SCIENCE CHINA
Information Sciences

• LETTER •

December 2019, Vol. 62 229102:1–229102:3
https://doi.org/10.1007/s11432-019-9930-4

# FClassNet: a fingerprint classification network integrated with the domain knowledge

Yao TANG, Ruilin LI, Yuhang LIU & Jufu FENG*

*Key Laboratory of Machine Perception (MOE), School of Electronics Engineering and Computer Science, Peking University, Beijing 100871, China*

Received 12 April 2019/Accepted 3 June 2019/Published online 18 September 2019

**Citation** Tang Y, Li R L, Liu Y H, et al. FClassNet: a fingerprint classification network integrated with the domain knowledge. Sci China Inf Sci, 2019, 62(12): 229102, https://doi.org/10.1007/s11432-019-9930-4

Dear editor,

Ever since fingerprints were initially used as evidence in criminal proceedings in 1892, the automated fingerprint identification system has been used in a variety of contexts [1]. The fingerprint classification techniques can be used to accelerate the procedure by only comparing the query fingerprint with those that have been labeled with the same class in the database. In particular, fingerprints are divided into four classes according to the Galton-Henry classification scheme [2] as Arch (Tented Arch), Left Loop, Right Loop, and Whorl. Fingerprint classification is still considered to be challenging because of the high intraclass variability and low interclass variability. Furthermore, the presence of complex noise in low-quality fingerprints, especially latent fingerprints, increases the difficulty in this task.

Rule-based methods are the most intuitive and simple methods for classifying fingerprints according to the location and number of singular points accompanied by the orientation field [3, 4]. However, hand-crafted rules are highly dependent on the accuracy of the feature extraction results, and a limited number of rules often do not allow to cover complex scenarios. Instead of hand-crafted features and rules, several learning-based algorithms have been proposed for learning discriminative features from the data [5–8]. However, these algorithms suffer from three major weaknesses. First, the underlying models are typically trained using natural images and are subsequently directly applied to fingerprint classification tasks without considering the domain knowledge of fingerprints. Second, these methods are usually considered to be black boxes that are difficult to interpret, analyze, and optimize. Finally, some large networks, such as AlexNet and VGG, are time-consuming.

In this study, an FClassNet is proposed for performing end-to-end fingerprint classification integrating a deep neural network and the domain knowledge. Because the orientation field contains all the information required for performing fingerprint classification, it is used as a signpost to guide the FClassNet design. FClassNet comprises the modules of backbone network construction, orientation field estimation, and hybrid classification. It offers the following three major advantages when compared with the previously proposed deep-learning-based methods. First, the hidden layers of FClassNet exhibit clear characteristics of fingerprints, including as the orientation field, which makes it easier to analyze the network's mechanism and further optimize it. Second, with the integration of the orientation field, FClassNet is disentangled into several modules which can be optimized and used separately. Finally, FClassNet is fast and small in size.

Our comprehensive experiments demonstrate that the proposed algorithm significantly outperforms other methods in terms of the accuracy of orientation field estimation and fingerprint classification. The main contributions of this study can be summarized as follows.

* Corresponding author (email: fjf@cis.pku.edu.cn)

© Science China Press and Springer-Verlag GmbH Germany, part of Springer Nature 2019 

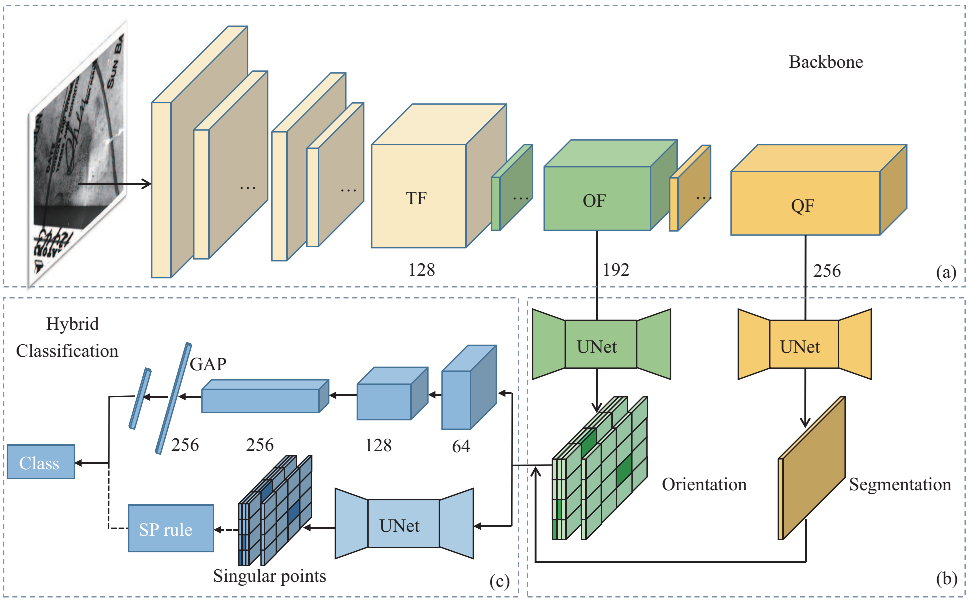


**Figure 1** (Color online) The overall architecture of the proposed FClassNet comprising three modules: (a) module contains the backbone network, (b) module performs orientation field estimation and segmentation using two UNets, and (c) module performs hybrid classification combining the orientation-field-based end-to-end classification and singular-point-based classification rules.

(1) The FClassNet that integrates a deep network and the domain knowledge is proposed for end-to-end fingerprint classification. FClassNet can classify the fingerprints in a robust and fast manner for achieving state-of-the-art classification results on both tenprint and latent fingerprints.

(2) The hidden layers of FClassNet exhibit clear fingerprint characteristics such as the orientation field, which makes FClassNet interpretable and easy to analyze. The orientation field estimation module achieves state-of-the-art results using fingerprints having different qualities.

(3) A hybrid classification algorithm is proposed to ensure complete use of the orientation field and boost the classification results. Further, the orientation-field-based end-to-end classification network and singular-point-based classification rules are designed and integrated.

*Methodology.* Because the orientation field contains all the information required for performing fingerprint classification, it is used as a signpost to guide the design of FClassNet. FClassNet is an end-to-end deep neural network and comprises the modules of backbone network construction, orientation field estimation, and hybrid classification. The overall architecture of FClassNet is illustrated in Figure 1.

(1) Backbone network. In fingerprint classification, the local region of a fingerprint is assumed to be a plane sine wave defined as

$$w(x, y) = A\cos(2\pi f(x\cos\theta + y\sin\theta)), \qquad (1)$$

where $\theta$ denotes the orientation and $f$ denotes the frequency of the local region. From this viewpoint, the orientation field becomes the most essential feature for describing fingerprints. Therefore, we consider the orientation field as a constraint to ensure that the network will learn this essential feature. However, segmentation is also considered to be a constraint because it allows to discriminate between areas containing fingerprints and not containing fingerprints, particularly important for low-quality fingerprints.

Here, we design a three-level fingerprint backbone network. The hidden layers from shallow to deep represent the texture, orientation, and quality characteristics of the fingerprints, respectively.

(2) Orientation field and segmentation. Two UNets are used to produce the orientation field and segmentation from the OF and QF layers based on the backbone network. Further, the architectures of UNets are illustrated in Appendix A.

Because the labels are not provided for the orientation field or segmentation and manual labeling is time-consuming and labor-intensive, we follow the concept of [9] to generate weak labels from paired data.

The orientation loss function is defined as

$$L_{\rm ori} = L_{\rm ce} + \lambda L_{\rm coh}, \qquad (2)$$

where $\lambda$ denotes the balance parameter, $L_{\rm ce}$ denotes the cross entropy loss, and $L_{\rm coh}$ denotes the orientation coherence loss. Orientation coherence reveals the characteristics of the fingerprint orientation as a consistent field and is an important regularization term. It can be defined as

$$\bar{d} = [\bar{d}_{\cos 2}(x,y), \bar{d}_{\sin 2}(x,y)],$$
$$||\bar{d}||_2 = \sqrt{(\bar{d}_{\cos 2}(x,y))^2 + (\bar{d}_{\sin 2}(x,y))^2},$$
$$L_{\mathrm{coh}} = 1 - \frac{\| \sum_{3\times 3}(\bar{d}) \|_2}{\sum_{3\times 3}(\|\bar{d}\|_2)}, \tag{3}$$

where $\bar{d}_{\cos 2}(x,y)$ and $\bar{d}_{\sin 2}(x,y)$ denote the sine and cosine of the double value of the orientation field, respectively, $\sum_{3\times 3}$ denotes the sum in a 3×3 neighborhood, and $\|\cdot\|_2$ denotes the two-norm of a vector. The closer the value of $L_{\mathrm{coh}}$ is to 0, the more consistent the orientation field will be.

For the segmentation loss function, we use the intersection over union (IoU) loss function, which is consistent with the segmentation target. The IoU loss function can be defined as follows:

$$L_{\mathrm{IoU}} = \frac{\sum_{i=1}^{N} y(i) \cdot p(i)}{\sum_{i=1}^{N} y(i) + \sum_{i=1}^{N} p(i) - \sum_{i=1}^{N} y(i) \cdot p(i)}, \tag{4}$$

where $y(i)$ denotes the ground truth value and $p(i)$ denotes the predicted value.

(3) Hybrid classification. To make full use of the orientation field, two branches of classification methods are designed. A four-dimensional vector representing the probability of a fingerprint being Arch (Tented Arch), Left Loop, Right Loop, or Whorl is acquired from the orientation field through a convolutional network. Singular points (SPs) are detected from the orientation field through a UNet, and the fingerprint class is acquired from the SPs based rules. A fusion algorithm, which is included in Appendix A, is designed to complementarily integrate the two methods.

*Performance evaluation.* We evaluate FClassNet in terms of the accuracy of the orientation field estimation and fingerprint classification using several databases having different qualities. Further, experiments on the public databases of NIST SD27 and NIST 4 demonstrate that the proposed method significantly outperforms the existing methods. As a supplementary experiment, we report the FClassNet performance over our inhouse CISL1000 database containing a large number of real fingerprints. It requires only 50 ms for FClassNet to classify a fingerprint, indicating that the proposed method can be used in practical situations. Because we acquire the probability vector from the last layer of the orientation-field-based classification network, a novel indexing method is proposed based on the probability vector at no additional costs. This probability vector provides flexible choices to balance the accuracy and candidate length. The details of the experimental results can be found in Appendix B.

*Conclusion.* This study proposes an FClassNet for performing end-to-end fingerprint classification that integrates a deep neural network and the domain knowledge. Because the orientation field contains all the information required for performing fingerprint classification, it is used as a signpost to guide the design of FClassNet. FClassNet has the following three major advantages when compared with the previously proposed deep-learning-based methods: the hidden layers are interpretable, the modules can be optimized and used separately, and the network is faster and smaller. The experimental results demonstrate that FClassNet achieves state-of-the-art results in orientation field estimation and fingerprint classification.

**Acknowledgements** This work was supported by National Natural Science Foundation of China (Grant No. 61333015).

**Supporting information** Appendixes A and B. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

**References**


1 Jain A K, Nandakumar K, Ross A. 50 years of biometric research: accomplishments, challenges, and opportunities. Pattern Recogn Lett, 2016, 79: 80–105
2 Henry E R. Classification and Uses of Finger Prints. London: HM Stationery Office, 1905
3 Karu K, Jain A K. Fingerprint classification. Pattern Recogn, 1996, 29: 389–404
4 Zhang Q, Yan H. Fingerprint classification based on extraction and analysis of singularities and pseudo ridges. Pattern Recogn, 2004, 37: 2233–2243
5 Jin J W, Liu Z L, Chen C L P. Discriminative graph regularized broad learning system for image recognition. Sci China Inf Sci, 2018, 61: 112209
6 Li Q Q, Zou Q, Ma D, et al. Dating ancient paintings of Mogao Grottoes using deeply learnt visual codes. Sci China Inf Sci, 2018, 61: 092105
7 Peralta D, Triguero I, García S, et al. On the use of convolutional neural networks for robust classification of multiple fingerprint captures. Int J Intell Syst, 2018, 33: 213–230
8 Michelsanti D, Guichi Y, Ene A D, et al. Fast fingerprint classification with deep neural network. In: Proceedings of the 12th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications, 2018. 202–209
9 Tang Y, Gao F, Feng J, et al. Fingernet: an unified deep network for fingerprint minutiae extraction. In: Proceedings of 2017 IEEE International Joint Conference on Biometrics (IJCB). New York: IEEE, 2017. 108–116