth of the network and the amount of data to recognition rate, by comparing the recognition rate of the CNN model with different depth and the recognition rate of the varying expansion degrees of dorsal vein data. Analyzing feasibility of EnsembleDCNN [2] method.

II. RELATED WORK

In recent years, the research methods for the identification of the dorsal hand vein make unceasing progress. In the existing recognition method, the recognition method based on texture and shape feature has its own progress, in which the local texture is stronger than the global texture with regard to the ability of describing the texture feature information.

In the recognition method based on the feature extraction of global texture information, there are methods of LDA [3] and Khan M et al. PCA [4], but the extracted information is limited and the recognized result is not ideal; The recognition method based on local texture information is mainly divided into dense texture description method, including methods of LBP [5], Lee JC et al. Gabor [6], and the sparse local texture description method, such as SIFT [7], where the OGMs + SIFT [8] created by Huang D et al. based on multi-key fusion feature matching is superior to other local texture description method in recognized effect .

There are obvious topological structures in the dorsal hand vein, and the shape information can also be used to characterize the matching. The commonly used recognition method of local shape description is the LBP [9] coding and BC coding studied by Zhu X et al. The global structural information is more effective than the description of local shape. For example, the recognition method which is created by Wang Y et al. based on FGM [10] using the graph model to match the graph, does not have enough representational capacity because of single shape information. The characterization of the shape information is not strong enough. However, LBP + BC + Graph [11], BC + Graph [12] and other methods which embedded texture information in the graphics structure can effectively improve the recognition rate.

Among the feature extraction method, the existing methods do not discriminative enough to the feature, and the feature selection is too dependent on artificial selection. Therefore, there are several inconvenience in the practical application of dorsal hand vein recognition, such as it needs plenty of time to describe the adjustment of sub-parameters and cannot ensure the accuracy of expression and the selection of features. Nevertheless, Yiding Wang et al. applied the deep learning method DBN [13] to the dorsal vein recognition, which is an attempt to the depth method, and has obvious advantages over the traditional PCA and LBP algorithms.

As above mentioned, the recognition method based on CNN, which uses CNN depth model to eliminate the work of selecting feature artificially, can select and express the depth feature of the image automatically in the case of having been preprocessed simply, thus ensured the accuracy of the selection of image feature and the validity of the representation.

III. IDENTIFICATION FRAMEWORK

In this paper, the process framework of vein recognition mainly includes the preprocessing of vein image, transforming the image data into the more efficient format in processing called LMDB (Lightning Memory-Mapped Database Manager); CNN network construction; network training; softmax logical regression classifier training and other steps. The processes are divided into training and identification; the process framework of identification is shown in Fig. 1.

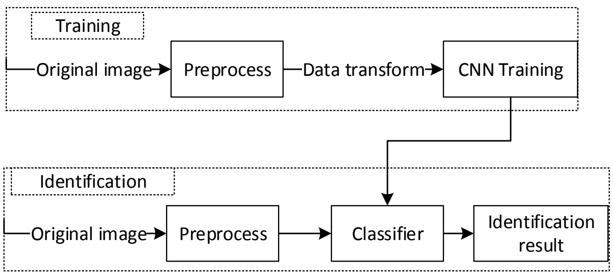


Fig. 1. The framework of dorsal hand vein recognition

IV. IMAGE PREPROCESSING

The data set used in this experiment is NIR (Near Infrared Reflection) vein image whose imaging resolution is not high, and need image preprocessing, which includes using centroid method to extract the image ROI (Region of Interest), using CLAHE (Contrast Limited Adaptive Histogram Equalization) [14] algorithm to enhance the contrast of the image.

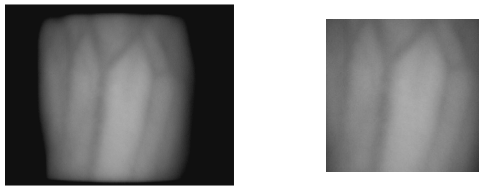
A. ROI Extraction

The coverage area of the collected image is larger than that of the dorsal vein, and the centroid method take centroid of image as the standard of ROI extraction. (x_0, y_0) as the centroid of the dorsal hand vein image, the calculation process is shown in equation (1) (2):

$$x_0 = \frac{\sum_{i,j} i \times f(i,j)}{\sum_{i,j} f(i,j)} \tag{1}$$

$$y_0 = \frac{\sum_{i,j} j \times f(i,j)}{\sum_{i,j} f(i,j)} \tag{2}$$

After finding the centroid of image, taking a subgraph of 360×360 pixels as the center, Fig. 2 (a) (b) show the original image and the extracted ROI region:

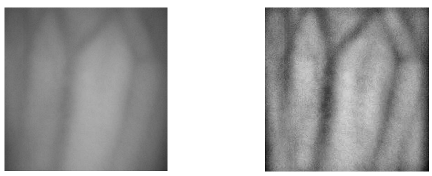


(a) (b)

Fig. 2. (a) Original image (b) ROI

B. Image Contrast Enhancement

After obtaining the ROI of the image, it is necessary to enhance the contrast processing of the image, and CLAHE which can limit the contrast adaptive histogram equalization is a commonly used vein image enhancement algorithm. The traditional histogram equalization algorithm is easy to cause the loss of image's detail information, which can affect the effect of recognition. CLAHE compared with the traditional method has obvious advantages. CLAHE is characterized by contrast limiting, and every small area in the image must use contrast limiting. CLAHE is achieved by cutting the histogram with a predefined threshold before calculating the cumulative histogram function to achieve the purpose of limiting the magnification. The adaptive histogram calculates the neighborhood histogram and the corresponding transform function for each pixel in the image. The bilinear interpolation is used to speed up the calculation of the algorithm. The original image is shown in Fig. 3. (a) The image is shown in Fig. 3. (b):



(a) (b)

Fig. 3. (a) Origin image (b) Enhanced image

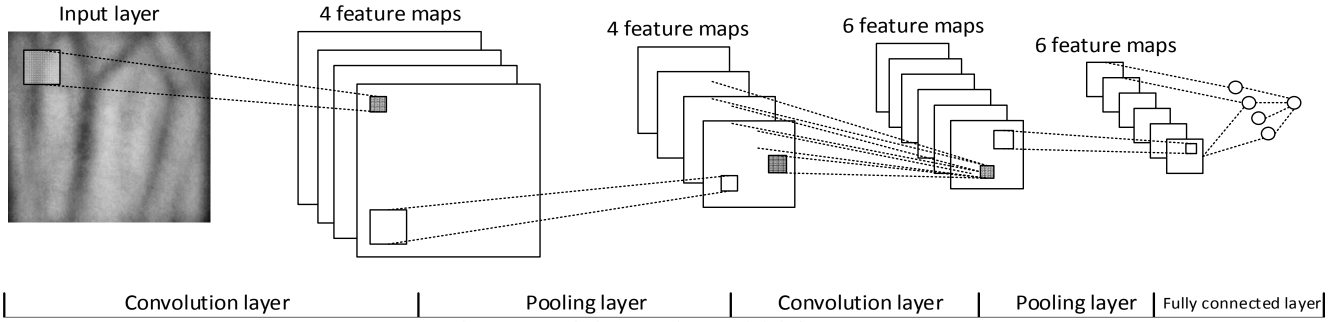


Fig. 4. Convolution neural network brief structure

V. Analysis of Network Structure

In this paper, the CNN network of deep learning is used, and the important components involved in the network and the overall structure of the network are analyzed before the experiment.

Convolution neural network is a type of the deep neural network, which is a special kind of image recognition method, which belongs to a very effective network with forward feedback. CNN has special structure in the treatment of various forms of deformation of the image with a high degree of invariance. The structure of a conventional convolutional neural network is shown in Fig. 4. The characteristics of each feature extraction layer of the convolutional neural network are different. The underlying layer is mainly concerned with the characteristics of the pixel level. After the feature extraction, the topology of the image content, the sequence type, and the structure type are extracted as a characterization.

The maximum limitation of conventional neural networks in image recognition is that it does not handle the local and global relationship of images well. In computer vision, natural language processing and speech recognition, the data are composed of low-level features into high-level characteristics, and can get the spatial correlation between different features. Due to the existence of convolution kernel, convolution neural network for processing the kind of multidimensional data has obvious advantages. Convolution neural networks have several important concepts: convolution layers, pooling layers, fully connection layers, activation functions, and so on.

- Convolution Layer: Using filters to process the input data is used for many types of feature extraction. The image is passed through a filter and a characteristic map is obtained. The result of each convolution is composed of multiple feature maps. Different filters can learn different features. The feature map is characterized by different characteristics.
- Pooling Layer: The main role is to reduce the connection between the convolution layers, reduce the size of the input data, and reduce the complexity of the operation. Common pooling methods are maximized, averaged, and randomized.
- Fully Connected Layer: The main function is the classifier, and the result is normalized by the softmax layer to obtain the probability value.
- Activation Function: The deep neural network is rich in the ability to express, deep is one of the factors. There is also an important factor in the non-linear processing unit that is activated function. The activation function compresses the input linear result of the previous layer into a specific range of values. The deep network has a nonlinear processing unit, which can theoretically fit any function. The commonly used activation function: Sigmoid, Tanh, ReLU.

Sigmoid：
$$\varphi(x) = \frac{1}{1+e^{-ax}} \tag{3}$$

Tanh：
$$\varphi(x) = \frac{1-e^{-2x}}{1+e^{-2x}} \tag{4}$$

ReLU：
$$\varphi(x) = \max(0,x) \tag{5}$$

In order to solve the problem that the CNN is difficult to train, in recent years there have been several classic CNN structures on ILSVRC: AlexNet [15], ZFNet [16], VGGNet [17], GoogleNet [18] and ResNet [19]. In the structure of network, the development direction of CNN is depth and reduce quantity of parameters. The deeper structure can better fit the objective function by adding nonlinearity, and can be better characterized, but requires a lot of training dates. In order to reflect the effect of network structure on vein recognition, the experimental results of AlexNet, CaffeNet and VGGNet were compared. SqueezeNet [20] is used to test the EnsembleDCNN method.

A. AlexNet and Reference-Caffenet

AlexNet structure is the champion of the ImageNet contest, and Reference-Caffenet is the structure that the Caffe deep learning framework defines for AlexNet. The network's input layer data is 227×227 three-channels image, and this structure includes five convolution layers, three pooling layers, three LRN layers, three full-connection layers, and ReLU active layers, Softmax layer, Dropout layers. Eight of them are mainly applied to feature learning and feature extraction. The main difference between the two structures is the order of the LRN layers and the pooling layers.

B. VGG-16 and VGG-19

VGGNet adjust the convolution kernel size on the basis of AlexNet, the first proposed the advantages of superposition of the small convolution kernels: the amount of parameters decreased, the characteristics of learning can be enhanced. The emergence of VGGNet explain the upgrade of the CNN depth can bring better recognition and detection results. VGG has a variety of different structures, this paper chooses structure D and E: VGG-16 and VGG-19 for experiments. The Conv structure is shown in Fig .5.

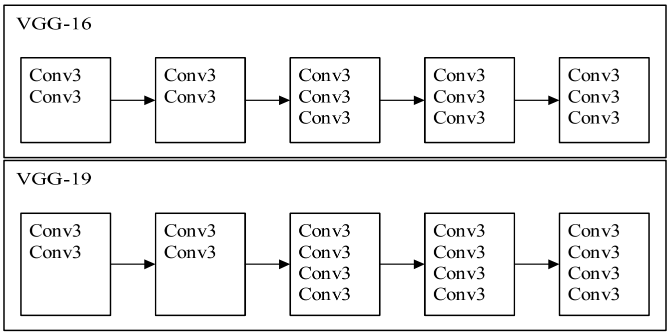


Fig. 5. Conv structure of VGGNet

C. SequeezeNet

SqueezeNet is a small size model, achieves AlexNet level accuracy with 50x fewer parameters. This smaller CNN architecture has at least three advantages: distributed training faster, require less bandwidth from cloud to car, more feasible to deploy on FPGAs. It is not to get the best CNN recognition accuracy, but to simplify the complexity of network, while achieving the public recognition. Its structure has a key module named fire module that separate the Conv to squeeze layer and expand layer. It is shown in Fig.6.

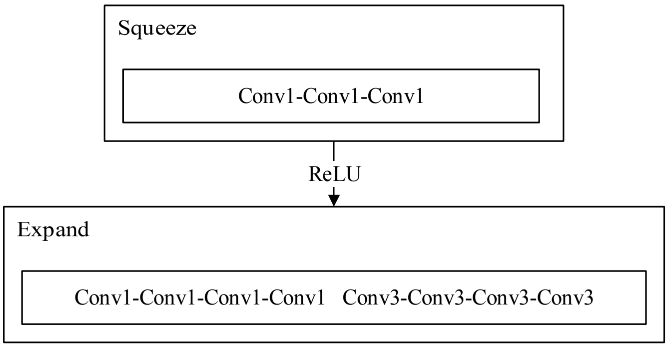


Fig. 6. Fire module of SqueezeNet

VI. EXPERIMENT AND RESULT ANALYSIS

This section is to achieve the results of dorsal hand vein recognition experiments and analysis based on CNN. Using Caffe deep learning convolution neural network framework to build the AlexNet, Reference-CaffeNet, and VGGNet. The process includes mainly: data set preparation, data conversion, model training, adjustment parameters and recognition process. And the experimental results were analyzed on the NCUT dorsal hand vein data set. Finally, we test the EnsembleDCNN method.

A. Data Set

The data set used in this paper is one of the larger data sets currently disclosed in the field of dorsal hand vein recognition [21]. The data set is collected by the near infrared camera, divided into Part A, Part B, Part C three parts. Part A consists of 102 different peoples with the left and right hand near infrared dorsal hand vein image composition, including 50 males, 52 females, each hand include 10 images; Part B include 101 individuals with a total of 2020 images; Part C by 134 individuals with a total of 2680 images. Three parts of the image size is same. But A, C part of the data set is more clear than the B part, the study found that the existing identification method set Part A as the main test data set.

B. Criteria for Judging

The recognition rate of the existing dorsal hand vein recognition method is mostly the result of the identification of 204 classes in Part A. In this paper, we will also test the CNN-based dorsal hand vein recognition method on the Part A data set. At the same time, the experimental data are expanded with Part A and Part C, and the relationship between the recognition effect and the data volume is analyzed. In the experiment, the data sets were divided into training set (G) and test set (P) by the training test ratios 4: 6 and 5: 5. The first stage of the experiment was to train AlexNet, Reference-Caffenet and VGGNet in different proportions of training and test data, and compare the results of the horizontal comparison experiment. The second stage was to fine-tune [22] the network with the training model of the ImageNet [23] data set, and compare the results of the longitudinal comparison experiment. The third stage is to expand the amount of data set for training, vertical comparison of experimental results. The fourth stage is the result of EnsembleDCNN method. The experimental results were compared with other dorsal hand vein recognition method to verify the effectiveness and feasibility of this method.

C. Experimental Results

In this paper, the experiment consists of three stages, each stage including: random selection of training set and test set; adjusting the appropriate batch size according to the hardware performance: GPU memory size; adjusting the optimization strategy according to the training result convergence; adjusting the learning rate, weight decay and other parameters. The adjustment of the model parameters and the training super parameters is the basis of experimental results. Experimental environment is win10 64-bit operating system, 32G memory, NVIDIA GTX 1080 graphics card, 11G memory, and Caffe deep learning architecture. The results of the training convergence are measured in terms of the number of iterations as shown in Table 1.

TABLE I. TRAINING CONVERGENCE RESULTS

Training Strategy	Iterations
Full training	10000
Fine-tuning	4000

It can be seen from this table, after 10,000 iterations the results of full training began to stabilize, fine-tuning after 4000 iterations began to show stable results. So in the training of deep learning model the appropriate fine-tuning can help to improve the training speed.

1) Stage one: At this stage, the data set Part A is trained in several CNN structures according to the ratio of 4: 6 and 5: 5, respectively. Finally, the training results are obtained. Table 2 shows the comparison of the test results.

TABLE II. TEST RESULT

Network Structure	G:P(5:5)	G:P(4:6)
AlexNet	97.3%	96.71%
Reference-CaffeNet	97.22%	96.3%
VGG-16	98.1%	97.51%
VGG-19	98.23%	97.2%

It can be seen from this table, VGGNet test results are superior to AlexNet and Reference-CaffeNet, and it can be concluded that more feature learning layers will improve the results of the dorsal vein hand recognition task. The richer the characteristic of learning, the more accurate the expression of the feature. In the case of making full use of existing resources, the increase in the network structure has improved the recognition rate.

The model of deep learning needs to be trained on large data to get excellent results, the purpose is to make the training of the underlying characteristics more diversified. Rich underlying features can help us train excellent high-level abstract features, large-scale data training model will help us to achieve better results in the face of specific tasks.

2) Stage two: Based on the model trained on the ImageNet dataset, fine-tuning the network. Because of the small amount of the dorsal hand vein dataset, this paper uses the method of transfer learning to train the model. The transfer learning is divided into: data transfer, model transfer and parameter transfer. Fine-tuning belongs to the method of parameter transfer in transfer learning. Table 3 are the results of the fine-tuning test.

TABLE III. FINE-TUNING TEST RESULT

Network Structure	G:P(5:5)	G:P(4:6)
AlexNet	99.1%	98.3%
Reference-CaffeNet	99.33%	98.2%
VGG-16	99.61%	98.43%
VGG-19	99.7%	98.7%

This table shows that after Fine-tuning the network test results have been improved. This is an effective way to improve the recognition result for the case of the small count of dorsal hand vein data.

3) Stage three: the experimental data were expanded and the Part A and Part C were merged with 468 classes, and the first two phases of experiment were repeated. The test results are shown in Table 4.

TABLE IV. PART A AND B TEST RESULT

Network Structure	G:P(5:5)	G:P(5:5)Fine-tuning
AlexNet	98.1%	99.1%
Reference-CaffeNet	97.7%	99..05%
VGG-16	98.3%	99.53%
VGG-19	98.5%	99.4%

Experimental results show that after the data amplification, part of the experimental recognition rate decreased. Analysis the reasons: Part A data set as a test standard, the data quality is better, the quality of Part C data set may affect the identification. The dorsal hand vein data amplification experiment will be studied later.

4) Stage four: in this stage we focus on the decrease of model size but not lose too much accuracy. We train five Squeeze networks in shuffled train dataset separately. And to combine the result from all networks, we use majority voting ensemble method. The brief structure shown in Fig.7.

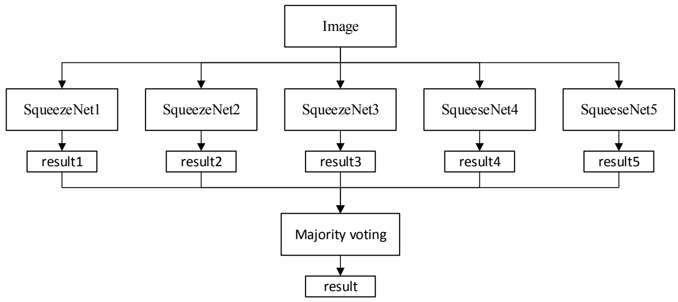


Fig. 7. Majority voting EnsembleDCNN

The result is shown in Table 5.

TABLE V. DIFFERENT ALGORITHM TEST RESULT

Algorithm	G:P	Result
OGMs+SIFT[8]	5:5	99.02%
OGMs+SIFT[8]	4:6	98.20%
BC+Graph[12]	5:5	97.82%
LBP+Graph[9]	5:5	96.67%
Multi-source Keypoint+SIFT[24]	5:5	99.61%
Multi-source Keypoint+SIFT[24]	4:6	99.35%
CSLBP+DBN[13]	5:5	98.5%
WSM[25]	5:5	99.31%
LBP+BC+Graph[11]	5:5	99.21%
AlexNet(ours)	5:5	99.1%
AlexNet(ours)	4:6	98.3%
Reference-Caffenet(ours)	5:5	99.33%
Reference-Caffenet(ours)	4:6	98.2%
VGG-16(ours)	5:5	99.61%
VGG-16(ours)	4:6	98.43%
VGG-19(ours)	5:5	99.7%
VGG-19(ours)	4:6	98.7%
SqueezeNet best(ours)	5:5	99.02%
EnsembleDCNN-5(ours)	5:5	99.52%

The experimental results in Table 5 are based on experiments in the Part A dataset at 5: 5 and 4: 6 ratios. It can be seen that the CNN-based dorsal hand vein recognition method has better result than most existing multi-feature fusion methods. And the result of EnsembleDCNN method is as well as VGG, but the model size is smaller than VGG and AlexNet. In the future, we may deploy the model on the mobile platform, so the smaller size model is necessary. The experimental results were obtained with cross validation, and Table 6 shows the results of the VGG-19 through the cross validation experiment.

TABLE VI. VGG-19 CROSS VALIDATION RESULT

Test1	Test2	Test3	Test4	Test5	Test6
99.15%	99.02%	99.63%	99.4%	99.7%	99.34%

After cross validation, the recognition rate can be significantly improved. In terms of recognition efficiency, the deep learning method is more efficient in online recognition than the traditional method of identifying selected features, and it will be more efficient as the network structure is continuously optimized. In practical application, compared with the traditional artificial selection of feature methods, the deep learning CNN method need less pretreatment, automatic selection of features more accurate and more convenient to use. Therefore, based on convolution neural network, the method of dorsal hand vein recognition is feasible and reliable. The application of convolution neural network in the field of dorsal hand vein recognition has great advantages. And it’s possible to deploy the small size model on the mobile platform.

VII. CONCLUSION

In this paper, a method of dorsal hand vein recognition based on convolution neural network in deep learning is proposed. CNN can learn images in end-to-end with a small amount of preprocessing, and parameter transfer makes feature extraction more efficient. The whole process not only guarantees the reliability of the feature, but also ensures the efficiency of recognition. The experimental results show that the recognition method based on convolution neural network is superior to most existing multi-feature fusion recognition methods, and deep learning method has advantages itself: high efficiency and feature selection is convenient. This method can be effective in practical application. With the development of deep learning technology and the expansion of the dorsal vein data set, the recognition rate will be further improved. The next step, we will use a large artificial dorsal hand vein data set to Full-training CNN and explore the new structure small model to get the more effective recognition method.

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