# Orientation Field Estimation for Latent Fingerprints with Prior Knowledge of Fingerprint Pattern

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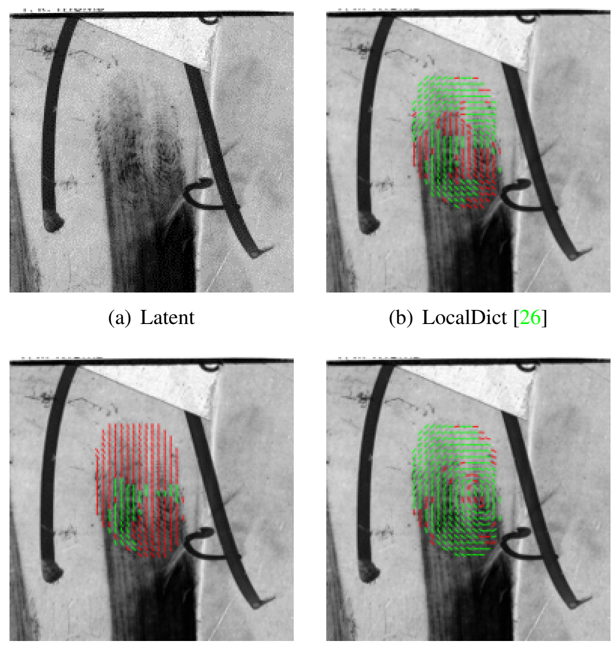
## Abstract

*Estimating orientation field for latent fingerprints plays a crucial role in latent fingerprints recognition systems. Due to poor quality and small area of latent fingerprints, however, the performance of the state-of-the-art algorithms is still far from satisfactory. Considering the intrinsic characteristics of fingerprints that the distribution of orientation field varies with the fingerprint patterns, we propose an orientation field estimation algorithm for latent fingerprints based on residual learning using prior knowledge of fingerprint patterns. Specifically, statistical distribution models of orientation field, for different fingerprint patterns, are calculated based on a large database consisting of 14,000 fingerprints with good quality using clustering method. The residual orientation fields and reliability scores, indicating the consistency with different statistical orientation models, are estimated using a deep network, named RefNet. Then the final orientation field is obtained by fusing the estimations according to their corresponding reliability scores. Experimental results on the widely used latent database NIST SD27 demonstrate that the proposed algorithm provides higher orientation field estimation accuracy compared with the state-of-the-art methods, and by enhancing latent fingerprints using estimated orientation field, the identification performance is further improved.*



(a) Latent (b) LocalDict [26] (c) Exhaustive Search [28] (d) Ours

Figure 1. Orientation field estimations of different algorithms. Note that the dictionary-based methods do not work well since the initial orientation field is sensitive to background noise and fingerprint pattern information is neglected. The green lines indicate the correctly estimated orientation elements (absolute difference is lower than 15 degrees), while the red lines over 15 degrees.

## 1. Introduction

Fingerprint is one of the most important and widely used biometric identifiers over the past decades, which has been applied in various aspects such as access control, security checking, mobile verification, and criminal investigation, due to its immutability and uniqueness [17]. Thanks to the rapid development of computer technologies, Automated Fingerprint Identification System (AFIS), including fingerprint acquisition, enhancement, feature extraction, recognition, etc., has shown superior performance, especially for plain and rolled fingerprints [10]. However, different from these fingerprints acquired in controlled environment, latent fingerprints, collected from crime scene, always encounter poor image quality (complicated background, blurred ridge patterns, structured noise, etc.) and partial observation, making it a challenging task to extract reliable features for fingerprint recognition [7].

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Generally, orientation field plays a crucial role in fingerprint enhancement, which is employed to improve ridge pattern clarity, eliminate structured noise, and recover corrupted areas in AFIS [20, 2]. Due to poor quality and partial observation, estimating orientation field from latent fingerprints automatically is still a challenging task. A number of algorithms have been proposed for orientation field estimation in latent fingerprints.

Priori knowledge has been introduced in existing latent fingerprint orientation field estimation algorithms. Global- and local- dictionaries are introduced to reject unreasonable local orientation patterns [11, 26, 6, 8]. Exhaustive search of large database is used to capture global constraints of fingerprints [28]. Typical local orientation patterns are learnt to convert the orientation field estimation to a classification task using convolutional neural network (CNN) [4, 5]. However, there are some limitations with such methods. Firstly, the dictionary-based methods need initial orientation field estimation implemented by simple and traditional local orientation estimation methods, which are sensitive to image noise, and thus will fail when the initial estimation is far from ground truth. Secondly, orientation estimation error around singular points is usually large. Besides, most methods consider global and local information separately, which means the global constraint and local features are not fully integrated. Therefore, methods to make better use of prior knowledge of fingerprints have yet to be explored.

In this paper, we propose a new method for latent fingerprint orientation field estimation to mitigate the issues aforementioned. The proposed framework consists of two parts, one from global guidance learning and the other for local feature extraction. The global guidance is explored by analyzing the general distributions of fingerprint orientation field, i.e. the average orientation fields for different fingerprint patterns, on a large database of orientation fields generated from 14,000 fingerprints with good quality. By introducing the statistical distribution as the reference orientation field, a deep network named RefNet, is utilized to estimate the residual between the reference and real orientation field, which is dominated by local ridge information. The idea is inspired by the assumption that orientation fields of different fingerprint patterns follow specific distribution, which has been demonstrated in [26]. However, different from the unified distribution used in [26], fingerprint pattern based distributions are explored in this paper.

Briefly, the main contribution is summarized as: fingerprint pattern based prior knowledge of orientation field, estimated from a large fingerprint database with good quality, is incorporated as the reference to guide orientation field estimation, thus reducing the model complexity and increasing the performance at the same time. We evaluate the proposed method on the popular latent fingerprints dataset, NIST SD27, and experimental results demonstrate the superiority of our algorithm over state-of-the-art methods in latent fingerprint orientation field estimation.

## 2. Related works

The orientation field of a fingerprint is usually considered as a combination of ridge orientation elements which are dominant ridge flows in local patches (*e.g.* $16\times16$). This property was directly applied for orientation field estimation in conventional algorithms, including gradient-based method [3], local Fourier analysis [9], and linear projection analysis [1]. However, only local information was considered in these approaches, making them sensitive to image noise which is very common in latent fingerprints. Considering the smoothness of orientation field, model parameters instead were predicted by some mathematical model-based methods to improve the robustness to image noise [30, 13, 19]. However, the incorporation of fingerprint prior knowledge was still not fully explored in such algorithms, resulting in unsatisfactory performance due to the strong and complicated noise in latent fingerprints.

Inspired by the idea that orientation elements are not assembled without constraints, Feng *et al*. [11] proposed a global orientation patch dictionary consisting of typical real orientation patches to correct noisy initial orientation field estimated by local Fourier analysis. To obtain the final orientation field estimation, potential candidates were selected from the dictionary according to the initial local orientation patches, and followed by a Markov random field (MRF) optimization. Based on this method, further, Yang *et al*. [26] proposed a set of localized orientation patch dictionaries with smaller patch size to replace the global dictionary. Different from [11], the localized dictionaries were conducted based on relative locations of fingerprint patches and more valid candidates were selected given the possible locations. However, orientation patches might be inconsistent with each other even with the MRF optimization since the dictionaries were conducted on local patches thus ignoring the global constraint. Later, instead of small patches, the whole orientation fields generated from a large database were used for building the dictionary to introduce global constraints of valid orientation field [28]. However, performance of these dictionary based methods relies on the accuracy of initial orientation field estimated using conventional algorithms which itself is sensitive to noise. Furthermore, such algorithms tend to fail around singular points where the distribution of ridge orientation is complicated, and time-consuming due to the operation of searching for candidates from dictionaries.

Due to the powerful discriminative ability of deep convolutional neural networks, deep learning has earned increasing attention in latent fingerprint image processing. Inspired by the success of CNN in variety of challenging tasks in computer vision, Cao *et al*. [4] proposed ConvNet to clas-

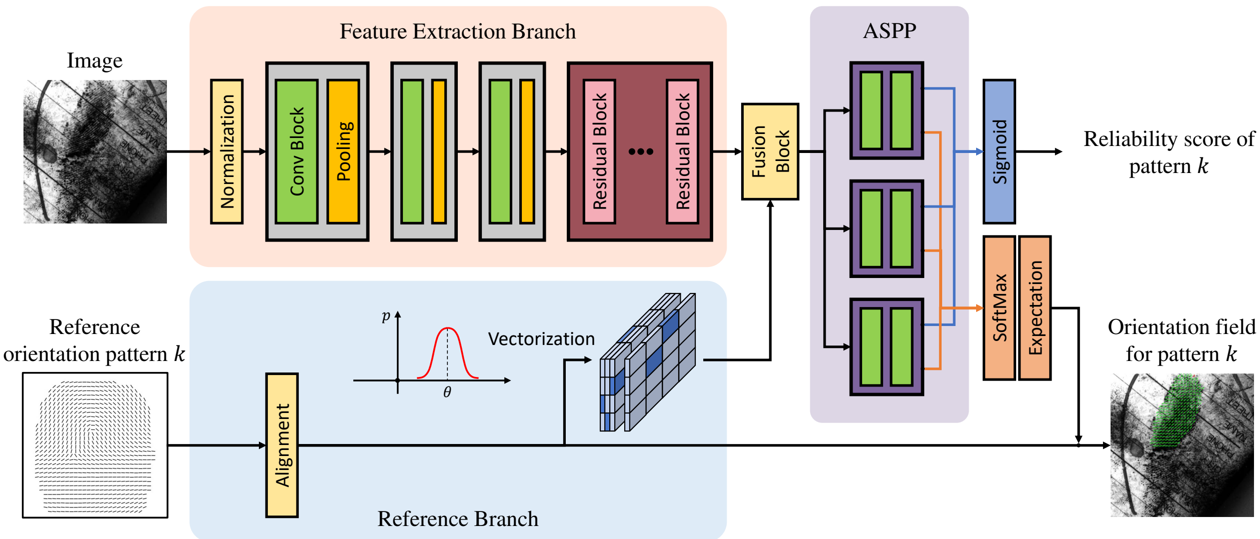



Figure 2. Overview of the proposed RefNet. The reference orientation pattern incorporates global information to accelerate network convergence and guide the orientation filed estimation. The final prediction is the weighted average of estimations which are generated based on different reference orientation patterns defined in Section 3.2.

sify the orientation field of a latent patch as one of the typical local orientation patterns clustered from a fingerprint database with good quality. Tang *et al.* [23] proposed a unified fingerprint processing framework implemented by deep network including fingerprint enhancement, orientation field estimation, segmentation, and minutiae extraction. Also, deep learning was utilized in other orientation field estimation approaches, *e.g.* regression convnets [21, 18] and deep expectation [22]. However, to the best of our knowledge, these CNN-based methods have not yet considered holistic information of fingerprint orientation field.

## 3. Method

In this paper, we aim to estimate orientation field of latent fingerprints. Statistical orientation field distributions of different fingerprint patterns are obtained firstly, which contribute to orientation field estimation in latent fingerprint by introducing global information. For each statistical distribution model, our proposed deep network (RefNet) utilizes this prior knowledge as a reference and produces the corresponding residual orientation field as well as a reliability score indicating the reliability of current estimation. The final orientation field estimation is obtained by fusing these orientation field estimations according to their reliability scores predicted. The schematic illustration of our algorithm is shown in Figure 2.

### 3.1. Training data preparation

To utilize the powerful discriminative ability of CNN, a number of latent fingerprints with orientation field annotations are required for training, which is not practical since manual annotation of orientation field is extremely time-consuming. In [23], a plain FingerNet was applied to obtain orientation field of rolled fingerprints and the annotations of latent fingerprint orientation field were generated by aligning matched rolled and latent fingerprints using expert marked minutiae, which are not easy to obtain either.

In this paper, a number of latent fingerprints with corresponding orientation field annotations are synthesized based on existing rolled fingerprint database, i.e. the first 14,000 fingerprints in NIST SD14. In order to simulate the characteristic of real latent fingerprints, including complicated background, texture noise, etc., we use additional images in another database MSRA-TD500 [27], collected for detecting text with various languages, fonts, sizes, and orientations in natural images, as background. A statistical plain fingerprint mask $M$ generated from various plain fingerprints in FVC2004 is also utilized to simulate the contact area in latents. Given the original rolled fingerprint $I_r$ and a random background image $I_b$, the synthesized fingerprint $I_s$ is obtained by cropping, normalizing, and minimizing

$$\begin{aligned} I_s &= \min(f(I_r, M), \hat{I}_b), \\ \hat{I}_b &= \frac{I_b - \mathrm{mean}(I_b)}{\mathrm{std}(I_b)} \cdot \mathrm{std}(I_r) + \mathrm{mean}(I_r), \end{aligned} \tag{1}$$

where $f(I_r, M)$ indicates randomly cropping and masking on $I_r$ with mask $M$. Examples of simulated latent fingerprints are shown in Figure 3. Consequently, orientation field generated from original rolled fingerprint with good quality, using FingerNet [23], is considered as groundtruth of synthesized latents for training RefNet.

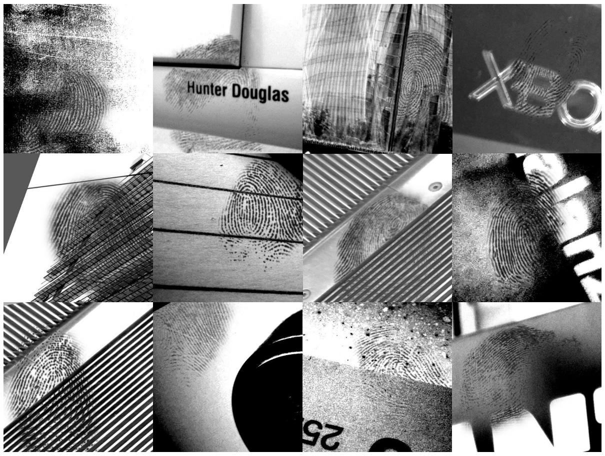



Figure 3. Latent fingerprints synthesized based on rolled fingerprints and additional background images for network training.

### 3.2. Orientation distribution

Normally, the ridge orientation follows similar distribution in the same part of fingerprints and varies in different parts. Obviously, this prior knowledge can be introduced as an auxiliary information to help to reject wrong prediction, which is similar with dictionary-based method [11, 26, 4].

In order to acquire the distribution model, all the orientation fields of rolled fingerprints in training data, are aligned to the same coordinate based on fingerprint's pose as the definition in [29]. All these poses of rolled fingerprints are estimated using a joint model proposed in [29]. After alignment, a clustering method such as K-means algorithm is applied to classify the various orientation fields into four patterns (including arch, twin loop, right loop, and left loop) and generate the center of each clustering, i.e. average orientation field, as shown in Figure 4. Therefore, given a new latent fingerprint, the corresponding coordinate system is estimated following pose estimation approach described in [29]. Then, each statistical orientation pattern, transformed based on the coordinate predicted previously, is used as a reference to assist orientation field estimation. Note that the transformed statistical orientation pattern has the same resolution with the orientation field to be estimated, i.e. $1/8$ size of original latent fingerprint in this paper.

### 3.3. Network architecture

Various deep learning based methods have been proposed for orientation field estimation, however, fingerprint prior knowledge has not been fully exploited in these algorithms. Inspired by the idea of residual learning in image super-resolution problems where the network asymptotically approximates the residual between the reference and real value [14], we propose a deep network to predict the residual angle $\theta_{\text{res}}$ between real orientation $\theta_{\text{gt}}$ and the

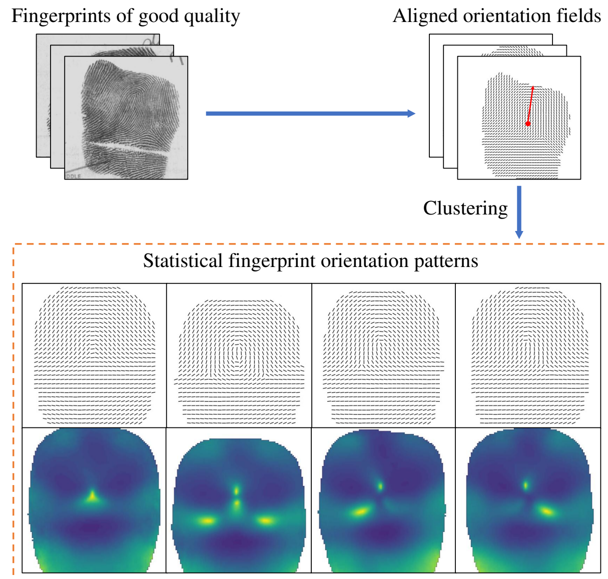



Figure 4. Statistical orientation patterns generated by clustering method. Four categories of orientation patterns are obtained and the bottom row is the standard deviation for each category. Obviously, the clustering results are consistent with the definition of fingerprint patterns, i.e. arch, twin loop, right loop, and left loop.

reference angle $\theta_{\text{ref}}$ aforementioned, as shown in Figure 2.

$$\theta_{\text{res}} = \theta_{\text{gt}} - \theta_{\text{ref}}, \theta_{\text{res}} \in (-90^\circ, 90^\circ]. \tag{2}$$

The proposed RefNet is customized from original FingerNet [23]. Specifically, the feature extraction module consists of 3 conv-pooling blocks, where each conv block is composed of a convolution, a BatchNorm, and a PReLU layer, followed by a max-pooling layer. And several residual blocks are used to improve the ability of extracting discriminative features. After that, considering the ridge orientation is undirected, which means $-90^\circ$ is consistent with $90^\circ$ while completely different for neural networks, the reference orientation field is not able to be utilized directly. Instead, the interval between $-90^\circ$ and $90^\circ$ is divided into $N$ cells with non-overlapping, inspired by [23], and a $N$-dimensional vector $\boldsymbol{p}_\theta \in \mathbb{R}^N$, where the $i$-th element $p_\theta^i$ indicates the probability of being equal to the typical value of $i$-th cell, is assigned to each orientation angle $\theta$. The vectorized reference orientation field is then concatenated with extracted features previously. ASPP-Net is adopted for capturing multi-scale information, and similarly, vectorized orientation is determined as the output of network followed by computing expectation to obtain the residual orientation field. The final orientation field estimation is obtained by adding the reference orientation field and the predicted residual orientation field.

According to the residual learning, it is reasonable to assume that given the reference orientation field with same fingerprint pattern as the latent, the estimation result is more reliable. Therefore, a reliability score, indicating the probability that the input fingerprint has the same fingerprint pattern with the reference orientation field, is predicted and utilized as weights for fusing estimations based on different reference orientation fields.

### 3.4. Objective functions

**Orientation Loss**: Recently, focal loss [15] has been successful in classification tasks and is proven effective in imbalanced classification. Hence we introduce the focal loss to alleviate data-imbalanced problem caused by the incorporation of reference orientation, i.e. the residuals are close to 0 in most areas. The orientation loss is defined as:

$$\mathcal{L}_{\mathrm{Ori}} = \frac{1}{|\Omega|}\sum_{\Omega}\sum_{i}^{N}\alpha(1-p_t^i)^{\gamma}\log(p_t^i), \quad p_t^i = y^i p^i + (1-y^i)(1-p^i), \tag{3}$$

where $\Omega$ is the region of interest (ROI), $p^i$ and $y^i$ is the $i$-th element of probability vector generated based on estimated residual angle $\hat{\theta}_{\mathrm{res}}$ and its groundtruth $\theta_{\mathrm{res}}$, respectively, and $N$ is the dimension of the probability vector. $\alpha$ and $\gamma$ are hyper-parameters to balance the importance of categories and mitigate easy example dominance respectively. We set $\alpha = 1.0$ and $\gamma = 2.0$ in the experiment.

**Smoothness Loss**: We also apply a regularization loss to constrain the smoothness of estimated residual orientation. Similar to [23], smoothness is determined by orientation coherence $Coh$ [3] and hence the smoothness loss is calculated as:

$$\mathcal{L}_{\mathrm{Smooth}} = \frac{|\Omega|}{\sum_{\Omega} Coh} - 1. \tag{4}$$

**Overall Loss**: The RefNet is optimized by minimizing the following overall objective function

$$\mathcal{L} = \mathcal{L}_{\mathrm{Ori}} + \lambda_{\mathrm{Smooth}}\cdot\mathcal{L}_{\mathrm{Smooth}} + \lambda_{\mathrm{Cls}}\cdot\mathcal{L}_{\mathrm{Cls}}, \tag{5}$$

where $\mathcal{L}_{\mathrm{Cls}}$ is reliability loss for predicting the reliability score, $\lambda_{\mathrm{Smooth}}$ and $\lambda_{\mathrm{Cls}}$ denotes the trade-off parameter for smoothness and reliability loss, respectively. We use focal loss in $\mathcal{L}_{\mathrm{Cls}}$ and set $\lambda_{\mathrm{Smooth}} = 1.0$ and $\lambda_{\mathrm{Cls}} = 1.0$ such that these loss functions have the same decreasing rate roughly.

### 3.5. Orientation post-processing

To further improve the smoothness of orientation field estimation, we apply an additional smoothing operation following the prediction of RefNet. Inspired by the definition of orientation coherence aforementioned, each orientation element $\theta_i$ is replaced by the average result of its neighborhood $\Omega_i$, defined as $3\times 3$ in this paper,

$$\hat{\theta} = \frac{1}{2}\mathrm{atan2}\Big(\frac{1}{|\Omega_i|}\sum_{j\in\Omega_i}\sin(2\theta_j), \frac{1}{|\Omega_i|}\sum_{j\in\Omega_i}\cos(2\theta_j)\Big). \tag{6}$$

Table 1. Quantitative comparison of different orientation field estimation algorithms on latent fingerprint database NIST SD27 and three subsets, in terms of average root mean square deviation (RMSD). "-M" denotes using manually marked fingerprint pose.

| Methods | All | Good | Bad | Ugly |
|---|---|---|---|---|
| STFT [9] | 32.51 | 27.27 | 34.10 | 36.36 |
| FOMFE [25] | 28.12 | 22.83 | 29.09 | 32.63 |
| GlobalDict [11] | 18.44 | 14.40 | 19.18 | 21.88 |
| LocalDict [26] | 14.35 | 11.15 | 15.15 | 16.85 |
| LocalDict-M [26] | 13.76 | 10.87 | 14.12 | 16.40 |
| ConvNet [4] | 13.51 | 10.76 | 13.94 | 16.00 |
| SparseCoding [16] | 16.38 | 12.57 | 16.88 | 20.22 |
| ExSearch-B [28] | 13.54 | 11.21 | 14.20 | 14.95 |
| ExSearch [28] | 13.01 | 10.85 | 13.99 | 14.27 |
| FingerNet [23] | 17.82 | 13.67 | 18.42 | 21.50 |
| Single | 12.46 | 9.91 | 12.91 | 14.65 |
| Single-M | 12.20 | 9.65 | 12.73 | 14.39 |
| Ours | **12.16** | **9.87** | **12.83** | **13.85** |
| Ours-M | **12.10** | **9.60** | **12.71** | **14.07** |

## 4. Experiments

We conducted experiments on the widely used latent fingerprint database NIST SD27 to compare the propose algorithm with state-of-the-art orientation field estimation algorithms. The database consists of 258 paris of latent and rolled fingerprints, which are divided into three subsets: 88 fingerprints are identified to be of good quality, 85 of bad quality, and the rest 85 of ugly quality. The orientation field estimation accuracy and identification accuracy using the enhanced latent fingerprints based on the estimated orientation field are reported respectively.

### 4.1. Implementation details

We implement our proposed RefNet on PyTorch with NVIDIA GeForce 2080Ti. Data augmentation is performed on training images, including random translation in range of $1/5$ width and height of image, rotation in range of $-45°$ to $45°$, horizontal flip, and additive Gaussian noise from a normal distribution $\mathcal{N}(0, 0.05)$ at each epoch of training. The number of cells $N$ in orientation vectorization is set to 180, i.e. $1°$ for each cell, to improve the accuracy of estimation. We update the weights of network using an Adam optimizer with initial learning rate of 0.0001 and momentum of 0.5. To avoid overfitting, a L2 regularization is used in our network with the value of $5\mathrm{e}^{-4}$. A total of 14,000 synthesized latent fingerprints are divided into training set and validation set in a ratio of 4 to 1. Finally, the whole network is trained from scratch, and the weights are initialized using kaiming initialization.

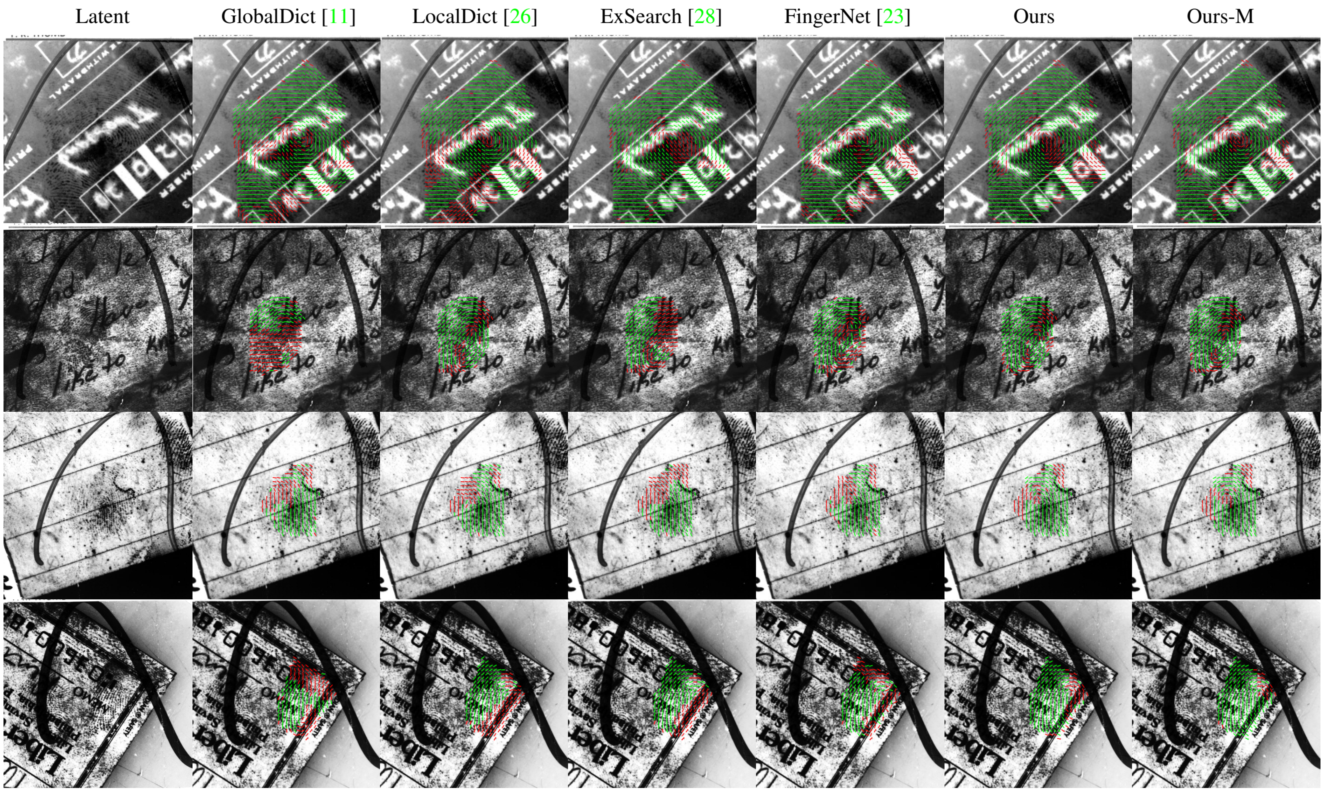


Figure 5. Examples of different algorithms. The green lines indicate the correctly estimated orientation elements (absolute difference is lower than 15 degrees), while the red lines with error over 15 degrees. "-M" denotes using manually marked fingerprint pose.

### 4.2. Deviation from groundtruth

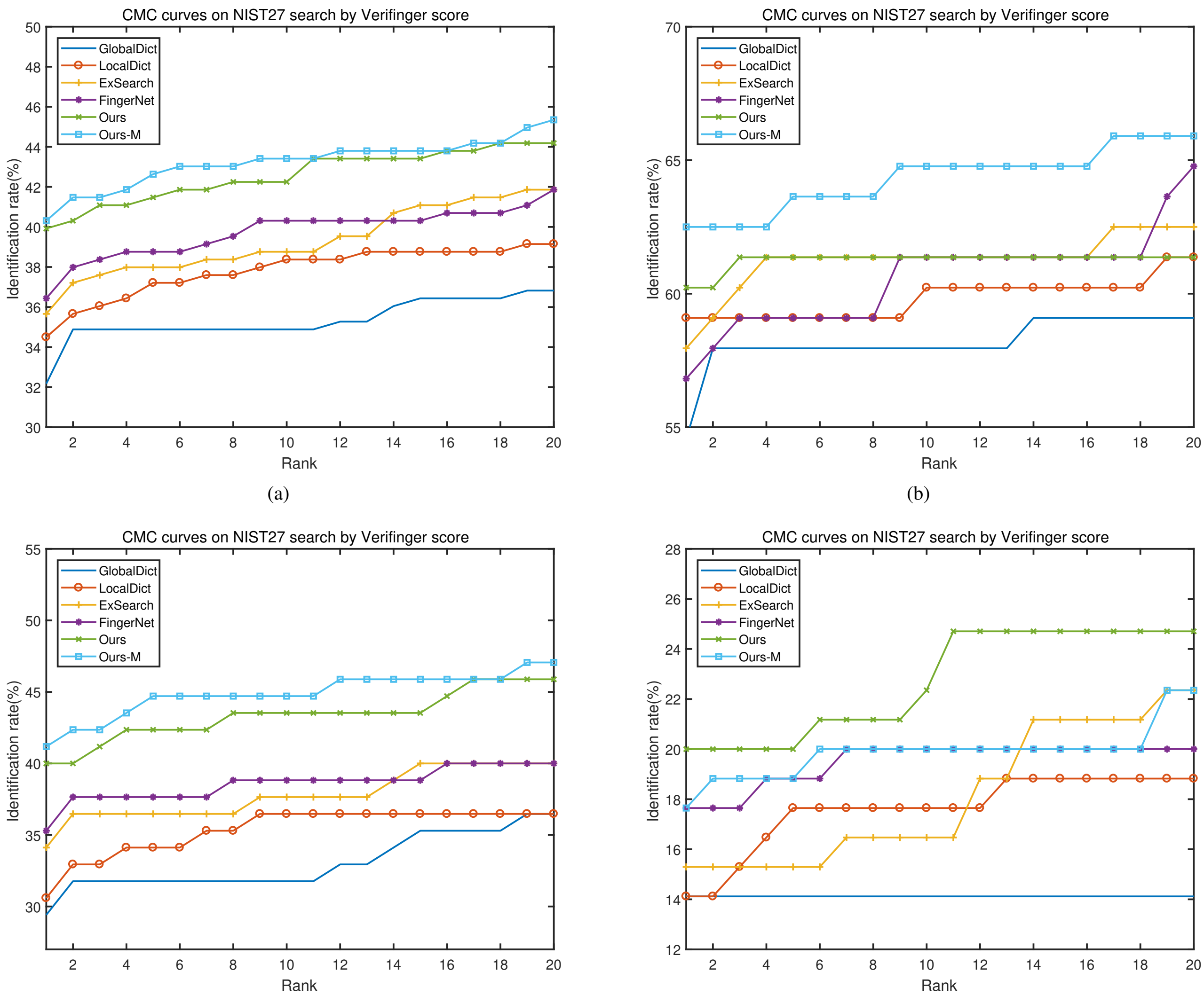
We use manually marked orientation field and fingerprint segmentation ROI of NIST SD27 in [11] as groundtruth. The accuracy of orientation field estimation is evaluated by the average Root Mean Square Deviation (RMSD) [24]. Quantitative comparison of our proposed approach is performed with following methods: (1) FingerNet method (FingerNet) [23]; (2) exhaustive search based method (ExSearch) and its boosting version (ExSearch-B) [28]; (3) sparse coding based method (SparseCoding) [16]; (4) ConvNet based method (ConvNet) [4]; (5) localized orientation field dictionary method (LocalDict) [26]; (6) global orientation field dictionary method (GlobalDict) [11]; (7) 2D Fourier expansion method (FOMFE) [25]; (8) local Fourier analysis method (STFT) [9]. Besides, only one reference orientation pattern (Single) without considering fingerprint type is also incorporated to explore the effect of fingerprint type on orientation field estimation performance.

As shown in Table 1, the proposed approach outperforms the comparison methods, and both the introduction of residual learning and fingerprint pattern are demonstrated to be effective. Meanwhile, it is observed that our approach based on automatic pose estimation has a competitive performance with the one with manually marked fingerprint pose, indicating that the proposed method is relative robust to the accuracy of pose estimation. Examples from different algorithms on three subsets with different quality are shown in Figure 5 visually.

### 4.3. Evaluation by fingerprint matching

As mentioned above, orientation fields are utilized to enhance latent fingerprints thus increasing ridge pattern clarity and eliminating complicated background noise. Thus we further carry out fingerprint matching experiment to examine the contribution of our proposed orientation field estimation in overall fingerprint identification system. We adopt Gabor filtering method [12], except for FingerNet [23] that generates enhanced latent fingerprint simultaneously, to enhance latent fingerprints based on estimated orientation field. A fixed ridge frequency of Gabor filter is set to 0.12 in this paper. The commercial software VeriFinger SDK 12.0 is used for extracting minutiae and computing matching scores between latent and rolled fingerprints. Additional database NIST SD14, consisting of 27,000 rolled fingerprints, is utilized as background to make the matching experiment more challenging and realistic.

We use the cumulative match characteristic (CMC) curve to evaluate the matching performance of different orien-




(a) (b) (c) (d)

Figure 6. CMC curves of different algorithms on latent fingerprint database NIST SD27 as well as three subsets: (a) all (258 latents), (b) good quality (88 latents), (c) bad quality (85 latents), (d) ugly quality (85 latents). "-M" denotes manually marked fingerprint pose.

tation field estimation algorithms on the latent fingerprint database NIST SD27 as well as three subsets, as shown in Figure 6. It is observed that the Rank-1 identification rate of the proposed approach is $4.0\%$ higher than the results from FingerNet [23] and exhaustive search [28] based method.

Average time of our approach for orientation field estimation, excluding pose estimation, is about 0.49 seconds per fingerprint on a computer with a NVIDIA GeForce 2080Ti GPU and a 2.1GHz CPU.

## 5. Conclusion

Orientation field estimation is important for latent fingerprint identification systems. In this paper, we proposed an orientation field estimation algorithm for latent fingerprints based on residual learning using fingerprint patterns prior knowledge. The proposed approach integrates the strength of deep networks in extracting discriminative features and statistical orientation distribution models of different fingerprint patterns, which is a reliable guidance for orientation field estimation. The experiments over popular latent fingerprint database NIST SD27 demonstrates the superior performance of our proposed method compared with the state-of-the-art algorithms.

## 6. Acknowledgment

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## References


[1] W. Bian, Y. Luo, D. Xu, and Q. Yu. Fingerprint ridge orientation field reconstruction using the best quadratic approximation by orthogonal polynomials in two discrete variables. *Pattern Recognition*, 47(10):3304–3313, 2014. 2

[2] W. Bian, D. Xu, Q. Li, Y. Cheng, B. Jie, and X. Ding. A survey of the methods on fingerprint orientation field estimation. *IEEE Access*, 7:32644–32663, 2019. 2

[3] J. Bigun and G. H. Granlund. Optimal orientation detection of linear symmetry. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 433–438, 1987. 2, 5

[4] K. Cao and A. K. Jain. Latent orientation field estimation via convolutional neural network. In *Proceedings of the IEEE International Conference on Biometrics*, pages 349–356, 2015. 2, 4, 5, 6

[5] K. Cao and A. K. Jain. Automated latent fingerprint recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 41(4):788–800, 2018. 2

[6] K. Cao, E. Liu, and A. K. Jain. Segmentation and enhancement of latent fingerprints: A coarse to fine ridge structure dictionary. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 36(9):1847–1859, 2014. 2

[7] C. Champod, C. Lennard, M. Stoilovic, and P. Margot. *Fingerprints and other ridge skin impressions*. CRC Press, 2016. 1

[8] C. Chen, J. Feng, and J. Zhou. Multi-scale dictionaries based fingerprint orientation field estimation. In *Proceedings of the IEEE International Conference on Biometrics*, pages 1–8, 2016. 2

[9] S. Chikkerur, V. Govindaraju, and A. N. Cartwright. Fingerprint image enhancement using STFT analysis. In *Proceedings of the International Conference on Pattern Recognition and Image Analysis*, pages 20–29. Springer, 2005. 2, 5, 6

[10] S. A. Cole. Suspect identifies: A history of fingerprinting and criminal identijication, 2009. 1

[11] J. Feng, J. Zhou, and A. K. Jain. Orientation field estimation for latent fingerprint enhancement. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(4):925–940, 2012. 2, 4, 5, 6

[12] L. Hong, Y. Wan, and A. Jain. Fingerprint image enhancement: Algorithm and performance evaluation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(8):777–789, 1998. 6

[13] S. Huckemann, T. Hotz, and A. Munk. Global models for the orientation field of fingerprints: An approach based on quadratic differentials. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 30(9):1507–1519, 2008. 2

[14] J. Kim, J. K. Lee, and K. M. Lee. Accurate image super-resolution using very deep convolutional networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1646–1654, 2016. 4

[15] T.-Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollár. Focal loss for dense object detection. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 2980–2988, 2017. 5

[16] S. Liu, M. Liu, and Z. Yang. Sparse coding based orientation estimation for latent fingerprints. *Pattern Recognition*, 67:164–176, 2017. 5, 6

[17] D. Maltoni, D. Maio, A. K. Jain, and S. Prabhakar. *Handbook of Fingerprint Recognition*. Springer Science & Business Media, 2009. 1

[18] Z. Qu, J. Liu, Y. Liu, Q. Guan, C. Yang, and Y. Zhang. Orienet: A regression system for latent fingerprint orientation field extraction. In *Proceedings of the International Conference on Artificial Neural Networks*, pages 436–446. Springer, 2018. 3

[19] S. Ram, H. Bischof, and J. Birchbauer. Modelling fingerprint ridge orientation using legendre polynomials. *Pattern Recognition*, 43(1):342–357, 2010. 2

[20] A. Sankaran, M. Vatsa, and R. Singh. Latent fingerprint matching: A survey. *IEEE Access*, 2:982–1004, 2014. 2

[21] P. Schuch, S.-D. Schulz, and C. Busch. Convnet regression for fingerprint orientations. In *Proceedings of the Scandinavian Conference on Image Analysis*, pages 325–336. Springer, 2017. 3

[22] P. Schuch, S.-D. Schulz, and C. Busch. Deep expectation for estimation of fingerprint orientation fields. In *Proceedings of the IEEE International Joint Conference on Biometrics*, pages 185–190, 2017. 3

[23] Y. Tang, F. Gao, J. Feng, and Y. Liu. Fingernet: An unified deep network for fingerprint minutiae extraction. In *Proceedings of the IEEE International Joint Conference on Biometrics*, pages 108–116, 2017. 3, 4, 5, 6, 7

[24] F. Turroni, D. Maltoni, R. Cappelli, and D. Maio. Improving fingerprint orientation extraction. *IEEE Transactions on Information Forensics and Security*, 6(3):1002–1013, 2011. 6

[25] Y. Wang, J. Hu, and D. Phillips. A fingerprint orientation model based on 2D fourier expansion (FOMFE) and its application to singular-point detection and fingerprint indexing. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 29(4):573–585, 2007. 5, 6

[26] X. Yang, J. Feng, and J. Zhou. Localized dictionaries based orientation field estimation for latent fingerprints. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 36(5):955–969, 2014. 1, 2, 4, 5, 6

[27] C. Yao, X. Bai, W. Liu, Y. Ma, and Z. Tu. Detecting texts of arbitrary orientations in natural images. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1083–1090, 2012. 3

[28] Q. Yin, J. Feng, J. Lu, and J. Zhou. Orientation field estimation for latent fingerprints by exhaustive search of large database. In *Proceedings of the IEEE International Conference on Biometrics Theory, Applications and Systems*, pages 1–9, 2018. 1, 2, 5, 6, 7

[29] Q. Yin, J. Feng, J. Lu, and J. Zhou. Joint estimation of pose and singular points of fingerprints. *IEEE Transactions on Information Forensics and Security*, 16:1467–1479, 2020. 4

[30] J. Zhou and J. Gu. Modeling orientation fields of fingerprints with rational complex functions. *Pattern Recognition*, 37(2):389–391, 2004. 2