Damaged Fingerprint Classification by Deep Learning With Fuzzy Feature Points

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Abstract—**As the world enters the information age, the need for identity verification becomes more and more urgent. Therefore, fingerprint identification technology is widely used in the field of personal authentication. With the efforts of researchers, the algorithms of fingerprint recognition have currently made great progress. However, the authentication of low quality fingerprint still needs further improvement. Aiming at imperfect fingerprints, we propose an improved damaged fingerprint recognition algorithm by feature points, based on Convolution Neural Network (CNN) of Deep Learning. Finally, the recognition rate based on Deep Learning is compared with the fingerprint identification algorithm based on Kernel Principal Component Analysis (KPCA) and k-Nearest Neighbor (KNN). Experiments' results show that fingerprint recognition based on Deep Learning has a higher recognition rate.**

Keywords-fingerprint identification; Convolution Neural Network (CNN); fuzzy feature points; recognition rate

I. INTRODUCTION

With the rapid development of social information, identification of personal identity has become an effective measure to safeguard national security and maintain social order. Traditional identification methods generally use the markers (such as keys and ID card) and knowledge (such as passwords and codes) to achieve the purpose of identity authentication and identification. However, these identification methods are carried out by means of object recognition, in which always exists the risk of loss, theft, or even be forged. Therefore, the biological identification technology is used to overcome these shortcomings of traditional authentication methods. Biological Identification Technology (BIT) [1] refers to using physiological characteristics for identity recognition, which generally exist in each individual but are different in features. Fingerprint recognition [2], palm geometry recognition, voice recognition, retina recognition, iris recognition, face recognition are all the means of BIT. Among them, the fingerprint identification technology has become a hot spot because of its convenient collection, the uniqueness of the fingerprint, and the reliability of identification.

Traditional fingerprint identification methods include two ways: supervision and semi-supervision [3]. Supervision is the way that provided the classification of all samples is known as much as possible to mark the data out of the training samples, therefore the ambiguity of the training samples is low while the cost of manpower and material resources is high. Semi-supervision is the way that classification of some training samples is known and the others are not, which has higher ambiguity with much lower cost. Of course there are some defects in both methods. Therefore, the more convenient unsupervised method has arisen which serves as a kind of computer learning through the training examples that have no concept marks to find the hidden structural knowledge in it. This paper is to study the characteristics of data by simulating the human brain on Convolution Neural Network, and then to classify the unknown samples.

Nowadays, most of the fingerprint identification systems are able to reach high accuracy with fast speed when handling the fingerprint image with high quality. However, the vigorous development of fingerprint recognition technology makes many people have a wrong idea: it is already quite excellent, the technical problems have been solved completely. The recognition accuracy is not satisfactory when dealing with blurred and damaged fingerprint. About 15%-20% of the fingerprint identification errors are caused by low quality or incomplete fingerprint [4] from the world's top fingerprint recognition algorithms in FVC2004 (Fingerprint Verification Competition). China's fingerprint database can only offer 20%-30% of superior fingerprint, which means still a large number of fingerprints suffer from peeling, scars and other defects. Judging from these results, the accuracy of fingerprint identification is still far below some claimed products in the market. So it becomes an urgent problem to be solved in the field of fingerprint identification which focuses on both effectiveness and accurateness. However, if we just use Deep Learning to classify blurred and damaged fingerprints, the recognition rate is even less than 50%. Thus it is necessary to effectively deal with the input images.

In this paper we put forward a fuzzy process of fingerprint feature points, in which a fuzzy image of fingerprint feature points represents the training sample. It greatly simplifies the steps of finding a specific number of matched feature points, but also improves the recognition rate towards the damaged and blurred fingerprint identification. Finally, the CNN algorithm is used to simulate the human brain, which automatically extracts the inherent features from the fuzzy graphs of feature points, and then recognizes and classifies the training samples. Experiment results show that the proposed method can greatly improve the recognition rate. The structure of this paper is organized as follows: Section II provides

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fingerprint identification process. Section III proposes the whole process of the proposed algorithm. Section IV displays the experiment process and results. Section V summarizes this paper and puts forward a prospect of the further research.

II. FINGERPRINT IDENTIFICATION TECHNOLOGY

Fingerprint is a kind of flower patterns formed by mastoid ridge lines that grow on the cutis of finger tail end, which is different from each one and is invariable for life. The process of fingerprint identification [5] is shown in Fig.1, which includes two main parts: offline and online part; both parts consist of four steps: fingerprint image acquisition, fingerprint image pre-processing, feature extraction and fingerprint matching.

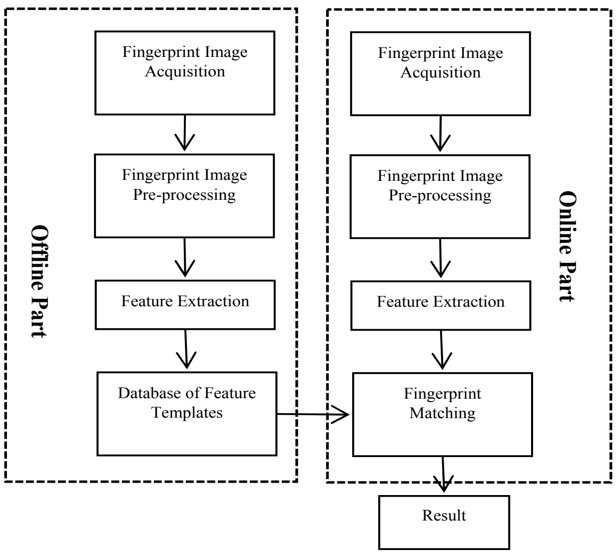


Figure 1. The process of fingerprint identification.

A. Pre-processing of Fingerprint Image

Fingerprint image pre-processing is a comprehensive application of various digital image processing techniques, and it is usually the first task to be done by the algorithm of fingerprint identification.

(1) Fingerprint enhancement. This step makes the fingerprint ridges much clearer and improves the convenience and accuracy of fingerprint feature extraction, avoiding the appearance of pseudo feature points.

(2) Fingerprint image binarization [6]. This step can effectively remove the large number of adhesion to facilitate subsequent fingerprint image thinning and reduce the complexity in fingerprint feature extraction and calculation.

(3) Fingerprint image thinning [7]. This step can refine the width of the ridge and make it more convenient to extract the details of the feature points, improving the accuracy of fingerprint matching.

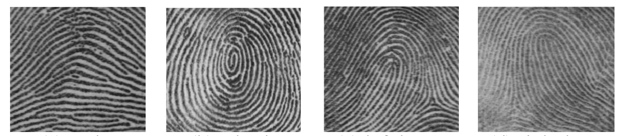
Images after pre-processing are showed in Fig.2.

(a) enhanced image (b) binary image (c) thinning image

Figure 2. Pre-processing fingerprint images.

B. Fingerprint Feature Extraction

Fingerprint feature points include: core, delta, ending bifurcation, et al. The shape features of fingerprint include six major categories: arch, tented arch, right loop, left loop, whorl and twin loop. Fig.3 shows some shapes of fingerprint.



(a) arch (b) whorl (c) left loop (d) right loop

Figure 3. The shape features of fingerprint.

Fingerprint feature extraction is an important part of the whole fingerprint identification system, its main task is to obtain the number, position and local ridge direction of fingerprint feature points by detecting two fingerprint images through a certain algorithm, which can facilitates subsequent fingerprint matching process [8].

C. Fingerprint matching

Fingerprint matching [9] is the final part of the fingerprint identification system following the previous steps of fingerprint acquisition, pre-processing and fingerprint feature extraction. Fingerprint matching mainly compares the new collection of fingerprint images with the fingerprint database, judging whether they are from the same finger, or from the same person by calculating the fingerprint similarity.

III. PROPOSED ALGORITHM

Different from the fingerprint recognition model based on Deep Learning, the model we proposed is an improved damaged fingerprint identification algorithm by fuzzy feature points, shown in Fig.4. This model uses the feature point number [10], position, and the relationship between point and point, which has a higher recognition rate.

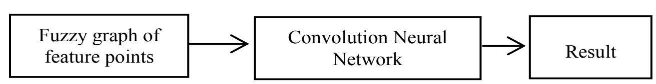


Figure 4. Damaged fingerprint identification with fuzzy feature points.

A. Fuzzy step of feature points

1. Core and delta extraction

The Poincare [11] formula is defined as the sum of the variation of each point's direction angle, this point locates in a closed digital curve with the center of testing point:

$$Poincare(x,y) = \frac{1}{2\pi}\sum_{k=0}^{N_p-1}\Delta(k) \tag{3.1}$$

among which,

$$\Delta|k| = \begin{cases} \delta(k), |\delta(k)| < \pi/2 \\ \pi + \delta(k), |\delta(k)| \le -\pi/2 \\ \pi - \delta(k), others \end{cases} \tag{3.2}$$

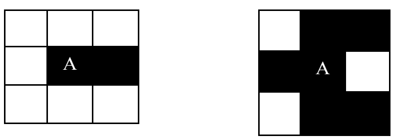
$$\delta(k) = \theta(x_{(k+1) \bmod N_p}, y_{(k+1) \bmod N_p}) - \theta(x_k, y_k) \tag{3.3}$$

Different properties of points correspond to different Poincare index values. The corresponding value of the center point is PI, while the delta point is -PI.

2. Endpoint and branch point extraction

Endpoint extraction: When scanning a point, the endpoint of which the absolute value between the 8 points around is 2*255 is extracted.

Branch point extraction [12]: When scanning a point, the branch point of which the absolute value between the 8 points around is 6*255 is extracted.



(a) Endpoint pixel model (b) Branch point pixel model

Figure 5. Endpoint and branch point pixel model

3. Fuzzy step

In order to fuzz the feature points, we adopt interpolation method of the radial basis function [13]; given the function $\phi : R_+ \to R$ and $\{X_j, \int_j\} \in R^d \otimes R$, we try to find the following form of function: We try to find an equation satisfying $\int_k = \sum a_j \phi(\|X_k - X_j\|)$

$$\int(X) = \sum a_j \phi(\|X - X_j\|) \tag{3.4}$$

And satisfy the function: $\int_k = \sum a_j \phi(\|X_k - X_j\|)$. There are some methods based on radial basis functions:

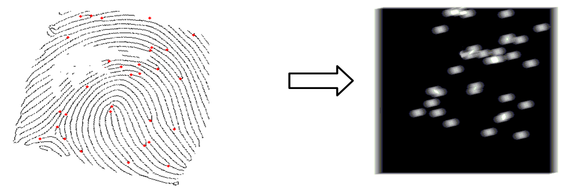
(i) Gauss distribution function of Kriging method: $\phi(r) = e^{-r^2/\sigma^2}$.

(ii) Multi-Quadric function of Hardy method: $\phi(r) = (c^2 + r^2)^{\beta}$, $\phi(r) = (c^2 + r^2)^{-\beta}$.

(iii) Thin plate spline of Duchon method: $\phi(r) = r^{2k} \ln r$, $\phi(r) = r^{2k+1}$.

This paper uses Kriging method, which is based on the locally optimal linear unbiased estimation and meets the error variance minimum theory of estimation. This method shows that the mean value of the theoretical estimation is equal to the mean value of actual sample.

The fingerprint feature point extraction method is used to extract all the features of the defect fingerprint, and then the features are fuzzed as shown in Fig.6. The purpose of this step is to weaken the specific fingerprint lines, highlighting the relationship between the different feature points and weakening their specific locations, leading to a higher rotation invariance.



(a) feature points of fingerprint （b） fuzzy graph of feature points

Figure 6. Fuzzy process of feature points.

B. Convolution Neural Network

Convolution neural network (CNN) is a kind of unsupervised multi-layer learning network, consisting of input layer, hidden layer and output layer. Among them, the hidden layer is the important link of the deep Convolution Neural Network to extract features. Each layer of CNN is composed of a plurality of two-dimensional planes, each of which comprises a plurality of independent neurons [14]. As a feed-forward neural network, it can extract the topology structures from 2D images. The parameters can be adjusted by the back propagation algorithm after the convolution and pool operation of the input images, providing the optimal parameters of the network. The convolution layer and the sampling layer from CNN are arranged in intervals, which facilitates the network a higher distortion tolerance.

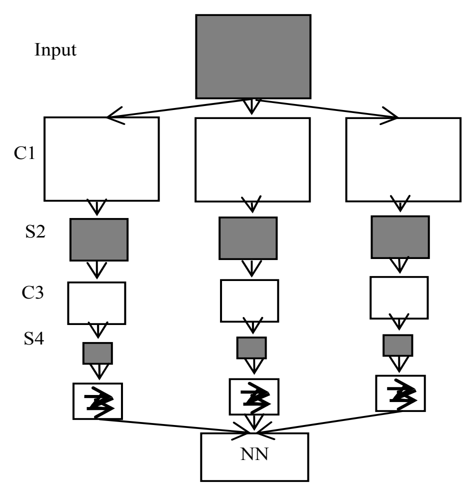


Figure 7. The structure of Convolution Neural Network.

1. Convolution process

In a convolution layer, feature maps of the upper layer are convoluted by a learning convolution kernel. Followed by an activation function, the output feature maps are achieved [15]. Each output map may be the results of the convolution of multiple input maps:

$$X_j^{\ell} = f\left(\sum_{i\in M_j} X_i^{\ell-1} * K_{ij}^{\ell} + b_j^{\ell}\right) \tag{3.5}$$

Here M_j represents a collection of the selected input maps.

In order to select the appropriate M_j, the following formula needs to be satisfied:

$$\delta_j^{\ell} = \beta_j^{\ell+1}\left(f'(u_j^{\ell}) \circ up(\delta_j^{\ell+1})\right) \tag{3.6}$$

Here *up (.)* represents an upper sampling operation, the expression is $up(X) \equiv X \otimes 1_{n\times n}$.

Bias based gradient is as follows:

$$\frac{\partial E}{\partial b_j} = \sum_{u,v} (\delta_j^{\ell})_{uv} \tag{3.7}$$

.in addition

$$\frac{\partial E}{\partial K_{ij}^{\ell}} = \sum_{u,v} (\delta_j^{\ell})_{uv} (P_i^{\ell-1})_{uv} \tag{3.8}$$

Here $(P_i^{\ell-1})_{uv}$ is the patch in $X_i^{\ell-1}$ which performed with the element-by-element multiplication in K_{ij}^{ℓ} during the convolution, the position value (u, v) of the output convolution map is the result of the patch in the upper layer with the position value (u, v) convoluted with the element-by-element multiplication in the convolution kernel [16].

2. Sampling process

Sub-sampling layer refers to the hidden layer of the S layer, there are N input maps with N output maps, but each output map becomes smaller, its formula is

$$X_j^{\ell} = f\left(\beta_j^{\ell} down(X_j^{\ell-1}) + b_j^{\ell}\right) \tag{3.9}$$

The *down (.)* here represents a sub-sampling function. The typical operation is generally summing all the pixels of different n*n blocks in the input images [17]. Thus the output images are reduced by n times in the two dimensions. Each output map corresponds to one multiplicative bias β and one additive bias b of its own.

IV. EXPERIMENTS RESULTS

The original images are from SF blind aligned fingerprint database, which are collected by optical fingerprint collector among 38 participants. Due to the incomplete pressing and stain on the finger tips, most part of the images may be imperfect for recognition and identification, shown in Fig.8. Simply removing the pictures may not be able to extract enough effective information, shown in Fig.9; In our experiments, each sample remains 20 fingerprint images. Then each sample is trained with 15 images with 5 images are identified. The original image size is 492*442.

(a) Blurred fingerprint (b) Imperfect pressing (c) Incomplete fingerprint

Figure 8. Several types of imperfect fingerprint images.

Figure 9. Abandoned images after pre-process.

The CNN model used in this paper has seven hidden layer, the activation function of each layer is a sigmoid function [18]. The image size is adjusted to the same size in the input layer to simplify the feature extraction. The parameters of CNN model [19] are set as In-96Conv11-96Poo13-256Conv5-256Poo13-384Conv3-384Conv3-256Conv3-256Poo13-4096Fc-1000Fc-Out. The parameters indicate that in the first hidden layer, kernel size is 11 and stride is 4 and a total of 96 complex features are extracted. After max-pooling, the maximum value is selected within the kernel size [20].

Based on our proposed algorithm, the experiments in this paper are divided into three steps:

(1) Pre-process the original image, such as enhancement binarization, denoising and thinning;

(2) Extract the entire feature points from the pre-processed image and fuzz them, the image size remains unchanged at 492*442;

(3) Input the fuzzy image into CNN for training and recognition; obtain the recognition rate.

Fig.6 shows the relationship between the iteration number and the training loss.Here, X axis and Y axis respectively represent the number of iterations and the training loss. It can be seen that the training loss is nonlinearly decreased as the iterations number increased. Therefore, in order to obtain a smaller training loss with shorter training time, we need to select an appropriate number of iterations.

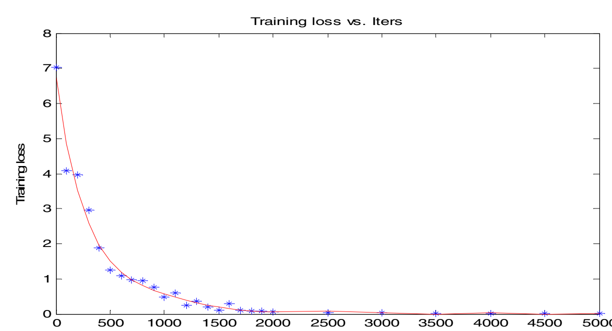


Figure 10. The relationship between the loss and the number of iterations.

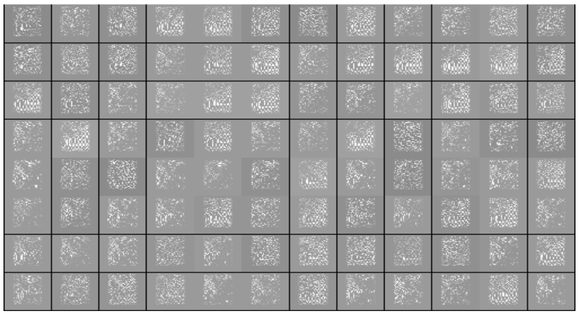


Figure 11. The 96 feature maps from the first convolution layer.

In order to verify the great advantage of Deep Learning in fingerprint recognition [21], we compare the performance by using Kernel Principal Component Analysis (KPCA) [22] algorithm and k-Nearest Neighbor (KNN) algorithm.

The experimental results are as follows: Table 1 listed the recognition rate differences based on the CNN and traditional fingerprint recognition algorithm, by changing the input images; Table 2 compares the different recognition rates of CNN, the traditional feature points matching method, KPCA and KNN.

TABLE I. THE RELATIONSHIP BETWEEN THE DIFFERENT INPUT IMAGES AND THE RECOGNITION

Algorithm	Input image	Recognition rate
CNN	Original fingerprint image	68.16%
	Pre-processed original fingerprint image	91.25%
	Fuzzy image of feature points	94.77%
Traditional feature points matching	Original fingerprint image	72.86%
	Pre-processed original fingerprint image	87.3%
	Fuzzy image of feature points	--

TABLE II. THE RELATIONSHIP BETWEEN THE DIFFERENT ALGORITHMS AND THE RECOGNITION RATES

Adopted algorithm	Recognition rate
CNN	94.77%
KPCA	77.89%
Traditional feature points matching	87.60%
KNN	45.77%

From above two charts, we can see that CNN algorithm has obvious advantages in the fingerprint recognition than other three fingerprint identification algorithms.

V. SUMMARY

For low quality fingerprint identification, the traditional fingerprint identification algorithms require complex modified processes, but still with a low recognition rate. And the automatic fingerprint identification method, namely CNN algorithm, not only improves the recognition rate, but saves processing time. The effective processing of the input images is the key step to improve the recognition rate. In future study, we need to conduct comprehensive researches on the processing of the input images, as well as strengthening the improvement of the algorithm.

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