Robust Fingerprint Matching Based on Convolutional Neural Networks

Yanming Zhu, Xuefei Yin, and Jiankun Hu(✉)

School of Engineering and Information Technology, University of New South Wales, Canberra, ACT 2600, Australia
{yanming.zhu,xuefei.yin}@student.unsw.edu.au, J.Hu@adfa.edu.au

Abstract. Fingerprint has been widely used in biometric authentication systems due to its uniqueness and consistency. Despite tremendous progress made in automatic fingerprint identification systems (AFIS), highly efficient and accurate fingerprint matching remains a critical challenge. In this paper, we propose a novel fingerprint matching method based on Convolutional Neural Networks (ConvNets). The fingerprint matching problem is formulated as a classification system, in which an elaborately designed ConvNets is learned to classify each fingerprint pair as a match or not. A key contribution of this work is to directly learn relational features, which indicate identity similarities, from raw pixels of fingerprint pairs. In order to achieve robustness and characterize the similarities comprehensively, incomplete and partial fingerprint pairs were taken into account to extract complementary features. Experimental results on FVC2002 database demonstrate the high performance of the proposed method in terms of both false acceptance rate (FAR) and false rejection rate (FRR). Thanks to the robustness of feature extraction, the proposed method is applicable of incomplete and partial fingerprint matching.

Keywords: Fingerprint matching · Convolutional Neural Networks
Fingerprint pairs · Relational features · Deep learning

1 Introduction

In recent years, biometric authentication has featured prominently for human verification and identification due to its robustness compared with password based security mechanism [6,13,18,19,22]. Among many biometrics, fingerprint has proved to be a very reliable human identification and verification index and has enjoyed superiority over other biometrics [14]. The dominance of fingerprint has been established by the continuous emergence of various automatic fingerprint identification systems (AFIS). A number of factors have caused bottlenecks towards achieving desired system performance, such as lack of reliable feature extraction algorithm, low accuracy of fingerprint alignment and difficulty of reliable similarity measurement between fingerprints [10,12,27]. Although lots of

J. Hu et al. (Eds.): MONAMI 2017, LNICST 235, pp. 56–65, 2018.
https://doi.org/10.1007/978-3-319-90775-8_5

efforts have been put into the development of a reliable system and tremendous progress has been made, we are still far from the goal.

Fingerprint matching, as the most popular and widely researched authentication system, can be classified into either identification or verification. Identification involves suggesting whether or not the query can find a match in the database, whereas verification involves deciding whether a query fingerprint matches the holding template. Both fingerprint identification and verification rely on accurate recognition of fingerprint features. The main challenges confronting fingerprint matching are the large intra-class variations (in fingerprint images from the same finger) and large inter-class similarity (between fingerprint images from different fingers) [26]. The intra-class variation can be caused by unequal pressure, partial overlap, non-linear distortion and sensor noise while the inter-class similarity is mainly due to limited number of fingerprint patterns [25].

Various methods have been developed to achieve effective fingerprint matching and a remarkable progress has been made. The fingerprint matching methods can be basically classified into two categories: (1) minutia-based methods [3,5,9,15,23] and (2) image-based methods [1,17,20,24]. The minutia-based methods achieve efficient fingerprint matching by extracting more matching features besides minutia locations and orientations [5,9,23] or by constructing more complex structures [3,15]. Jain et al. [9] proposed using pores and ridge contours besides minutia points and a three level matching strategy to achieve high-resolution fingerprint matching. Choi et al. [5] incorporated ridge feature with minutia and obtained good results. Thuy et al. [23] increased ridge-valley structure features and proposed the local Thin-Plate-Spline deformation model to deal with non-linear distorted fingerprints. Cappelli et al. [3] proposed a novel Minutia Cylinder-Code representation based on 3D cylinder structures to improve the matching effectiveness. Medina-Perez et al. [15] improved fingerprint verification by using Minutia triplets. These methods are suitable for one-to-many fingerprint matching and can gain favorable results. However, they are not compatible with different fingerprint sensors such as higher sensor resolution and large sensors. Moreover, minutia-based methods may lead to unsuccessful matching when the two fingerprint images have different number of minutiae points or when they possess the fingerprint portions without significant information. Therefore, image-based methods were proposed to solve the above problems.

The image-based methods consider the overall fingerprint characteristics rather than minutiae points alone and utilize more discriminatory information such as curvature, density and ridge thickness. Most of the image-based methods use filter bank to achieve the local texture feature analysis [14]. Sha et al. [20] proposed combining the directional features with average absolute deviation features to construct fingercode for the filter bank. Nanni and Lumini [17] proposed local binary pattern (LBP) based on a multi-resolution analysis of the local fingerprint patterns, which is a Gabor filter-based discriminator with low computational complexity. Tico et al. [24] proposed extracting local texture from the wavelet transform of a discrete image to achieve fingerprint recognition. Benhammadi et al. [1] proposed a hybrid descriptor to construct texture map by combining the minutiae orientations. However, these methods require significantly larger storage space and higher running time and the performance is degraded on fingerprint images where minutiae points are not extract precisely and reliably.

Based on the above analysis and inspired by the superiority of convolutional neural networks for various classification tasks [2,8,11], in this paper, we proposed a novel fingerprint matching method based on Convolutional Neural Networks (ConvNets). The fingerprint matching problem is formulated as a classification system, in which an elaborately designed ConvNets is learned to classify each fingerprint pair as a match or not. A key contribution of this work is to directly and jointly learn relational features from raw pixels of fingerprint pairs. In order to achieve robustness and characterize the similarities comprehensively, incomplete and partial fingerprint pairs were utilized to extract complementary features and achieve data augmentation. By fully exploiting the spatial correlation between fingerprint pairs, the proposed method achieves high performance in terms of both FAR and FRR.

The rest of the paper is organized as follows: Sect. 2 presents the proposed methods in detail. Experimental results and analysis are provided in Sect. 3. The paper is concluded and the future work is discussed in Sect. 4.

2 The Proposed Method

In this section, we present the details of our method as depicted in Fig. 1. The basic idea of the proposed matching method is to classify each fingerprint pairs

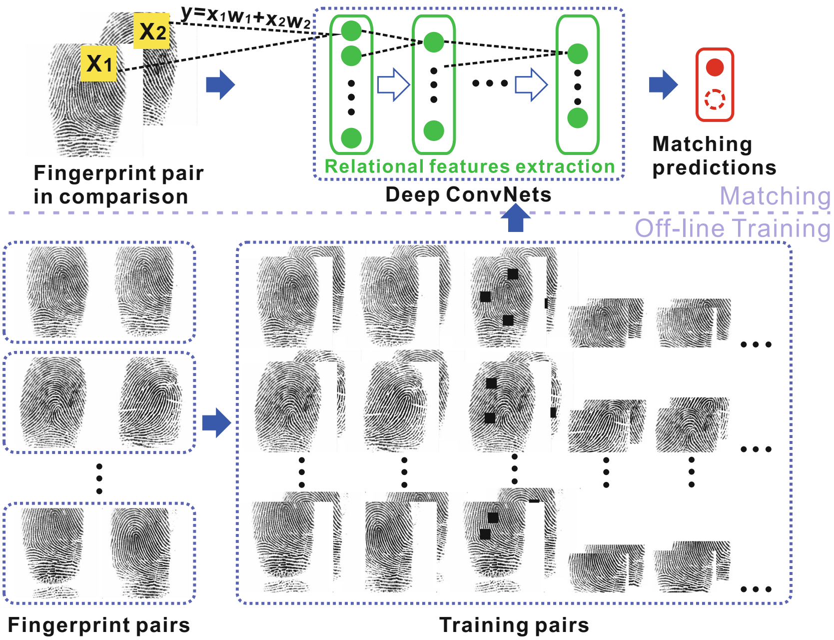

Fig. 1. Framework of the proposed method.

as either match or not using a elaborately designed ConvNets. For an input fingerprint pair in comparison, the relational features are extracted directly from the raw pixels by the pre-learned ConvNets (Sect. 2.2). Then, the extracted features are fully connected to a single neuron, which indicates whether or not the two impression images belong to the same fingerprint. In order to improve robustness of predictions, data augmentation is achieved by taking incomplete and partial fingerprint pairs into account (Sect. 2.1).

2.1 Fingerprint Pairs Preparation

Different from other fingerprint matching methods which extract features from each images separately and calculate the similarity at later stages, in this paper, we propose to jointly extract relational features from fingerprint image pairs. There are two kinds of fingerprint pairs: inter-class pairs constructed by fingerprints from different fingers and intra-class pairs constructed by fingerprints from the same finger. Due to the 2D acquisition characteristic of fingerprint image, the number of different impressions for one finger object is limited. Different impressions are usually varying at rotations and translations. A sample of different impressions of one finger object is shown in Fig. 2.

Fig. 2. Sample finger impressions from FVC2002 database: from (a) to (f) are the first six impressions of one finger used to construct the training pairs.

Based on this situation and on the purpose of improving robustness, we propose using incomplete and partial fingerprint image pairs to do the data augmentation. Figure 3 shows the proposed six variational fingerprint images based on one fingerprint impression. In order to extract relational features jointly, the fingerprint pairs are constructed by using fingerprint images with the same size. For example, in Fig. 3, fingerprint pair consists of image (a) and (b) is acceptable while fingerprint pair consists of image (a) and (c) is unacceptable. Considering the spatial correlation between fingerprint pairs, each input pair generates two modes by changing the order of two images. Figure 4 shows the two possible modes for a pair of fingerprint images.

In conclusion, for each finger object, 36 variational fingerprint images are generated by the proposed data augmentation method based on 6 original fingerprint impressions and are used to construct the intra-class pairs. Thanks to the proposed two modes, 396 intra-class pairs are finally generated to overcome the limitation of impression shortage for one finger object. In the experiment, we

Fig. 3. Variational fingerprint images for one fingerprint impression. From left to right: (a) the original fingerprint impression, (b) incomplete fingerprint image with random missing blocks, (c) and (d) partial fingerprint images sized $\frac{4}{5}$ of original fingerprint image and (e) and (f) partial fingerprint images sized $\frac{3}{5}$ of original fingerprint image. (c) and (d) and (e) and (f) differ slightly in the ranges of regions.

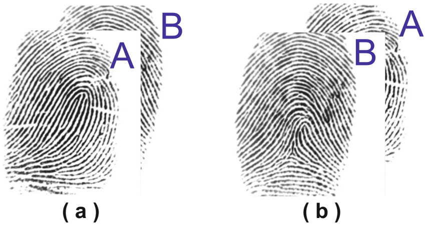

Fig. 4. Two modes for a pair of fingerprint images: (a) fingerprint pair mode with image A in the front and image B at the back and (b) fingerprint pair mode with image B in the front and image A at the back.

generate the same number of inter-class pairs by randomly selecting the impressions of different fingers.

2.2 ConvNets Architecture

The ConvNets is trained to classify a fingerprint pair in comparison as a match or not. The overall architecture of the proposed ConvNets model is shown in Fig. 5. The ConvNets consists of four convolutional layers, which can be expressed as:

$$y_j = b_j + \sum_i w_{ij} * x_i, \tag{1}$$

where $*$ is the convolution, x_i and y_j are the i-th input and the j-th output, respectively. w_{ij} is the convolution kernel connecting the i-th input and the j-th output and b_j is the bias for the j-th output. According to the study in [21], successive convolution by small filters equals to one convolution operation by a lager filter but effectively enhances the model's discriminative power and reduces the number of filter parameters to learn. In this paper, we propose to downsize the input training pairs and use small filters of 3×3 for all convolutional layers. For example, the original image size of 388×374 in FVC2002 DB1 database is resized and downsized to 97×93. ReLU [7] activation function is utilized after all but the last convolutional layers, which can be express as:

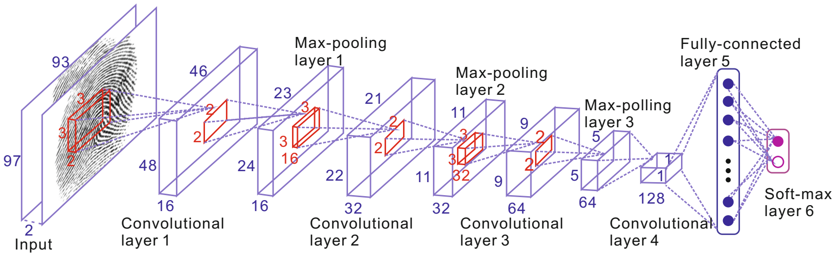

Fig. 5. Sample finger impressions from FVC2002 database: from (a) to (f) are the first six impressions of one finger used to construct the training pairs.

$$y'_j = max(0, y_j). \tag{2}$$

where y'_j is the output of y_j after ReLU. The dropout [11] is employed as a regularizer on the fully-connected layer in the case of overfitting. In the experiment, the dropout ratio is set to be 0.5. The proposed ConvNets output is a two-way softmax, which can be express as:

$$y_p = \frac{exp(x_p)}{\sum_{q=1}^{2} exp(x_q)} \quad (p = 1, 2), \tag{3}$$

where x_p is the total input to an output neuron p and y_q is its output.

Since each layer extracts features from all the maps in the previous layer, relations between fingerprint pairs are modeled. With the network deepening, more global and higher-level relations between the two fingerprints are modeled. These high-level relational features make it possible for the top layer neurons in ConvNets to predict whether the two input fingerprint come from the same finger.

3 Experimental Results

In this section, we evaluate the performance of the proposed method on the most widely used public domain database FVC2002, which is an international competition database for fingerprint verification algorithms [16]. This database contains four distinct subsets: DB1, DB2, DB3 and DB4 and its summary is presented in Table 1. All the experiments are implemented in Matlab R2016a and run on a laptop with Intel Core i7 CPU at 2.6 GHz, 16 GB RAM and 256 GB hard drive.

Different from the existing fingerprint matching methods that apply similarity thresholding to predict the matching result of two fingerprints, the proposed method outputs a probability distribution over two classes (being the match or not), which directly indicates the matching result. Therefore, it is impossible to do the comparative experiments and to evaluate the performance of the proposed method in terms of some existing benchmark metrics such as ROC Curve and equal error rate (EER). In this paper, we use the following two metrics to quantitatively evaluate the performance of our method.

Table 1. Details of FVC2002 fingerprint database

	Sensor type	Image size (pixel)	Number	Resolution (dpi)
DB1	Optical sensor	388×374 (142K)	100×8	500
DB2	Optical sensor	296×560 (162K)	100×8	569
DB3	Capacitive sensor	300×300 (88K)	100×8	500
DB4	SFinGe V2.51	288×384 (108K)	100×8	About 500

False Acceptance Rate (FAR). This is the rate of occurrence of a scenario of two fingerprints from different fingers found to match, which is defined as:

$$FAR = \frac{N_f i}{N_t i + N_f i}, \tag{4}$$

where $N_f i$ is the number of accepted imposter matches and $N_t i$ is the number of rejected imposter matches.

False Rejection Rate (FRR). This is the rate of occurrence of a scenario of two fingerprint from same finger failing to match, which is defined as:

$$FAR = \frac{N_f g}{N_t g + N_f g}, \tag{5}$$

where $N_f g$ is the number of rejected genuine matches and $N_t g$ is the number of accepted genuine matches.

In the experiment, we use the first six impressions of each finger to train the ConvNets and use the remaining two impressions to do the test. As mentioned in Sect. 2.1, 396 intra-class pairs can be generated for each finger object. Therefore, we totally generate 39600 intra-class training pairs labeled as match and 39600 inter-class training pairs labeled as unmatch for each subset DB1, DB2, DB3 and DB4 to train the ConvNets, respectively. When the size of the input image changes in different subset, the map size in the following layers of the ConvNets will change accordingly. For each subset, each pair of two impressions are tested thus there are 100 genuine matches and 4950 imposter matches in our experiments. The fingerprint image pairs are firstly aligned by method in [4] to reduce the relative rotation between two fingerprint impressions and improve the robustness of relational feature extraction. Quantitative evaluation of the proposed method is shown in Table 2.

As shown in the table, FRR of 0% demonstrates the performance of the proposed method to model relational features and to identify fingerprint from the same finger. Meanwhile, the values of FAR are comparatively low, which makes the proposed method applicable in both commercial and criminal applications. The failure rates of matching for fingerprints from different fingers may be caused by the registration process, as both the rotation and translation operations tend to generate overlapping in fingerprints. Variations of the failure rates for different

Table 2. FAR and FRR vaules in percentage (%) for the four datasets

	FAR	FRR
DB1	1.69	0
DB2	1.15	0
DB3	0.42	0
DB4	0.79	0

subsets may be due to the differences in image quality and contrast of each subset. Visual inspection of fingerprints in the four subsets confirms this trend.

Thanks to the off-line training, the matching time of the proposed method is extremely short. The average matching time for one fingerprint pair is less than 1 s.

4 Conclusion

In this paper, we propose a novel fingerprint matching method based on Convolutional Neural Networks (ConvNets). The fingerprint matching problem is formulated as a classification system, in which an elaborately designed ConvNets is learned to classify each fingerprint pair as a match or not. A key contribution of this work is to directly and jointly learn relational features from raw pixels of fingerprint pairs. In order to achieve robustness and characterize the similarities comprehensively, incomplete and partial fingerprint pairs were utilized to extract complementary features and achieve data augmentation. By fully exploiting the spatial correlation between fingerprint pairs, the proposed method achieves high performance in terms of both FAR and FRR. Thanks to the robustness of relational feature extraction and extremely matching time, the proposed method is applicable to both commercial and criminal applications.

In the future, we will apply the proposed method to incomplete and partial fingerprint matching.

Acknowledgments. The authors would like to thank the support from ARC project LP120100595.

References

1. Benhanmadi, F., Amieouche, M.N., Hentous, H., Beghdad, K.B., Assanii, M.: Fingerprint matching from minutiae texture maps. Pattern Recogn. **40**(1), 189–197 (2007)
2. Cao, K., Jain, A.K.: Latent orientation field estimation via convolutional neural network. In: Proceedings of IEEE International Conference on Biometrics (ICB), pp. 349–356, September 2015
3. Cappelli, R., Ferrara, M., Maltoni, D.: Minutia cylinder-code: a new representation and matching technique for fingerprint recognition. IEEE Trans. Pattern Anal. Mach. Intell. **32**, 2128–2141 (2010)

4. Chang, S.H., Cheng, F.H., Hsu, W.H., Wu, G.Z.: Fast algorithm for point pattern-matching: invariant to translations, rotations and scale changes. Pattern Recogn. **30**, 311–320 (1997)
5. Choi, H., Choi, K., Kim, J.: Fingerprint matching incorporating ridge features with minutiae. IEEE Trans. Inf. Forensics Secur. **6**, 338–345 (2011)
6. Connie, T., Goh, M.K.O., Teoh, A.B.J.: A grassmannian approach to address view change problem in gait recognition. IEEE Trans. Cybern. **47**(6), 1395–1408 (2017)
7. Dahl, G.E., Sainath, T.N., Hintion, G.E.: Improving deep neural networks for LVCSR using rectified linear units and dropout. In: Proceedings of IEEE International Conference on Acoustic Speech Signal Process, pp. 8609–8613, May 2013
8. Ding, C., Tao, D.: Robust face recognition via multimodal deep face representation. IEEE Trans. Multimed. **17**(11), 2049–2058 (2015)
9. Jain, A.K., Chen, Y., Demirkus, M.: High-resolution fingerprint matching using level 3 features. IEEE Trans. Pattern Anal. Mach. Intell. **29**, 15–27 (2007)
10. Jin, Z., Lim, M.H., Teoh, A.B.J., Goi, B.M., Tay, Y.H.: Generating fixed-length representation from minutiae using Kernel methods for fingerprint authentication. IEEE Trans. Syst. Man Cybern.: Syst. **46**(10), 1415–1428 (2016)
11. Krizhevsky, A., Sutskever, I., Hinton, G.E.: ImageNet classification with deep convolutional neural networks. In: Proceedings of Advance in Neural Information Processing Systems, pp. 1097–1105 (2012)
12. Lim, M.H., Teoh, A.B.J.: A novel encoding scheme for effective biometric discretization: linearly separable subcode. IEEE Trans. Pattern Anal. Mach. Intell. **35**(2), 300–313 (2013)
13. Low, C.Y., Teoh, A.B.J., Toh, K.A.: Stacking PCANet+: an overly simplified convnets baseline for face recognition. IEEE Sig. Process. Lett. **24**(11), 1581–1585 (2017)
14. Maltoni, D., Maio, D., Jain, A.K., Prabjakar, S.: Handbook of Fingerprint Recognition, 2nd edn. Springer, London (2009). https://doi.org/10.1007/978-1-84882-254-2
15. Medina-Perez, M.A., Garcia-Borroto, M., Gutierrez-Rodriguez, A.E., Alramirano-Robles, L.: Improving fingerprint verification using minutiae triplets. Sensors **12**, 3148–3437 (2012)
16. Miao, D., Maltoni, D., Cappelli, R., Wayman, J.L., Jain, A.K.: FVC2002: second fingerprint verification competition. In: Proceedings of 16th International Conference on Pattern Recognition, pp. 811–814 (2002)
17. Nanni, L., Lumini, A.: Descriptors for image-based fingerprint matchers. Expert Syst. Appl. **36**(10), 12414–12422 (2009)
18. Oh, B.S., Jehyoung, J., Toh, K.A., Beng Jin Teoh, A., Jaihie, K.: A system for signature verification based on horizontal and vertical components in hand gestures. IEEE Intell. Syst. **28**(6), 52–55 (2013)
19. Oh, B.S., Toh, K.A., Teoh, A.B.J., Kim, J.: Combining local face image features for identity verification. Neurocomputing **74**(16), 2452–2463 (2011)
20. Sha, L., Zhao, F., Tang, X.: Improved fingercode for filterbank-based fingerprint matching. In: Proceedings of IEEE International Conference on Image Processing, pp. 895–898 (2003)
21. Simonyan, K., Zisserman, A.: Very deep convolutional networks for large-scale image recognition (2014). http://arxiv.org/abs/1409.1556
22. Sufi, F., Khalil, I., Hu, J.: ECG-based authentication. In: Stavroulakis, P., Stamp, M. (eds.) Handbook of Information and Communication Security, pp. 309–331. Springer, Heidelberg (2010). https://doi.org/10.1007/978-3-642-04117-4_17

23. Thuy, H., Thi, N., Huan, H.X., Ky, N.N.: An efficient method for fingerprint matching base on local point model. In: Proceedings of 2013 IEEE International Conference on Computing, Management and Telecommunications, pp. 334–339 (2013)
24. Tico, M., Immonen, E., Ramo, P., Kuosmanen, P., Saarinen, J.: Fingerprint recognition using wavelet features. In: Proceedings of IEEE International Symposium on Circuits and Systems, pp. 21–24 (2001)
25. Wang, Y., Hu, J.: Global ridge orientation modeling for partial fingerprint identification. IEEE Trans. Pattern Anal. Mach. Intell. **33**(1), 72–87 (2011)
26. Wang, Y., Hu, J., Phillips, D.: A fingerprint orientation model based on 2D fourier expansion (FOMFE) and its application to singular-point detection and fingerprint indexing. IEEE Trans. Pattern Anal. Mach. Intell. **29**(4), 573–585 (2007)
27. Wong, W.J., Teoh, A.B., Kho, Y.H., Wong, M.D.: Kernel PCA enabled bit-string representation for minutiae-based cancellable fingerprint template. Pattern Recogn. **51**, 197–208 (2016)