LATENT FINGERPRINT ENHANCEMENT USING GABOR AND MINUTIA DICTIONARIES

Miao Xu, Jianjiang Feng, Jiwen Lu, Jie Zhou

Department of Automation, Tsinghua University

ABSTRACT

Latent fingerprints play important roles in law enforcement agencies. Due to its poor quality caused by unclear ridge structure, uneven contrast and overlapping patterns, a latent fingerprint enhancement is necessary for reliable feature extraction. Gabor function is widely used to characterise ridge structure and used in fingerprint enhancement. However, gabor function can not capture the details of minutia that is the end point or bifurcation of ridge. To utilize the prior knowledge of both ridge and minutia, we propose to construct both ridge and minutia dictionaries, and propose a two-step multi-scale patch based sparse representation to enhance the ridge using ridge dictionaries and enhance the minutia with both dictionaries. Experimental results show that two-step SR algorithm outperforms the SR only using gabor dictionary and gabor filter on both minutia extraction accuracy and matching accuracy.

Index Terms— Fingerprint enhancement, sparse representation, orientation field, gabor dictionary, minutiae dictionary

1. INTRODUCTION

Latent fingerprints refer to the impressions that left on objects or surface unintentionally [1], and they play important roles in law enforcement agencies to identify criminals and terrorists. However, such fingerprints are usually of low quality due to unclear ridge structure, uneven contrast and overlapping patterns [2]. Thus, features of the latent fingerprint are traditionally manually marked so that they can be matched by automated fingerprint identification systems (AFIS). However, manually marking features (1) is time-consuming, (2) has a compatibility problem since features of full fingerprints are automatically extracted, (3) is short of repeatability for the reason that the features marked by different people or the feature marked by the same person at different time are often different. To address this problem, latent fingerprint enhancement is needed to enable reliable feature extraction.

There are a number of algorithms aims to enhance the latent fingerprints. Gabor filter is a widely used method, which require ridge orientation and frequency to be estimated firstly [3][2][4]. Recently, sparse representation [5][6][7] is used to enhance latent fingerprints and achieve better enhancement performance than gabor filter. However both gabor filter and dictionary have the gabor form which can well characterise ridge but can not capture the details of minutiae, which leads to wrong and missing minutiae. Minutia is the most important feature of fingerprints and has large impact in fingerprint matching.

In order to address this limitation, we propose to construct both ridge and minutia dictionaries to utilize the prior knowledge of both ridge and minutia structure. Two-step multi-scale patch based sparse representation algorithm is proposed to enhance latent fingerprints using both ridge and minutia dictionaries. Firstly, the fingerprint is decomposed by Relative Total Variation model. The texture component is enhanced in the following steps. Secondly, orientation field is computed using a state-of-the-art orientation field estimation method [4] and local gabor and minutiae dictionaries are constructed guided by orientation field. Thirdly, fingerprint is enhanced by multi-scale patch sparse representation using local gabor dictionaries. Finally, initial minutiae are extracted and the regions near the minutiae are re-enhanced using both gabor and minutiae dictionaries.

2. THE PROPOSED ALGORITHM

In this section, we will present the major steps of the proposed algorithm: latent fingerprint decomposition with relative TV model, orientation field computation, gabor and minutiae dictionaries construction, and fingerprint enhancement via sparse representation.

2.1. Latent fingerprint decomposition with Relative Total Variation model

Since latent fingerprints have a lot of irrelevant contents (the background of the fingerprint), we first use the Relative Total Variation model (RTV) [8] to discard that. RTV can decompose an image into two components: structure and texture (as shown in Fig. 1). The texture component, which contains the ridge pattern and some noise, is used for further enhancement, while the structure part, which looks like the piecewise smoothing result, is discarded.

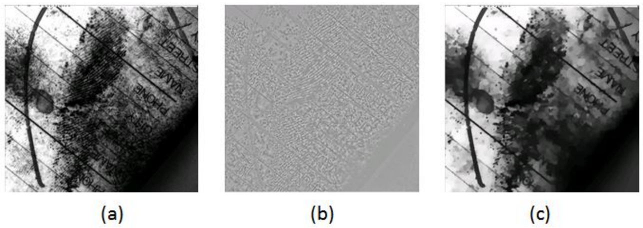

Fig. 1. (a) A latent fingerprint and its RTV decomposed components: (b) texture and (c) structure.

2.2. Orientation field computation

Orientation field is an important feature of latent fingerprint, which plays important roles in latent fingerprint enhancement [4][2][3]. Inspired by [7], we construct the dictionary guided by orientation field in order to decrease both the size of dictionary and the probability of choosing the wrong basis when restoring by sparse representation. For now, there are many orietation field estimation algorithms, such as [9][10][2][4][11]. In this paper, we use the algorithm proposed by Yang et al. [4] because compared with traditional methods, it exploits stronger location-dependent prior knowledge and has higher accuracy.

2.3. Gabor and minutiae dictionaries construction

Larkin and Fletcher [12] proposed that a fingerprint image can be represented as a 2D amplitude and frequency modulated (AM-FM) signal. An ideal fingerprint can be represented as [13]:

$$I(x, y) = \cos(\Psi(x, y)). \tag{1}$$

The phase $\Psi(x, y)$ can be uniquely decomposed into two parts [14]: the continuous phase and spiral phase:

$$\Psi(x, y) = \Psi_C(x, y) + \Psi_S(x, y). \tag{2}$$

The continuous phase corresponds to the sinusoidal-shaped waves of ridges in the grey-scale image. The spiral phase, which consists of a set of N spirals, corresponds to minutiae. A minutia emerges after adding a spiral. Each spiral has general form:

$$\Psi_S(x, y) = \arctan(\frac{y - y_n}{x - x_n}) + k * \pi \tag{3}$$

in which (x_n,y_n) denotes the coordinates of the spiral, $k = 0$ refers to a bifurcation minutia, and $k = 1$ refers to an end point minutia (see Fig. 2). Gabor dictionary was used in [5][6][7] since it can well characterize the sinusoidal-shaped waves of ridges and has both frequency-selective and orientation-selective properties [3]. The general form of 2D Gabor functions is:

$$h(x, y, \theta, f) = \exp\{-\frac{1}{2}[\frac{{x_\theta}^2}{{\delta_x}^2} + \frac{{y_\theta}^2}{{\delta_y}^2}]\}\cos(2\pi f x_\theta + \varphi_0) \tag{4}$$

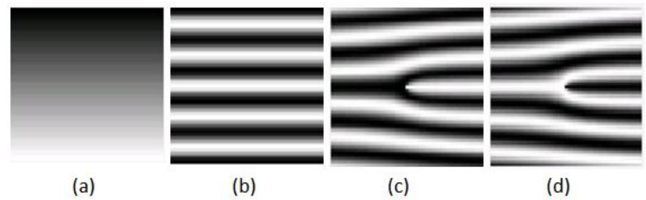

Fig. 2. Relationship among minutia, continuous phase, and spiral. (a) Continuous phase given by $2\pi f y$. (b) Grey-scale image given by $\cos(2\pi f y)$. (c) grey-scale image given by $\cos(2\pi f y + \arctan(\frac{y}{x}))$. (d) Grey-scale image given by $\cos(2\pi f y + \arctan(\frac{y}{x}) + \pi)$.

$$x_\theta = x\cos\theta + y\sin\theta \tag{5}$$
$$y_\theta = -x\sin\theta + y\cos\theta. \tag{6}$$

However, Gobor dictionary only contains continuous phase. So, it can not restore the minutiae perfectly. Thus, in this paper, we propose to construct minutia dictionary by adding a spiral to gabor dictionary to capture more information of ridges. The minutia dictionary's atoms have the general form:

$$\begin{aligned} h(x, y, \theta, f) &= \exp\{-\frac{1}{2}[\frac{{x_\theta}^2}{{\delta_x}^2} + \frac{{y_\theta}^2}{{\delta_y}^2}] \times \cos(2\pi f x_\theta \\ &+ \arctan(\frac{x_\theta - x_n}{y_\theta - y_n}) + k\pi) \end{aligned} \tag{7}$$

in which (x_n, y_n) denotes the location of the minutia, and the other notations have the same meaning as in equation (4).

To construct the dictionary, a set of atoms is constructed by varying the parameter of equations(4) and (7). In this paper, we choose the frequency f varying from 6 to 12 at step of 1, the initial phase φ_0 varying from 0 to 5π/6 at step of π/6, and $\delta_x = \delta_y$ equal to the patch size. In gabor dictionary, the orientation θ varies from $\theta_i - \delta$ to $\theta_i + \delta$ at step of δ, in which θ_i means the orientation at location i estimated in section 2.2, and δ equals to $\pi/20$ to cover the situation when the orientation field estimation is not exactly correct. In minutia basis, since the spirals generated by θ and $\theta + \pi$ are different, we choose the orientation θ varying from $\theta_i - \delta$ to $\theta_i + \delta$ at step of δ and from $\theta_i + \pi - \delta$ to $\theta_i + \pi + \delta$ at step of δ, and we select 9 minutia locations (x_n, y_n) equally distributed on the dictionary patches.

2.4. Fingerprint enhancement via sparse representation

Sparse representation has been proven to be powerful tool in many fields due to the fact that important classes of signals such as audio and images have naturally sparse representations with respect to fixed or learned bases [15][16][17]. Mathematically, sparse representation consider that a signal $y \in \mathbb{R}^n$ can be decomposed as $y = D\alpha + e$. $D \in \mathbb{R}^{m \times n}$ is an over-completed dictionary, $\alpha \in \mathbb{R}^n$ is a sparse coefficients vector having a few of non-zeros coefficients, and e is noise. Thus, each patch of latent fingerprint can be restored using :

$$\hat{Y} = D\alpha \tag{8}$$

$$\alpha = \text{argmin}_{\alpha} 0.5\|x - D\alpha\|_2^2 + \lambda\|\alpha\|_0 \tag{9}$$

in which λ is a tuning parameter to constrain the sparsity of α. Equation (9) is solved using Orthogonal Matching Pursuit algorithm implemented in SPAMS (a SPArse Modeling Software) [18][19].

For the reason that smaller patch size can preserve more ridge details and larger patch size can restore the ridge corrupted by noises. In this paper, we adopt the multi-scale patch based sparse representation [6]: first reconstruct fingerprint with small patch size (set to 21 in this paper) using λ_1, and then iteratively reconstruct the bad quality region using larger patch size (plus 4 for each iteration) with λ_2 until there is no bad quality region or arriving maximum iteration (set to 5 in this paper). Since the texture signal to be enhanced is weak, λ_1 is usually smaller than λ_2.

Although gabor and minutiae dictionaries can characterise both ridge and minutiae structure, using both dictionaries from beginning will generate fake minutiae along the ridge corrupted by noises. A better way is to reconstruct the ridge with gabor dictionary and reconstruct the minutiae with minutiae dictionary. Thus, we propose a two-step sparse representation methods to enhance latent fingerprints. Firstly, fingerprint is enhanced by multi-scale patch sparse representation using local gabor dictionaries (with $\lambda_1 = 0.05$, $\lambda_2 = 0.4$). And then, Verifinger SDK is used to extract the minutiae and the regions near the minutiae (an ellipse region alone the orientation with $r_1 = 8, r_2 = 4$) are re-enhanced using both gabor and minutiae dictionaries (with $\lambda_1 = 0.04$, $\lambda_2 = 0.15$). In this way, the corrupted ridges are recovered in the first step, and the minutiae can preserved well in the second step (as shown in Fig. 3).

3. EXPERIMENTAL RESULTS

In this section, the widely used NIST SD27 latent fingerprint database that contains 258 latent fingerprints and their corresponding rolled fingerprints is used to evaluate the performance of our method and gabor filter [3]. All the enhancement algorithms are tested with the same manually marked ROI of each latent, and the same automatically estimated orientation [4]. The same SDK (Verifinger SDK 6.2, which is a commercial fingerprint SDK with high full fingerprint matching accuracy and fast matching speed) is used to extract minutiae and compute matching score. Two types of evaluations were performed: (1) direct evaluation of the accuracy of minutiae extraction based on the enhanced fingerprints. (2) evaluation of matching accuracy.

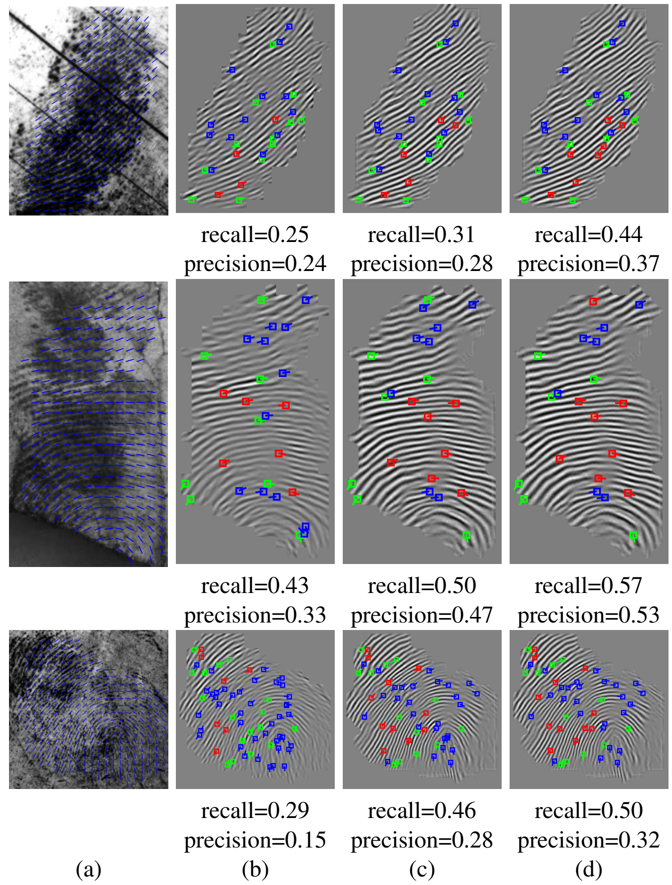

Fig. 3. (a)Several fingerprints with its estimated orientation field [3] and its enhancement results using: (b) gabor filter [4]; (c) sparse representation using only gabor dictionary; (d) two-step sparse representation. The correct, missing, wrong minutiae are marked with red, green, blue rectangle respectively.

3.1. Accuracy of minutiae extraction

Minutia is the most important feature in fingerprint matching. Combining with fixed minutiae extraction and matching algorithm, better enhancement algorithm is expected to provide higher minutiae extraction accuracy and higher matching accuracy. Given the manually marked minutiae for the latent fingerprints in NIST27 database, we call an extracted minutia a correct minutia if the distance between the extracted and manually marked minutia is less than 10 pixels and the angel difference is less than 20 degrees. The other extracted minutiae are called wrong minutiae, and the manually marked minutiae that have no corresponding extracted minutiae are called missing minutiae.

Fig. 3 shows fingerprint enhancement results using three algorithms: gabor filter [3], SR based on gabor dictionary and the two-step SR using both gabor and minutiae dictionaries. The correct, missing, wrong minutiae are marked with red, green, blue rectangle respectively. As we can see, compared

Method	Recall	Precision	Average distance	Average angle difference
gabor filter[4]	0.4725	0.2903	5.1939	**1.9641**
SR-gabor	0.4912	0.3532	5.1342	2.0731
two-steps SR	**0.4916**	**0.3616**	**5.0959**	2.0515

Table 1. Accuracy of minutiae extraction on the latent fingerprints of NIST27 database

with gabor filter, the results of SR have clearer ridge structure, since the gabor filter calculate the probability of each pixels belonging to the ridge pixel by pixel while the results based on SR are constructed by a linear combination of gabor atoms and have structure consistency. Especially for the region where ridge is corrupted by noises and the ridge structure is weak, the results of gabor filter is also weak, while SR can reconstruct the ridge structure clearly. Compared with SR only using gabor dictionary, the proposed two-step SR, reconstructing the minutiae region using a more specified dictionary, has better enhancement near minutiae and thus decreases the number of wrong minutiae and increase the number of correct minutiae (due to more accurate localization of minutiae).

Quantitatively, we use four measures to evaluate the accuracy of minutiae extraction: (1) recall (the number of correct minutiae/the number of manually marked minutiae); (2) precision (the number of correct minutiae/the number of extracted minutiae); (3) average distance between extracted and manually marked minutiae; and (4) average angle difference between extracted and corresponding manually marked minutiae.

The evaluation on the NIST27 database is shown in Table 1. As we can see, SR-gabor has higher recall, precision, smaller average distance, and larger average angle difference than gabor filtering, and the two-step SR has higher recall, higher precision, smaller average distance and average angle difference than SR-gabor. In general, SR is better than gabor filter, and the two-steps SR is the best.

3.2. Matching accuracy

Our final goal of enhancement is to improve the latent matching accuracy. In this section, Cumulative Match Characteristic (CMC) Curve is used to evaluate the matching performance and three latent fingerprint enhancement algorithms are compared by conducting matching experiment on the NIST27 database. To make the evaluation more realistic and challenging, 27,000 rolled fingerprints (file fingerprints) in NIST SD14 database as well as the other 257 rolled fingerprints in NIST SD27 database are used as the background

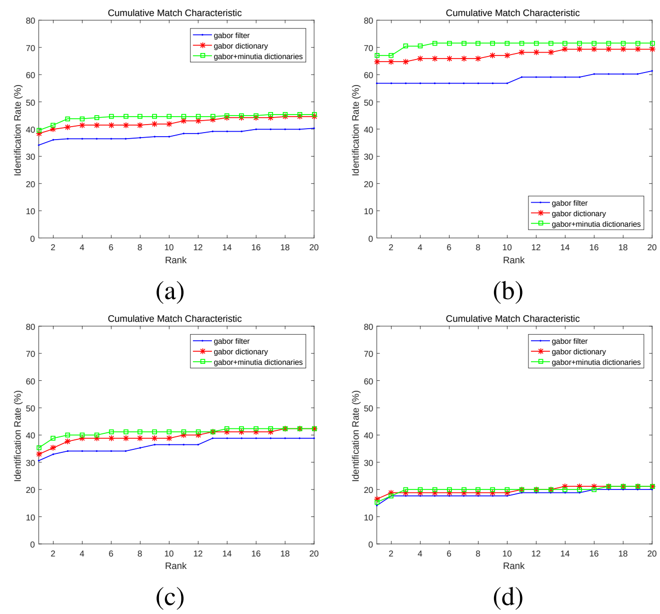

Fig. 4. CMC curves of three latent fingerprint enhancement algorithms on the NIST27 latent database and subsets: (a) all (258 latents); (b) good quality (88 latents); (c) bad quality (85 latents); (d) ugly quality (85 latents).

database. Each fingerprint (both latent and rolled fingerprints) is enhanced using each enhancement algorithm. Since rolled fingerprints have higher quality than latents, a smaller λ is expected. We set $\lambda_1 = 0.05, \lambda_2 = 0.2$ while using gabor dictionary, and set $\lambda_1 = 0.04, \lambda_2 = 0.1$ while using both dictionaries.

The CMC curves on NIST27 database and the three subsets (good, bad, ugly quality) are shown in Fig. 4. As we can see, SR-gabor outperforms the gabor filter on all, good, bad, ugly latent fingerprints, and the two-step SR outperforms SR on all, good and bad subsets while is comparable on ugly subset. The results are consistent with the results in section 3.1.

4. CONCLUSION

In this paper, we propose a two-step SR algorithm to utilize both ridge and minutia prior knowledge: Firstly, the texture component of fingerprint is extracted via RTV model. Secondly, local gabor and minutiae dictionaries are constructed guided by orientation field. Thirdly, the texture component is enhanced by multi-scale patch sparse representation using local gabor dictionaries. Finally, minutiae is extracted and the regions near the minutiae are re-enhanced using both gabor and minutiae dictionaries. In this way, ridges are recovered in the first step, the minutiae can preserve details in the second step and our enhancement can achieve both higher minutia extraction accuracy and higher matching accuracy.

5. REFERENCES

[1] Christophe Champod, Chris J Lennard, Pierre Margot, and Milutin Stoilovic, *Fingerprints and other ridge skin impressions*, CRC press, 2004.

[2] Jianjiang Feng, Jie Zhou, and Anil K Jain, "Orientation field estimation for latent fingerprint enhancement," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 35, no. 4, pp. 925–940, 2013.

[3] Lin Hong, Yifei Wan, and Anil K Jain, "Fingerprint image enhancement: algorithm and performance evaluation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 8, pp. 777–789, 1998.

[4] Xiao Yang, Jianjiang Feng, and Jie Zhou, "Localized dictionaries based orientation field estimation for latent fingerprints," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 36, no. 5, pp. 955–969, 2014.

[5] Xiaoduan Wang and Manhua Liu, "Fingerprint enhancement via sparse representation," in *Proceeding of the 8th Chinese Conference on Biometric Recognition*, pp. 193–200. Jinan, China, 2013.

[6] Manhua Liu, Xiaoying Chen, and Xiaoduan Wang, "Latent fingerprint enhancement via multi-scale patch based sparse representation," *IEEE Transactions on Information Forensics and Security*, vol. 10, no. 1, pp. 6–15, 2015.

[7] Kaifeng Wei and Manhua Liu, "Latent fingerprint enhancement based on orientation guided sparse representation," in *Proceeding of the 11th Chinese Conference on Biometric Recognition*. Chendu, China, 2016, pp. 205–213.

[8] Li Xu, Qiong Yan, Yang Xia, and Jiaya Jia, "Structure extraction from texture via relative total variation," *ACM Transactions on Graphics (TOG)*, vol. 31, no. 6, pp. 139, 2012.

[9] Sharat Chikkerur, Alexander N Cartwright, and Venu Govindaraju, "Fingerprint enhancement using STFT analysis," *Pattern Recognition*, vol. 40, no. 1, pp. 198–211, 2007.

[10] Yi Wang, Jiankun Hu, and Damien 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*, vol. 29, no. 4, pp. 573–585, 2007.

[11] Kai Cao, Eryun Liu, and Anil K Jain, "Segmentation and enhancement of latent fingerprints: A coarse to fine ridgestructure dictionary," *IEEE transactions on pattern analysis and machine intelligence*, vol. 36, no. 9, pp. 1847–1859, 2014.

[12] Kieran G Larkin and Peter A Fletcher, "A coherent framework for fingerprint analysis: are fingerprints holograms?," *Optics Express*, vol. 15, no. 14, pp. 8667–8677, 2007.

[13] Jianjiang Feng and Anil K Jain, "Fingerprint reconstruction: from minutiae to phase," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, no. 2, pp. 209–223, 2011.

[14] Dennis C Ghiglia and Mark D Pritt, *Two-dimensional phase unwrapping: theory, algorithms, and software*, vol. 4, Wiley New York, 1998.

[15] Michael Elad, Mario AT Figueiredo, and Yi Ma, "On the role of sparse and redundant representations in image processing," *Proceedings of the IEEE*, vol. 98, no. 6, pp. 972–982, 2010.

[16] John Wright, Yi Ma, Julien Mairal, Guillermo Sapiro, Thomas S Huang, and Shuicheng Yan, "Sparse representation for computer vision and pattern recognition," *Proceedings of the IEEE*, vol. 98, no. 6, pp. 1031–1044, 2010.

[17] Zheng Zhang, Yong Xu, Jian Yang, Xuelong Li, and David Zhang, "A survey of sparse representation: algorithms and applications," *IEEE access*, vol. 3, pp. 490–530, 2015.

[18] Julien Mairal, Francis Bach, Jean Ponce, and Guillermo Sapiro, "Online learning for matrix factorization and sparse coding," *Journal of Machine Learning Research*, vol. 11, no. Jan, pp. 19–60, 2010.

[19] Julien Mairal, Francis Bach, Jean Ponce, and Guillermo Sapiro, "Online dictionary learning for sparse coding," in *Proceedings of the 26th annual International Conference on Machine Learning*. ACM, 2009, pp. 689–696.