Research on fingerprint triangle region recognition Based on Convolutional Neural Networks

Ai Le, Zhizhong Zhang

[1]Institute of Criminal Science and Technology, People's Public Security University of China, Beijing 100038, China

[2]State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China

Keywords: Neural network, minutiae, fingerprint image, convolutional layer

Abstract: In today's society, the growing instability has made identification technology a hot issue. Most traditional methods are based on a series of hand-defined preprocesses such as binarization. However, these preprocesses require strong prior knowledge. And that will lead to dropped or false extractions of minutiae. In this paper, a fingerprint triangle region recognition approach based on deep convolutional neural networks is proposed, which directly extract minutiae on raw fingerprint images without any preprocess since we tactfully take the advantage of the strong representative capacity of deep convolutional neural networks (including JudgeNet and LocateNet). Results show that our approach performs better in accuracy and robustness.

1. Introduction

With the continuous development of society, privacy security and life security have become the hot issues of people's attention, because only in this way can we get enough protection. This stimulates the development of biometric technology. As the most reliable and popular biometric technology, fingerprint recognition technology is widely used in many important applications. Although the existing fingerprint identification technology has been widely developed, it is still a difficult problem for many researchers to think of the identification technology with faster speed and higher efficiency through fingerprint acquisition, especially for the identification of fingerprint triangle region.

This article puts forward that minutiae is used to determine the uniqueness of fingerprint. At present, in most matching algorithms, it is an important task in the extraction step to extract fingerprint minutiae accurately and eliminate false minutiae effectively. However, in real life, automatic detail extraction is not an easy task, because noise elements and inadequate image contrast can produce false minutiae and hide the real one.

In recent years, theoretical studies have shown that deep architecture has strong representational ability and can learn more Abstract features [1]. This means that deep networks have stronger learning ability and better generalization performance. Convolutional neural networks (CNN) [2], which consists of a series of convolution layers, convergence layers and other types of layers, is one of the most popular deep architecture. With its framework advantages, it has reached the most advanced level in computer vision, speech recognition, natural language processing and other fields [3]. In view of the good performance of deep CNN in many related aspects, we skillfully introduce them into fingerprint minutiae extraction.

The rest of this paper is organized as follows. Section 2 analyses and summarizes the relevant technical concepts; Section 3 introduces the design process of the self-algorithm in detail; Section 4 introduces the implementation steps of the algorithm; Section 5 verifies the algorithm through experiments; Section 6 summarizes the work of the full text.

  DOI: 10.25236/isaicn.2019.008

2. Related Technical Theories

2.1 Fingerprint recognition technology

In ancient times, fingerprint recognition has been used. For instance, fingerprints, which were widely used, were used as evidence for identification by fingerprinting in the Tang Dynasty. Archaeologists also confirmed that they were left on some ceramic utensils. There are fingerprints of artisans. Until the end of the 19th century and the beginning of the 20th century, fingerprint recognition officially entered the eyes of researchers, through a series of scientific means to achieve fingerprint recognition technology. In 1823, according to the global structure of fingerprint lines, the first set of fingerprint classification schemes was proposed, which divided the fingerprints into nine categories. In 1864, the first paper on fingerprint recognition technology was proposed. Since then, fingerprint recognition technology has entered the public's field of vision, more and more researchers are investing in the research of fingerprint recognition, which involves a wide range of applications, including pattern recognition, signal processing, applied science and other multidisciplinary [4] [5].

2.2 Convolutional neural networks

The convolutional neural network was first proposed by Kunihiko in 1980 [6]. In 1998, Yann LeCun et al. used CNN (Le-Net) for handwriting recognition and achieved quite good results [7]. In the 2000s, CNN was redefined and simplified [8], and its role was fully exerted in [9] [10], with far-reaching effects. In 2006, some scholars proposed the theory of deep learning, which promoted the further promotion of convolutional neural networks. Since then, classical algorithms for convolutional neural networks have emerged one after another. In particular, in 2016, the artificial intelligence robot developed by a team owned by Google and the master of the chess master Li Shishi, the artificial intelligence in this war defeated the master of Go with a score of 4-1, which will be based on convolution. The artificial intelligence of neural networks has pushed the peak of research.

2.3 Triangle area

For the fingerprint triangle area, due to the irregularity of the fingerprint triangle area, it is necessary to find a good triangle area [11], mainly considering the following aspects: 1. The size of the triangle area: the triangle area should not be too large, the area Too large not only increases the matching calculation amount, but also reduces the adaptability of the template; the triangular area cannot be too small, otherwise the matching condition is too loose and loses the original meaning. 2. The versatility of the triangular area: the triangular area needs to adapt to the fingerprints input at different positions and at different angles, and also satisfies the versatility in the case of noise.

3. Algorithm Design

3.1 Overview of the algorithm

The details are special patterns in the fingerprint image that can be easily distinguished by the human eye. But when it is automatically extracted by a computer, this is not an easy task, especially in low quality images. Grayscale, noise, line width and acquisition conditions present different poses in different images, and some manual design pre-processing is particularly difficult. Convolutional neural networks, as one of the best deep neural networks, can implement a formalized form that automatically provides a degree of translation invariance [12]. When sufficient data is provided, it can achieve an effect similar to (or even above) the human eye. Therefore, we apply convolutional neural networks to detail extraction.

3.2 Training process

(1)JudgeNet: JudgeNet is a training set that determines whether there are details in the relevant areas of the input patch, as shown in Figure 1. JudgeNet involves several convolutional neural networks and its output is the average of these networks. Each major architecture network is shown in Figure 2, which contains a series of connected convolutional layers, pooling layers and complete connection layers. The output layer is a binary classifier that is applied to decision making.

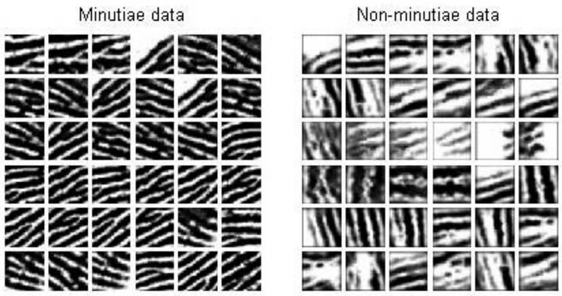

Figure 1 Training data of JudgeNet

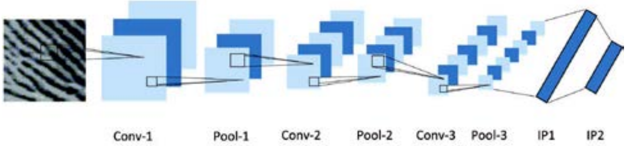

Figure 2 Network architecture

Each convolutional layer performs the convolution operation on a number of square kernels. The kernel acts as a filter, several filters work together to extract the input function, and the output graph is activated by nonlinear application of the convolution response.

After the convolution operation, maximum pool should be used to reduce the dimensions. The output of the maximum pool layer is given by the maximum activation of the non-overlapping block region. After a series of convolution and convergence, the output is converted to 1D eigenvectors and applied to several complete connection layers. These layers perform internal eigenvectors to further extract features. Two softmax functions are then used for the output layer to ensure that the probability of a given input patch belongs to each class. Softmax function is expressed as follows, is the probability of x belongs to j,, K is the number of classes, K=2.

$$S(x)_j = \frac{\exp^{x_j}}{\sum_{k=1}^{K} \exp^{x_k}} \tag{1}$$

Network parameters of training set are optimized jointly by minimizing misclassification. So JudgeNet can be used to deal with detail-checking issues.

(2)LocateNet: LocateNet is trained to handle detailed location problems. The input is a 45×45 pixel patch with a detail point in the relevant area (27×27 pixels in the central area). Each relevant area is 9×9 pixels, as shown in Figure 3.

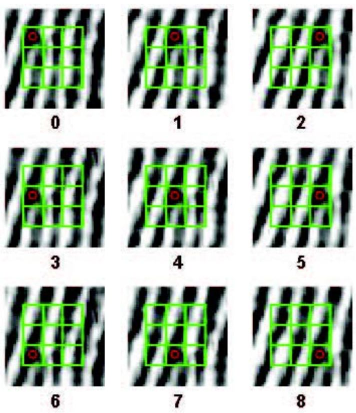

Figure 3 Training Data of LocateNet

LocateNet is a convolutional neural network with a similar architecture to JudgeNet (see Figure

1). But the output layer of LocateNet is level 9 softmax function (in formula (1), K = 9).

3.3 Forecasting process

JudgeNet and LocateNet were well trained to make predictions. The overall prediction process is as follows:

1) The fingerprint image was divided into patches of 45×45 pixels (9 pixels in step size) and extended to 63×63 pixels. Therefore, each 9×9 pixel area will be contained in the relevant area of the 9 patches (27×27 pixels in the center) except for the edge of the image.

2) The patch applies to trained JudgeNet and gets the probability of containing one or more details. Patches with higher probability than a certain threshold t1 are candidates (we set t1 = 0.5).

3) Candidate patches are used as input to LocateNet. We can get the probability.

4) Given the overlapping images, each cell may involve several adjacent patches, making it easy to predict multiple times. In this paper, each probability of the region will be concerned, and the mean of the probabilities will also be calculated. The small region with an average probability greater than the threshold t2 (t2 = 0.5) contains a detail point. The central point of these small areas will be identified as the location of the detail points.

4. Algorithm Implementation

4.1 Data augmentation

Considering the particularity of fingerprint data, it is impractical to obtain a large number of fingerprints. In this paper, real-time fingerprint scanning (GA/T 625-2010) was obtained on the basis of Chinese technical specifications, and a total of 200 tagged fingerprint images were obtained. The images have a resolution of 640×640 pixels and 500 ppi. Each usually contains 80 to 120 valid detail points.

In order to obtain sufficient training data, the images were segmented into overlapping patches. Overlapping operations can greatly expand the ability of training data. More importantly, considering the direction of the patch will not affect the judgment of detail, each patch rotates 90°, 180°and 270°, which quadruple the number, as shown in Figure 4.

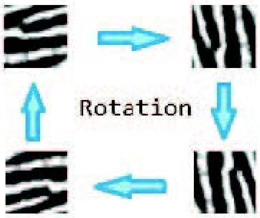

Figure 4 Rotation data increase

4.2 Model averaging

The deep architecture is a model with relatively high complexity. It tends to be a relatively low classifier, but it's very biased [31]. To mitigate large differences and improve accuracy, networks of different training data are independent. Averaging these different network outputs can help improve accuracy. This technique has been proved to be effective in our experiments (see section below).

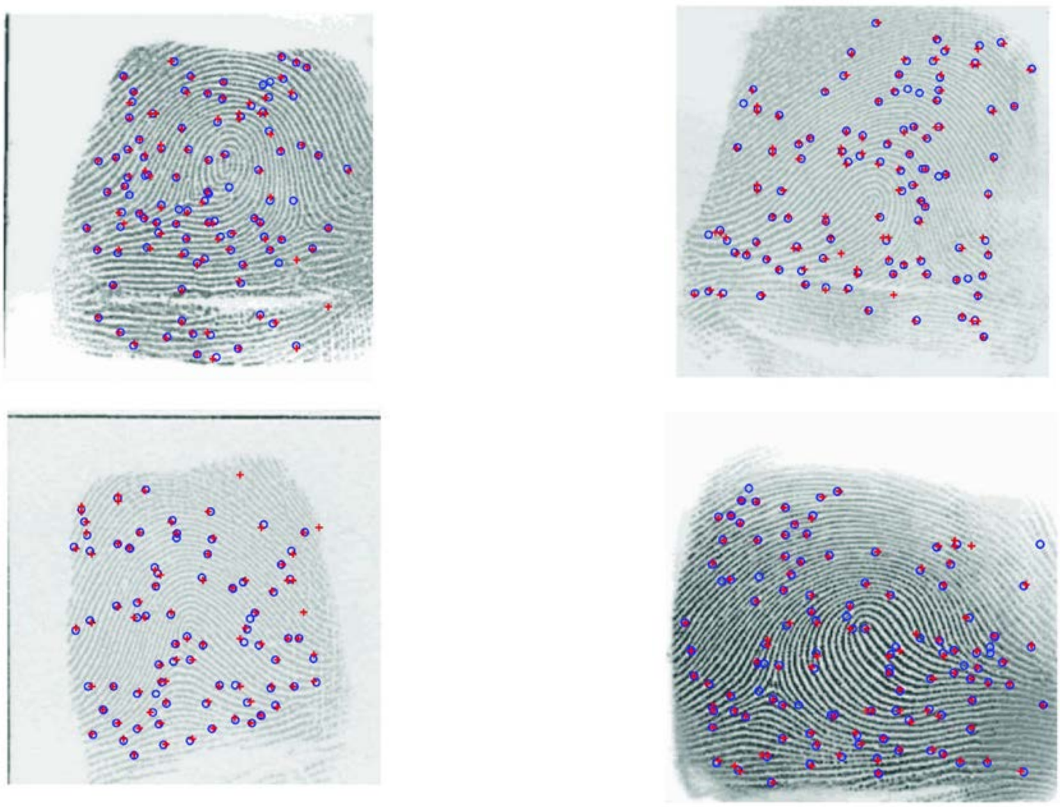

Figure 5 Four samples of the test set

5. Experimental Result

Most of the experiments were conducted using the deep learning framework Caffe [13], which was developed by the Berkeley Visual and Learning Center (BVLC). This section has conducted a number of experiments to verify that our method has high precision and good performance. The test set is a fingerprint image randomly sampled from the Chinese Criminal Investigation Fingerprint Database. The result is shown in Figure 5. The blue circle indicates the true detailed position (marked by a human expert) and the red plus sign indicates the result of our method.

6. Conclusion

In this paper, we have effectively utilized the significant advantages of deep convolutional neural networks, and creatively proposed an excellent method for extracting details and identifying fingerprints directly in fingerprint images without any preprocessing. JudgeNet is trained to select candidate patches in areas that may contain details, and then LocateNet is used to determine the exact location of the details. The main frameworks of both networks is a convolutional neural network. The algorithm in this paper has significant advantages in terms of accuracy and robustness.

References

[1] Bengio, Y. Learning Deep Architectures for AI [J]. Foundations and Trends? In Machine Learning, 2009, 2(1):1-127.

[2] Behnke S. Hierarchical Neural Networks for Image Interpretation [J]. Lecture Notes in Computer Science, 2003, 2766(3):1345-1346.

[3] Bengio Y, Courville A, Vincent P. Representation Learning: A Review and New Perspectives [J]. IEEE Transactions on Pattern Analysis & Machine Intelligence, 2012, 35(8):1798-1828.

[4] Li Zhang, Pu Li, Kaiteng Wu. Directionless Triangle Matching Fingerprint Recognition [J]. Journal of Image and Graphics, 2017, 22(9):1214-1221.

[5] Jie Tian, Xinjian Chen, Yangyang Zhang, etc. New Developments in Fingerprint Recognition Technology [J]. Progress in Natural Science, 2006, 16(4):400-408.

[6] Fukushima K. Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position [J]. Biological Cybernetics, 1980, 36(4):193-202.

[7] Lecun Y L, Bottou L, Bengio Y, et al. Gradient-Based Learning Applied to Document Recognition [J]. Proceedings of the IEEE, 1998, 86(11):2278-2324.

[8] Simard P Y, Steinkraus D, Platt J C. Best Practices for Convolutional Neural Networks Applied to Visual Document Analysis [C]// null. IEEE Computer Society, 2003.

[9] Ciresan D C, Meier U, Masci J, et al. Flexible, High Performance Convolutional Neural Networks for Image Classification [C]// IJCAI 2011, Proceedings of the 22nd International Joint Conference on Artificial Intelligence, Barcelona, Catalonia, Spain, July 16-22, 2011. DBLP, 2011.

[10] Schmidhuber J, Meier U, Ciresan D. Multi-column deep neural networks for image classification[C]// Computer Vision & Pattern Recognition. 2012.

[11] Jian Lu, Zhiyi Qu. Fast Algorithm for Fingerprint Triangle Area Recognition and Location Based on Template Matching [J]. Journal of Lanzhou Univeristy, 1992(S1):101-106.

[12] J. Bouvrie, Notes on convolutional neural networks, 2006.

[13] Jia Y, Shelhamer E, Donahue J , et al. Caffe: Convolutional Architecture for Fast Feature Embedding[J]. 2014.