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Fingerprint enhancement with dyadic scale-space

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Abstract

Fingerprint enhancement is a critical step in automatic fingerprint verification system. Most of the existing enhancement uses a set of contextual filters to enhance fingerprint. The main drawback of these methods is these contextual filters based on the local information of the fingerprint, such as ridge width, orientation, curvature etc. This information is unreliable in the areas corrupted by the noise. This paper introduces the scale space theory in the computer vision to enhance the fingerprint. In the enhancement process, decompose fingerprint into a series of images and organize the images by courser to finer scheme. Thus a globe and integrate interpretation is available and it enables us to get rid of the influence of noise to the largest extent. Experiments show our algorithm is fast and improve the performance of fingerprint verification system.

Keywords: Fingerprint; Enhancement; Minutiae; Dyadic scale space

1. Introduction

Fingerprint identification is one of the most important biometrics technologies which have received increasingly more attention recently. Both the academic and industry developed their own algorithms and techniques for fingerprint recognition. Fingerprint verification competition has been held twice, the FVC2000 and FVC2002 respectively (Maio et al., 2002a,b). Most automatic systems for fingerprint recognition are based on minutiae matching (Ratha et al., 1996; Jain et al., 1997; Vajna, 2000). In this paper, minutiae are restricted to endpoint and bifurcation (Fig. 1). The minutiae are not uniformly distributed in the fingerprint, and the positions of the minutiae are decided by the ridge which ends abruptly or diverges into branch ridges. In order to get high recognition performance, a critical step is to automatically and reliably extract minutiae from the fingerprint image. The problem of automatic minutiae detection has been thoroughly studied but never completely solved. The main reason is that the fingerprint quality is often too low, the noise and contrast deficiency can produce fake minutiae and miss valid minutiae.

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Fig. 1. Minutiae representation.

Several approaches to automatic minutiae extraction have been proposed. O'Gorman (1989) presented a technique for enhancement based on the convolution of the image with a filter oriented according to the directional image. In order to enhance the fingerprint, Hong et al. (1998) used the structure tensor to estimate the orientation and classified the fingerprint image into recoverable corrupted region and unrecoverable corrupted region. In the recoverable region a Gabor filter was used to enhance the fingerprint image. Almansa and Lindeberg (2000) treated the ridge in a local region as a cylindrical sine wave, exhaustive discussion about shape adaptation could be got in that reference. Sherlock et al. (1992) used a frequency-domain filtering through position-dependent filters to enhance fingerprint.

All these approaches computed the orientation field, based on the orientation to enhance fingerprint, binarized the image, thinned the binary image, and at last extracted minutiae. In order to overcome some disadvantages of these approaches, Maio and Maltoni (1997); Jiang et al. (2001), putted forward the method that directly detects minutiae in the gray-scale fingerprint. Their method need not the binarization and thinning processes. However, this method also is very difficult to find the minutiae correctly in the low quality fingerprint image or in the image captured in low resolution sensor (Maio and Maltoni, 1998).

All of these existing minutiae extraction methods used a set of contextual filters to enhance the fingerprint based on the local estimates, such as orientation, and curvature etc. Due to the existence of noise, these methods result in unreliable estimates and sometimes introduce artifacts.

The fingerprint image is the pattern of ridges and valleys on the surface of the fingertip. A fingerprint expert is often able to recognize whether two fingerprints are coming from same finger combining the local and global information. In some regions of fingerprint image where fingerprint quality is low but its surrounding region could give some texture information, we could use this information to enhance the low quality regions.

Due to the existence of noise, some fingerprint features are submerged. False estimated parameters will lead to poor enhancement. So when enhancing fingerprint, we utilize the whole information to get rid of the noise and retained the true characters. In order to use the global information, we use the method of scale space theory in computer vision to enhance the fingerprint image. We all know, in some scales, people only see the sketch of the image while in other scales people can find the detailed component in the image. Scale space

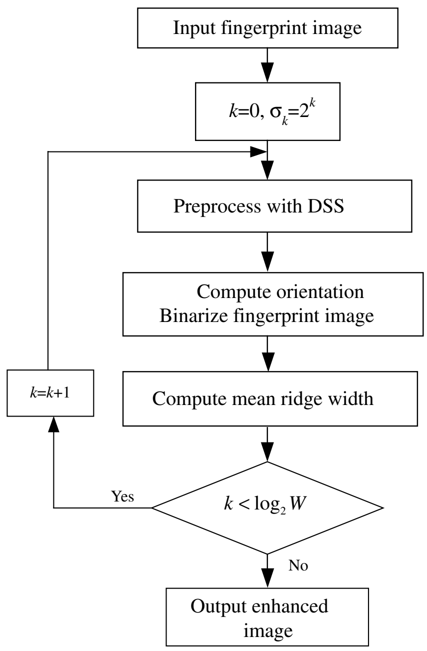


Fig. 2. Block diagram of the enhancement algorithm.

theory just is to simulate the behavior of human vision.

This paper introduces the Dyadic Scale-Space (DSS) in the computer vision to enhance the fingerprint. Some previous work could be found in our published literature (Cheng et al., 2002). We first decompose the fingerprint image into a series of images at different scales, then analyze and organize whole characters and details, at last combine the creditable information to enhance the fingerprint image. The steps of our enhancement are shown in Fig. 2.

In the following sections, we will describe in detail our enhancement method. Section 2 introduces the scale space theory. We discuss DSS theory to enhance the fingerprint in Section 3. And Section 4 gives our experiments, we conclude in the last section.

2. Linear scale space

Scale-space theory (Witkin, 1983) provided a canonical framework for modeling visual operations at multiple scales. The scale-space representation $L : R^2 \times R \to R$ of a two-dimensional image f is defined as the one-parameters family of functions obtained by convolving f with Gaussian kernel:

$$L(\cdot,\cdot;t) = f(\cdot,\cdot) * g_t(\cdot,\cdot,\cdot)$$

where

$$g_t(x,y,\theta) = \frac{1}{2\pi t}\,\mathrm{e}^{-\frac{(x\cos\theta)^2+(y\sin\theta)^2}{2t^2}}$$

and the parameter t is called scale parameter. θ is the direction of the pixel (x,y).

Although fingerprint images are non-isotropic, we use the linear scale-space to detect the feature because in local region, the ridge is a line. And the convolution is along the ridge direction, as we adapt the filter to ridge direction.

Equivalently, these family images can be generated by the solution to the diffusion equation:

$$\partial_t L = \frac{1}{2}\nabla^{\mathrm{T}} \sum \nabla L$$

with initial condition $L(\cdot,\cdot;0) = f(\cdot,\cdot)$.

In scale-space, with the increase of the scale, the number of the details decreases and the noise is successively suppressed gradually. The feature of the image in large scale exists in the image of small scale, while weak signal will disappear in the large scale space. Those existing in the image of large scale are global structure.

Using a series of scale $\sigma_1, \sigma_2, \ldots, \sigma_n$ to filter the image f, note the scale-space representation as L_{σ_k}, $k = 1, 2, \ldots, n$ with scale σ_k. We define the details between two scales as following:

$$D_k = L_{\sigma_k} - L_{\sigma_{k+1}}, \quad k = 1, 2, \ldots, n-1 \tag{1}$$

Let:

$$D_0 = f - L_{\sigma_1} \tag{2}$$

When we get the scale-space representation and its details, construct the image f:

$$f = \sum_{k=0}^{n-1} D_k + L_{\sigma_n}$$

3. Fingerprint enhancement with dyadic scale-space

3.1. Preprocessing with DSS

In computer vision, scale-space theory often is used as image segmentation, edge extraction. Those concerned are the object's outline. Unlike other images, fingerprint image has its own characteristics. The fingerprint is the flow-like pattern. The ridges are alternated with valleys. Our algorithm first decomposes the fingerprint image into a series of images to avoid the noise in different scales. Then we combine the images to get a more credible image. Each time we reduce the noise to some extent. After several iterations, we get the final enhanced image. In the process of enhancing the fingerprint image using scale-space theory, we face two problems: one is how to select different scales, and the other is how long the series is. Now we discuss these questions as following.

Analogical to the wavelet, we use the dyadic scale to decompose the fingerprint image. The scale is selected as following:

$$\sigma_k = 2^k, \quad k = 1, 2, \ldots, n_0$$

The scale in this form is called dyadic, and the scale-space is called dyadic scale-space. The detail of the dyadic scale-space refers to literary (Cong and Ma, 1996, 1997).

So the length of the series is decided by n_0. We note the mean width of fingerprint as W, and $n_0 = \lceil \log_2 (2 * W) \rceil$. How to calculate W is discussed later.

We get the smoothed image of the fingerprint image f using dyadic scale-space:

$$L_k = f * g_{2^k}(x, y, \theta), \quad k = 1, 2, \ldots, n_0$$

According to Eqs. (1) and (2), the detail image are noted D_k, $k = 0, 1, \ldots, n_0 - 1$.

The effect of the noise is reduced in the image L_k. Its gray values reflect the ridge value. And the D_k contains the information that L_k contains but is lost in L_{k+1}. Due to D_k containing the noise too, we smooth it with scale 2^{k+1}:

$$L'_k = D_k * g_{2^{k+1}}(x, y, \theta)$$

In the traditional enhancement algorithm, they smoothed the fingerprint image and lost D_k. We know when we over-smooth image, some true information is lost with the noise. In our algorithm, the image L'_k preserves the true information that is lost as noise.

We note E_{k-1} as the image obtained through the scale 2^{k-1}, now we get the image E_k at the scale 2^k. Let

$$s_1 = E_{k-1}(i, j)$$

$$s_2 = L_{k+1}(i, j)$$

$$s_3 = L'_k(i, j)$$

$$t_1 = |s_2 - s_3|$$

$$t_2 = \begin{cases} s_2 + s_3 - t_1 & \text{if } s_2 + s_3 - 255 \leqslant 0 \\ 255 - t_1 & \text{else} \end{cases}$$

Then

$$E_k(i, j) = \begin{cases} 255 & t_2 = 0 \\ \quad \text{or } s_1 \geqslant s_2 + s_3 & \\ 0 & t_2 \neq 0, \\ \quad s_1 \leqslant t_1 & \\ (s_1 - t_1) * 255/t_2 & t_2 \neq 0, \\ \quad s_1 < s_2 + s_3 & \end{cases} \tag{3}$$

Because the gray value in the $L_{k+1}(i, j)$ is smoothed to reduce the noise, and the gray value L'_k is credible, so we compare the gray value of $L_{k+1}(i, j)$ with $L'_k(i, j)$ and get the result image which is affected by the noise least. Each time, through this step, the noise is reduced and the result is shown in Fig. 3.

3.2. Orientation image

Each time, after we get the image E_k, we segment the image into foreground and background. All the processing after segmentation is applied to the foreground region only, which could reduce computation time.

In the block size of $(2^k + 1) * (2^k + 1)$, if the number of the pixels which gray value are larger than a threshold is less than a threshold, the block is background. Otherwise, the block is foreground.

(a) (b)

Fig. 3. (a) Original image and (b) enhanced image with DSS ($k = 1$).

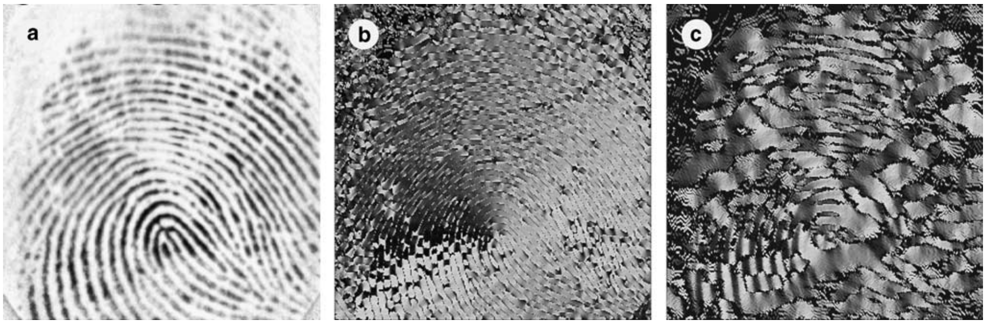


Fig. 4. Orientation of gradient: (a) original fingerprint, (b) smoothed gradient ($k = 1$) and (c) smoothed gradient ($k = 3$).

After get L_k, we could get the gradient in pixel-wise, ∇L_k. So the orientation could be:

$$O(i,j) = \tan^{-1}\left(\frac{\partial L_k}{\partial y} \Big/ \frac{\partial L_k}{\partial x}\right) + \frac{1}{2}\pi$$

However, we can see from the Fig. 4 that for small k high fluctuations remain, while a larger k leads to entirely useless results. In order to overcome this disadvantage, we need other method to compute the orientation field.

The orientation image plays very important role in the image analysis. Several methods for estimating image directional information have been proposed in the past, such as matched-filter approach (Maio et al., 2002b), high-frequency power method (O'Gorman, 1989). But the simplest approach is based on gradient computation. This method is very simple and efficient. Many researchers also adopt this method (Ratha et al., 1995; Perona, 1998; Bazen and Gerez, 2002). However, Jain et al. (1997) proposed a hierarchy approach to compute the block orientation precisely. In order to compute each pixel' orientation, we also use the Jain's approach as following:

(1) Compute the gradients $\partial_x(i,j)$, $\partial_y(i,j)$ at each pixel in the input image
(2) Estimate the orientation at pixel (i,j)

$$v_x = \sum_{u=i-W/2}^{u=i+W/2} \sum_{v=j-W/2}^{j+W/2} (2 * \partial_x(i,j) * \partial_y(i,j))$$

$$v_y = \sum_{u=i-W/2}^{i+W/2} \sum_{v=j-W/2}^{j+W/2} (\partial_x^2(i,j) - \partial_y^2(i,j))$$

$$\theta(i,j) = \frac{1}{2}\tan^{-1}\left(\frac{v_y}{v_x}\right)$$

where W is 16. Compared with Jain's algorithm, we do not use the block orientation as each pixel's direction in the block. Although we get more refined resolution of the orientation field from above method, we spend more computing time. In order to speed up process of orientation field computation, we use a sliding window to efficiently calculate each pixel's direction in the entire fingerprint image, as Fig. 5. In our method, the sliding window is used many times to speed up process of orientation field and filter etc. Fig. 6 shows an example of the orientation image estimated with our algorithm.

3.3. Compute the mean ridge width

Our aim to compute the mean ridge width is to control the iterative times. So we get the ridge width based on the binary image of E_k. In order to

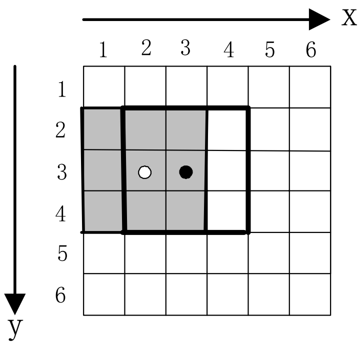


Fig. 5. The sliding window.

Fig. 6. Improved orientation of (a) in Fig. 3 ($k = 3$).

get the binary image, we smooth the E_k with window 3×3 and 7×7:

$$E_k^{2m+1}(i,j) = \frac{1}{m^2}\sum_{u=i-m}^{i+m}\sum_{v=j-m}^{v=j+m} E_k(u,v)$$

where $m = 1, 3$.

Then we binarize the image E_k based on the smoothed image E_k^3 and E_k^7 using Eq. (4):

$$E_k(i,j) = \begin{cases} 255, & E_k(i,j) \geqslant \frac{1}{2}(E_k^3(i,j) + E_k^7(i,j)) \\ 0, & \text{else} \end{cases} \tag{4}$$

Now compute the mean ridge width of the binary image E_k, see Fig. 7.

Define a set Ω as the ridges of the image E_k:

$$\Omega = \{(i,j)|E_k(i,j) = 0\}$$

For any point $p_0 \in \Omega$, the ridge width $D(i_0, j_0)$ of the ridge at the location of point p_0 is:

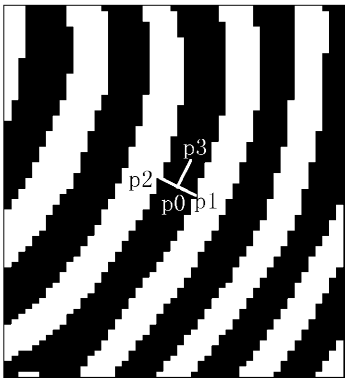


Fig. 7. Demonstration of computing the ridge width.

$$D(i_0,j_0) = \begin{cases} |\overline{p_2p_1}| + \dfrac{1}{|\cos(O(i_0,j_0)|}, & O(i_0,j_0) \leqslant 45 \\ |\overline{p_2p_1}| + \dfrac{1}{|\sin(O(i_0,j_0)|}, & O(i_0,j_0) > 45 \end{cases}$$

Here:

$$\overline{p_2p_1} = \{(i,j)|i - i_0 = \tan(O(i_0,j_0))(j - j_0), \\ (i,j) \in \Omega\}$$

So the mean ridge width W is defined:

$$W = \frac{\sum_{(i,j)\in\Omega} D(i,j)}{|\Omega|} \tag{5}$$

According to the width W, we decide whether the iteration does not continue. If k is larger than $\lceil \log_2(W) \rceil$, we stop our algorithm, otherwise continues our algorithm.

In our method, we construct the lookup table in order to speed up computation of filter and ridge width. For example, for ridge width, we create the arrays of the offsets of x, y coordinates for each orientation, So we can locate the points p_1p_2 quickly.

3.4. Extract minutiae

After through several iterations, we get the enhanced image E. We thin the binary image E with the method introduced in (Naccache and Shinghal, 1984), and obtained the thin image in which each ridge has a width of one pixel. In thinned image E, if a pixel (i,j) in a ridge is an endpoint, it must satisfy the following condition

$$\sum_{u=-1}^{1}\sum_{v=-1}^{1} E(i+u, j+v) = 2$$

And if it is bifurcation point, it must satisfy

$$\sum_{u=-1}^{1}\sum_{v=-1}^{1} E(i+u, j+v) = 4$$

Due to the effect of the noise, we will get some false minutiae according to above equation. Some post-process procedures are used to eliminate the false minutiae.

Fig. 8 is illustrated our main results in the process of DSS.

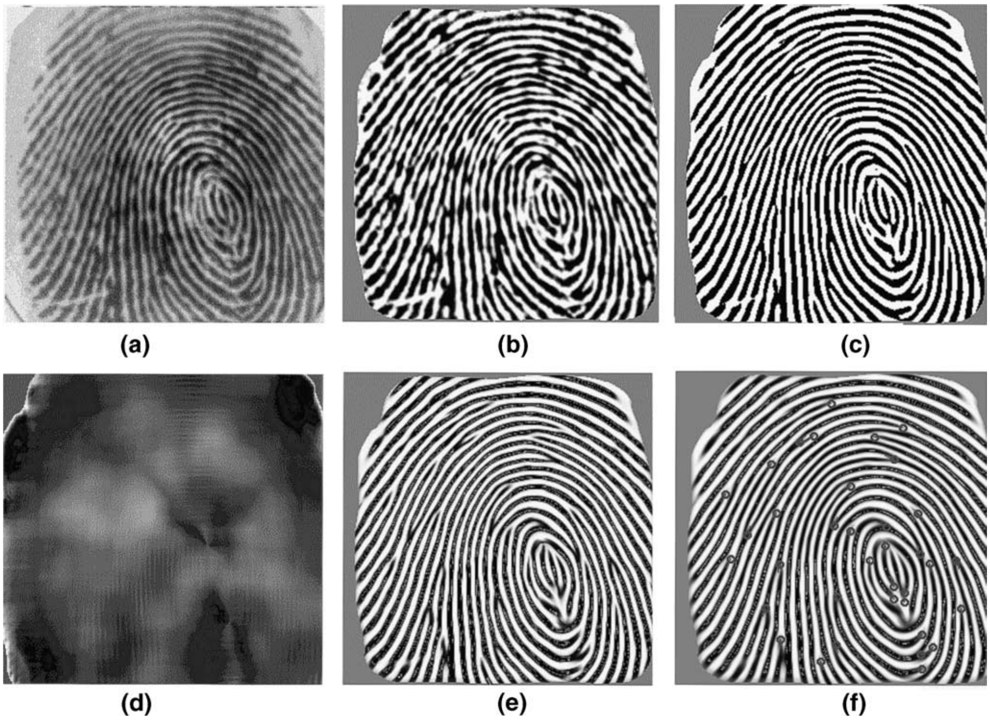


Fig. 8. Examples of enhancement results, (a) is the input image, (b) is the enhanced image $k = 1$, (c) is the enhanced image $k = 2$, (d) is the ridge width image that ridge width is converted to gray value, (e) is enhanced image $k = 3$, (f) is the detected minutiae set.

4. Experimental results

The technique proposed in this paper has been adopted in a biometric system for fingerprint identification. The aim of this section is to demonstrate the result of proposed approach could be used in AFIS.

The purpose of fingerprint enhancement algorithm is to improve the clarity of ridges and valleys in the fingerprint. The result of the enhancement is evaluated by the fingerprint quality and the enhanced fingerprint is suitable for minutiae extraction algorithm. But how to measure the quality is very difficult thing, in particular lacks of a true reference.

In the literature (Hong et al., 1998), the authors used two methods to evaluate their enhanced results, one is the *goodness index* (GI), which compared true minutiae that human expert identify out, with the minutiae that are extracted in enhanced fingerprint image. The other was that they incorporated the enhanced method into their fingerprint verification system and examined whether improving the system performance. In literature (Jiang et al., 2001), the authors also used the second method to evaluate their approach's efficiency.

In the literatures (Almansa and Lindeberg, 2000; Sherlock et al., 1992), authors used different enhancement approaches to extract minutiae, and use a statistical model to prove that their method is better than others.

In this paper, in order to assess our enhancement method, we evaluate the computing efficiency, and use the statistical method to compare with performances of extraction minutiae as literature (Maio and Maltoni, 1997). At last, we incorporate our enhancement approach into an AFIS, which provides a more objective assessment of the performance.

All the experiments are performed in a PIII 800 MHz PC.

4.1. Efficiency

We test our algorithm in the four databases of FVC2000 (Maio et al., 2002a,b). We first run our enhancement algorithm in whole database, and record the whole expense time for each database. The average time to process a fingerprint image is illustrated in Table 1. Although our method use a multi-scale method to enhance fingerprint image iteratively, the efficiency is very good. The computable time is not more than 1 s, suitable for an online application.

Fig. 9 illustrates the enhancement results of our method and Hong's method (Hong et al., 1998).

4.2. Performance comparison

Given a minutiae set D obtained by above mentioned minutiae extraction algorithm, our goal in this context is to compare minutiae D with M of true minutiae marked by the forensic experts. Consider following sets:

Table 1
Computing time in FVC2000 databases

Database	Image size	Average time (s)
Db1_a	300×300	0.412
Db2_a	256×364	0.439
Db3_a	448×478	0.802
Db4_a	240×320	0.341

$\mathrm{FP} = D - M$: False minutiae set detected by extraction algorithm.
$\mathrm{FN} = M - D$: Missed minutiae set by extraction algorithm.

$\mathrm{LC} = \mathrm{CC} \cup \mathrm{FC} = D \cap M$: Correctly extracted minutiae. Let M_d be a minutia extracted by our method and M_e be a minutia marked by an expert, if M_d and M_e are located in a same neighborhood: $|M_\mathrm{d} - M_\mathrm{e}| < R_0$, regard M_d and M_e as a same minutia, here $R_0 = 8$. Set CC is the collection of correctly classified minutiae, FC is false classified minutiae set. Some AFIS does not use the minutiae type information, in this case, the minutiae of LC are all correct by minutiae extraction algorithm.

The accuracy of our minutiae detection algorithm in terms of the relative sizes of the sets FN, FP, LC with respect to the size of D or M:

FN/M: The proportion of missed minutiae. If assume 6–12 minutiae pairs are enough to ensure a legally positive identification, we see that relatively high values of FN/M are still admissible.
FP/D: The proportion of false minutiae. Certain matching algorithms are sensitive to the FP/D.
LC/D: The proportion of correctly extracted minutiae. The higher CC/D is, more correctly detected minutiae are, two fingerprints are more easier matching.

Almansa and Lindeberg (2000) compared the performances of five methods on the database in-

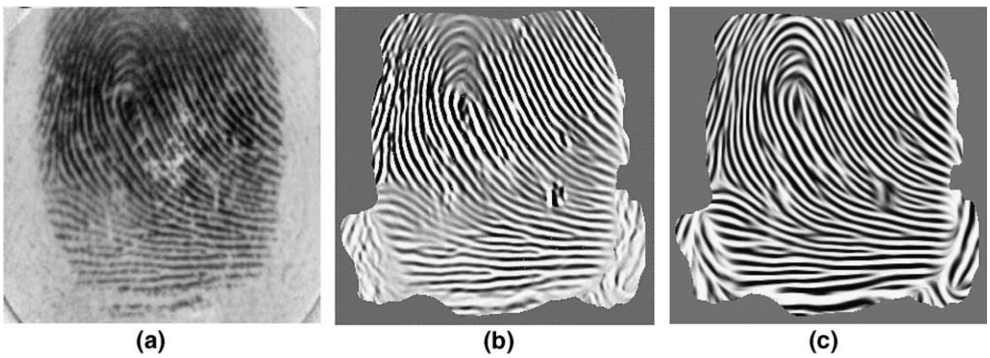
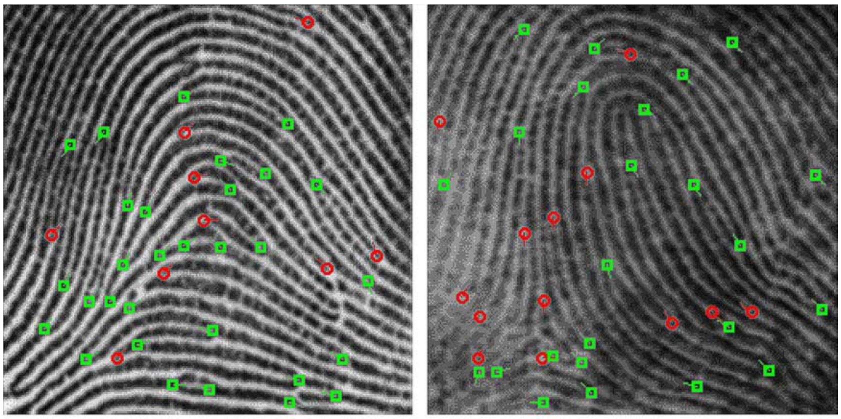


Fig. 9. Results of fingerprint enhancement with two methods. (a) is low quality fingerprint image, (b,c) are results of enhancement with Hong's method and our method, respectively.



No.1 No.13

Fig. 10. Detected minutiae with our method. (○) represents ridge end points, (□) represents bifurcation points. The minutiae extracted by experts are shown in literature (Almansa and Lindeberg, 2000).

cludes 14 fingerprint images. The all minutiae are detected by experts manually, in which minutiae sets of two fingerprint images can been seen in (Almansa and Lindeberg, 2000), but the minutiae of other fingerprint images are not published. Due to the minutiae could be different extracted by different experts, so, in order to objectively compare with the method of Almansa and Lindeberg (2000) and Cong and Ma (1996) only compared with Almansa and Lindeberg (2000) on the published images. We also test as Cong and Ma (1996). Note the method as A in (Almansa and Lindeberg, 2000), as G in (Cong and Ma, 1996), our method as DSS. Fig. 10 is the minutiae extracted by DSS. The performance illustrated in Table 2.

Compared with Almansa and Lindeberg (2000) and Cong and Ma (1996), our method can attain higher accuracy in correctly detected minutiae. In an AFIS, the ratio of correctly extracted minutiae is a critical parameter.

We further estimate our method in the database NIST27. NIST27 includes 258 tenprint images, and experts have marked the true minutiae position and orientation. Fig. 11 is the illustration of minutiae extracted by our method and experts

Table 2
Results comparing three different methods in images No. 1 and 13

	IM images 1 and 13		
	A (%)	G (%)	DSS (%)
FN/M	0.0	28.0	12.
FP/D	3.6	3.6	8.3
FC/D	20.0	19.6	9.7
CC/D	19.9	76.8	81.9

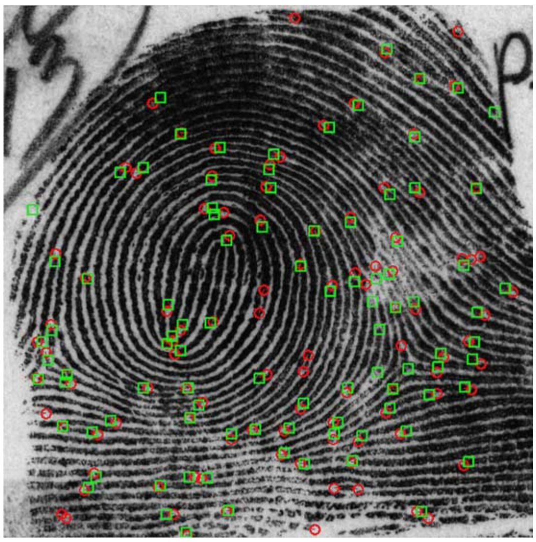


Fig. 11. Detected minutiae with our method and manually in NIST27. The minutiae marked by experts and extracted using DSS respectively. (○) represents minutiae marked by experts, (□) represents minutiae by DSS algorithm.

Table 3
Results of minutiae detection for our method DSS

	M	D	FN	FP	CC	FN/M	FP/D	CC/D
Image 1	106	97	15	6	91	0.142	0.062	0.938
Image 2	99	115	17	33	82	0.172	0.287	0.713
Image 3	101	109	14	22	87	0.139	0.202	0.798
Image 4	120	118	18	16	102	0.15	0.136	0.864
Image 5	142	134	15	7	127	0.107	0.052	0.948
Image 6	112	109	21	18	91	0.188	0.165	0.835
Image 7	88	77	17	6	71	0.193	0.078	0.922
Image 8	92	87	10	5	82	0.109	0.057	0.943
Image 9	102	115	11	24	91	0.108	0.209	0.791
Image 10	109	130	10	31	99	0.092	0.238	0.762
Mean						0.140	0.1486	0.8514
SD						0.036	0.085	0.085

Table 4
Comparison performances

	Db1			Db2		
	EER	FMR100	ZeroFMR	EER	FMR100	ZeroFMR
PA24	2.36	2.82	4.64	2.35	2.64	5.36
PA21	4.97	7.21	21.04	3.48	4.89	12.89
PA20	6.71	9.39	15.86	15.92	21.00	26.36
PA16	16.28	24.0	40.82	18.69	28.64	52.54
PA22	17.34	40.39	60.93	16.29	48.46	81.25
PA03	50.00	100.00	100.00	50.00	100.00	100.00
DSS	2.48	3.21	18.17	2.90	9.96	21.96
FGabor	4.95	13.42	16.28	1.77	4.35	5.46

manually. Table 3 is the performance of minutiae detection for our method in 10 images.

From Table 2, correctly extracted minutiae are consisted with the minutiae marked by experts.

4.3. Evaluation with verification performance

In FVC2002 databases, the quality of many fingerprint images is very low. We first use DSS and Gabor algorithms (Hong et al., 1998) to enhance the fingerprint respectively, and note the Gabor enhancement method as FGabor. Then use the minutiae matching algorithm in literature (Jiang and Yau, 2002). Compared with the method in (Jiang and Yau, 2002), our matching algorithm only depends on three parameters for minutiae: position, orientation and type, but not use the number of ridges between two minutiae points.

Table 5
Comparison performances

	Db3			Db4		
	EER	FMR100	ZeroFMR	EER	FMR100	ZeroFMR
PA24	6.62	9.68	20.43	3.70	5.54	17.71
PA21	9.36	16.54	54.89	6.45	14.43	45.93
PA20	10.03	18.82	33.96	3.50	5.43	15.11
PA16	18.65	28.82	45.54	13.53	23.71	36.57
PA22	14.96	39.07	69.43	10.05	24.43	49.68
PA03	50.00	100.00	100.00	50.00	100.00	100.00
DSS	5.13	18.21	23.35	4.39	15.96	21.82
FGabor	9.25	18.42	22.03	5.67	13.96	25.5

There are three important parameters to a fingerprint verification system: EER, FMR and FNMR. For the FMR test, the first print of each finger is matched against the first print of all other fingers, leading to 4950 impostor attempts, for FNMR test, each print of every finger is matched against all other prints of the same finger, leading to 2800 genuine attempts. The EER is equal error rate of the system, for which FMR and FNMR are equal. The performance results are shown in Tables 3 and 4. In convenient to comparison, we also list the performances in the six academic participants of the FVC2002.

From Tables 4 and 5, the recognition performance based on our enhancement algorithm is competitive with other six academic participants.

5. Conclusion and discussion

Fingerprint enhancement is a very critical step for AFIS. Traditional technology of fingerprint enhancement is based on the local estimates. Due to the existence of noise, some local characters are unreliable. Based on these estimates could cause to poorly enhance image. We proposed a new algorithm to enhance fingerprint image combining the whole and local characters. In this paper, we use the DSS to decompose the image into two images, the noise is reduced in each image every iterative. Through several times, often 3, we get the final result. The advantage of this method is that false information is reduced to the largest extent. Experiments on FVC2002 databases show that our enhancement algorithm could improve the online verification performance.

The configuration of the ridges and valleys in the local neighbourhoods varies with the quality of input fingerprint images. A well-defined shape-based enhancement such as: sinusoidal-shaped wave or a Gabor filter is not always suitable. In these approaches some global characters are needed to enhance fingerprint image.

In our experience, all kinds of enhancement algorithms are very good for good quality fingerprint image, when the quality of fingerprint image decreases, special effort must be paid for the low quality regions. If the global ridge and valley model of the fingerprint are constructed, then the ridges and valleys in the low quality regions can be restored by the model.

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