An Improved Method for Fingerprints' Singular Points Detection based on Orientation Field Partition

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Abstract

As a global feature of fingerprints, singular point plays important roles in fingerprint model, synthesis fingerprint, fingerprint classification, fingerprint alignment and so on. In our previous work, a rapid and effective fingerprint singular points detection method was proposed. That method detects singular points based on partitioning the orientation field into a serious non-overlapping homogenous areas. However, for the same orientation field, different partition schemes may lead to different singular point extraction results, especially for poor quality fingerprint images. For eliminating the uncertainty, we employ three different partition schemes simultaneously for each orientation field, and combine the three extraction results to make the final decision. Experiment proves that: this method is more accuracy than the previous one.

Keywords: *fingerprint recognition; singular point; orientation field partition; homogenous areas*

1. Introduction

Accurate automatic personal identification is critical in a wide range of application domains such as smartcard, electronic commerce, and automated banking. Biometrics, which refers to identifying an individual based on his or her physiological or behavioral characteristics, is inherently more reliable and more capable in differentiating between an authorized person and a fraudulent imposter than traditional methods such as knowledge-based [password or personal identification number (PIN)] and token-based[passport or driver license]. Among all biometric traits, fingerprints have one of the highest levels of reliability and have been extensively used for civilian purposes such as access control, financial security and so on.

As a global feature of fingerprint, Singular Point (SP) plays very important roles in fingerprint model [1-3], synthesis fingerprint [4, 5], fingerprint classification [6, 7], minutiae-based matching [8] *etc.* SP is regarded as the point with discontinuous orientations, Henry gives out more specific definition: a core is the topmost point of the innermost curving ridge and a delta is the center of triangular regions where three different ridges flows meet [9]. Typical SPs (core and delta points) are shown in Figure 1.

During the past years, lots of methods have been proposed for extracting finger- prints' SPs, which can be broadly classified into the following categories:

(1) Poincare index based methods [7, 10-12], this category usually calculates the cumulative changes along a counter-clockwise closed contour in orientation field to judge whether there exists a SP. However, owing to the computation of cumulative changes for each point, the operational efficiency is low, furthermore, they still exist issues like choosing the best shape and size for closed contours ([11] adopts multi-scale method to solve the problem of size, and receives better results, but the author also admits that it increases the burden of computation).

(2) Probability analysis based methods, including parzen window method [13], orientation histogram [14], multi-space KL [15], ridge flow codes method [16] *etc.* This category mainly depends on the probability distribution of pixel's orientation. When orientation distribution in a region is observed more equivalent than its neighbors, this region is regarded as a SP. Although such methods can locate SPs, they can not distinguish the types.

(3) Shape analysis based methods, these methods try to analyze the shapes of ridges or orientations, and consider $\cap$-like regions or $\cup$-like regions as core points, Δ-like regions as delta points, typical methods including [17, 18]. However, such methods burden complicated computation and lack robustness.

(4) Other methods, such as Gaussian-Hermite moments and PCA based method [19], corner detecting and ridge tracking based method [20], and so forth. Such methods are also up against high computational complexity and low efficiency.

Figure 1. Core Point and Delta Point in Fingerprint

In our opinion, being a good SPs detecting method, it should satisfy the following requirements:

- Integrated function, it means positioning SPs and distinguishing the types (core or delta points) accurately;
- High accuracy, that refers to low MDR (Missed Detection Ratio) and FDR (False Detection Ratio);
- Good utility, that is simpleness and high efficiency.

Up to the present, most of methods have focused on the first two requirements, especially for pursuing high accuracy, they added lots of complicated operations which have weakened the methods' utility seriously. However, utility is also very important for the methods applied to AFIS since AFIS holds two significant applications: identification on large scale databases (which contain millions of fingerprints or more) and Embedded System based identification (such as fingerprint door lock system).

In [16], we have proposed a rapid fingerprints' SPs extraction method by using POAD feature. Experiments shown that its speed was 13.24 times faster than the classic poincare index method achieved better utility, however, its accuracy was not very satisfied. In this paper, we extend the work and aim to promote its accuracy performance.

2. Related Work and Discussion

Through the partitioning of orientation fields, [16] proposed a new feature called Point Orientation Abundance Degree (POAD), and bring forward a simple, effective method for rapid detection of fingerprint SPs. The method mainly includes: fingerprint's orientation field partition, SPs localization and type distinguishing.

We firstly introduce the correlative definitions in [16]:

Definition 1(homogeneous area): For point (x, y), let its orientation is $O(\mathrm{x}, \mathrm{y})$, then the homogeneous area $\Theta_{(\alpha,\beta)}$ is defined as followed:

$$\Theta_{(\alpha,\beta)} = \{(\mathrm{x}, \mathrm{y}) | \alpha \le \mathrm{O}(\mathrm{x}, \mathrm{y}) < \beta; 0 \le \alpha, \beta < \pi\} \tag{1}$$

Definition 2(homogeneous area sorting): Supposing fingerprint's orientation field is divided into N non-overlapping homogeneous areas Θ_i ($1 \le i \le N$), then the ascending order of homogeneous areas ($\Theta_1, \Theta_2, \ldots, \Theta_i, \ldots, \Theta_N$) satisfy that:

$$\forall (\mathrm{a}, \mathrm{b}) \in \Theta_{\mathrm{j}}, (\mathrm{c}, \mathrm{d}) \in \Theta_{\mathrm{j+1}} \Rightarrow O(\mathrm{a}, \mathrm{b}) < \mathrm{O}(\mathrm{c}, \mathrm{d}) \quad 1 \le \mathrm{j} \le \mathrm{N-1} \tag{2}$$

Definition 3(Point Orientation Abundance Degree): For point (x, y), let it as the center point to form a circular region $R(x, y, r)$ with radii r, POAD is the collection of homogeneous areas' sub-regions, the explicit description is:

$$POAD(x, y) = \{\Omega_i | \Omega_i \in \Theta_i; \Omega_i \in R(x, y, r)\} \tag{3}$$

where Ω_i denotes the sub-region of Θ_i. Figure 2 presents the POADs at SPs(here 1,2,4,5 are amplified figs for core points; 3,6 for delta points).

Based on the observation of illustrated POADs at SPs and numerous experiment results, [16] concluded the following two rules:

Rule 1: The POAD at SP comprises sub-regions from all homogenous areas, and all sub-regions concentrate upon SP, that is:

$$POAD_{SP} = \bigcup_{i=1}^{N} \Omega_i \tag{4}$$

Rule 2: Noting $(\Theta_1, \Theta_2, \cdots, \Theta_i, \cdots \Theta_N)$ as ordinal sequence, for core points, we can get an ordinal sequence in counter-clockwise, while for delta points, we can get the ordinal sequence in clockwise.

The two rules buildup the foundations for SPs localization and type distinguishing respectively. For validating the integrated function of detecting SPs with POAD strictly, [16] gives out a proof, and the details can be found in Appendix A.

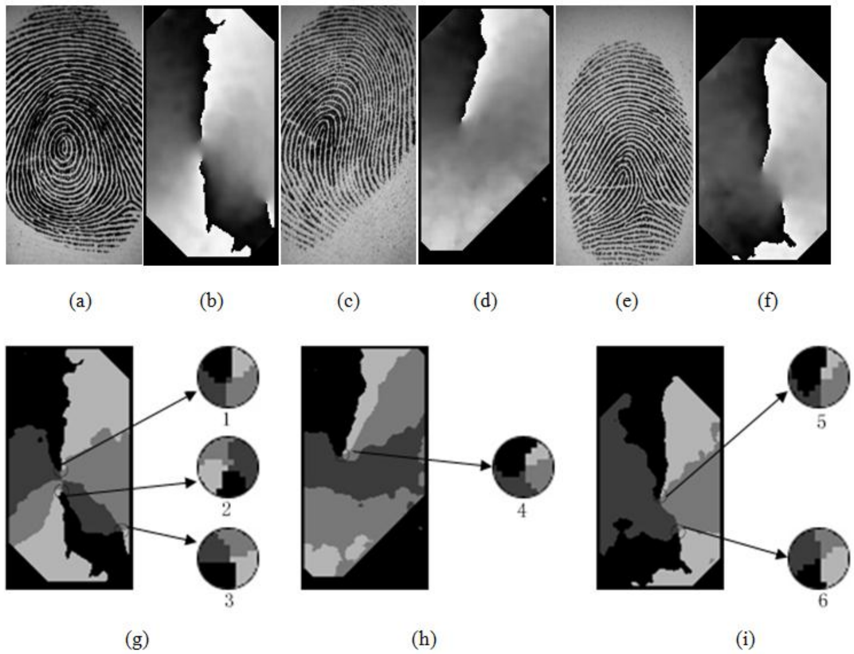

Figure 2. The homogenous areas of fingerprint orientation filed and the magnified maps for SP's POAD. (a), (c), (e) are original images; (b), (d), (f) are the corresponding orientation results in gray-level value forms; (g), (h), (i) are the homogenous areas and the magnified maps for SPs' POAD.

Homogeneous areas reveal different distributions under different orientation partition. Theoretically speaking, no matter how the homogeneous areas distribute, SPs should always be the convergences of all homogeneous areas. But in practice, owing to various noises, some seriously polluted areas' orientation field can not be calculated exactly, if these incorrect orientations happen to be at the boundary of orientation partition, the partitioning results will be affected. Figure 3 shows two different orientation partition schemes, for the first,

$$\Theta_1^1 = \left\{ (x,y) \middle| \frac{7}{8}\pi \le O(x,y) < \pi \cup 0 \le O(x,y) < \frac{\pi}{8} \right\},$$

$$\Theta_2^1 = \left\{ (x,y) \middle| \frac{\pi}{8} \le O(x,y) < \frac{3}{8}\pi \right\}, \Theta_3^1 = \left\{ (x,y) \middle| \frac{3}{8}\pi \le O(x,y) < \frac{5}{8}\pi \right\},$$

$\Theta_4^1 = \left\{ (x,y) \middle| \frac{5}{8}\pi \le O(x,y) < \frac{7}{8}\pi \right\}$ (as fig.2(c) shows); for the second,

$$\Theta_1^2 = \left\{ (x,y) \middle| 0 \le O(x,y) < \frac{\pi}{4} \right\}, \ \Theta_2^2 = \left\{ (x,y) \middle| \frac{\pi}{4} \le O(x,y) < \frac{\pi}{2} \right\},$$

$\Theta_3^2 = \left\{ (x,y) \middle| \frac{\pi}{2} \le O(x,y) < \frac{3}{4}\pi \right\}$, $\Theta_4^2 = \left\{ (x,y) \middle| \frac{3}{4}\pi \le O(x,y) < \pi \right\}$ (as Figure 3(d) shows).

By comparing the areas circled by red lines, we can find that: in Figure 3(c), the trend of convergence is not obvious, if we try to detect SPs with POAD, the delta point will be missed; however, in Figure 3(d), the delta point can be extracted exactly. Figure 3 shows the missing ectraction error caused by different partition schemes, at the same time, the false ectraction error can also caused by different partition schemes.

Based on the analysis above, we can conclude that: for the same orientation field, different partition schemes may lead to different singular point extraction results, especially for poor fingerprint images. For eliminating the uncertainty, for each orientation field, we will employ three different partition schemes simultaneously, and combine the three extraction results to make the final decision. The detail will be described in the next section.

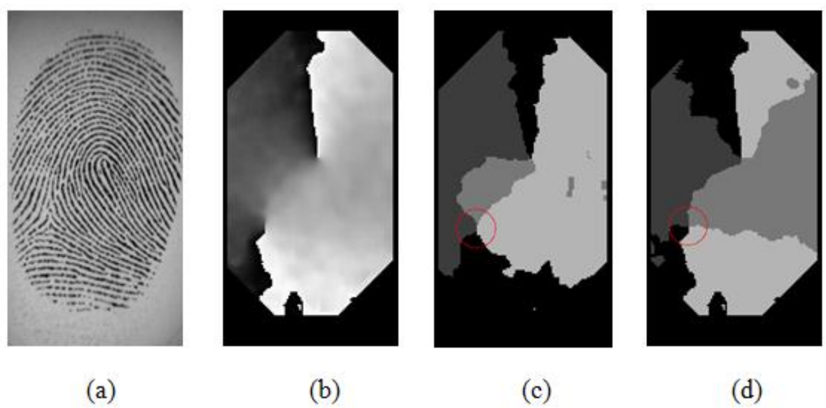

Figure 3. The distributions of homogenous areas under different partition schemes. (a) original image; (b) the orientation field; (c),(d) the distribution of homogenous regions under partition schemes.

Since Definition 1and Definition 2 in [16] are not suit to the different partition schemes, we redefine the homogeneous area as followed:

Definition 4(redifined homogeneous area): Supposing fingerprint's orientation field is divided into N non-overlapping homogeneous areas, the i-th homogeneous area Θ_i ($1 \le i \le N$) is defined as:

$$\Theta_i = \left\{ (x,y) \middle| \frac{(i-1)}{N}\pi \le (O(x,y)+\omega_0) \bmod \pi < \frac{i}{N}\pi; 0 \le \omega_0 < \frac{\pi}{N} \right\} \quad (5)$$

here $O(x,y)$ means the local ridge orientation of point (x,y), ω_0 is a constant which adjusts the range of orientation for each homogeneous area. In this definition ,When $N=4$, $\omega_0 = \frac{\pi}{8}$, it is the first partition scheme mentioned above; When $N=4, \omega_0 = 0$, it is the second.

3. The Implementation

The main procedure is:

For each fingerprint, partitioning the orientation field with three schemes.

Scheme1($N = 4, \omega_0 = 0$): $\Theta_1^1 = \left\{ (x, y) \middle| 0 \le O(x, y) < \frac{\pi}{4} \right\}$,

$\Theta_2^1 = \left\{ (x, y) \middle| \frac{\pi}{4} \le O(x, y) < \frac{\pi}{2} \right\}$, $\Theta_3^1 = \left\{ (x, y) \middle| \frac{\pi}{2} \le O(x, y) < \frac{3}{4}\pi \right\}$,

$\Theta_4^1 = \left\{ (x, y) \middle| \frac{3}{4}\pi \le O(x, y) < \pi \right\}$; Scheme2($N = 4, \omega_0 = \frac{\pi}{12}$):

$\Theta_1^2 = \left\{ (\mathrm{x, y}) | \ 0 \le \mathrm{O(x, y)} < \frac{\pi}{12} \cup \frac{5\pi}{6} \le O(\mathrm{x, y}) < \pi \right\}$,

$\Theta_2^2 = \left\{ (\mathrm{x, y}) | \ \frac{\pi}{12} \le O(\mathrm{x, y}) < \frac{\pi}{3} \right\}$, $\Theta_3^2 = \left\{ (\mathrm{x, y}) | \ \frac{\pi}{3} \le O(\mathrm{x, y}) < \frac{7\pi}{12} \right\}$,

$\Theta_4^2 = \left\{ (\mathrm{x, y}) | \ \frac{7\pi}{12} \le O(\mathrm{x, y}) < \frac{5\pi}{6} \right\}$; Scheme3($N = 4, \omega_0 = \frac{\pi}{6}$):

$\Theta_1^3 = \left\{ (\mathrm{x, y}) | \ 0 \le \mathrm{O(x, y)} < \frac{\pi}{6} \cup \frac{11\pi}{12} \le O(\mathrm{x, y}) < \pi \right\}$,

$\Theta_2^3 = \left\{ (\mathrm{x, y}) | \ \frac{\pi}{6} \le O(\mathrm{x, y}) < \frac{5\pi}{12} \right\}$, $\Theta_3^3 = \left\{ (\mathrm{x, y}) | \ \frac{5\pi}{12} \le O(\mathrm{x, y}) < \frac{2\pi}{3} \right\}$,

$\Theta_4^3 = \left\{ (\mathrm{x, y}) | \ \frac{2\pi}{3} \le O(\mathrm{x, y}) < \frac{11\pi}{12} \right\}$.

For each scheme, locating SPs and distinguishing their types with the method proposed in [16], the resules are marked as: SP_set1, SP_set2, SP_set3.

Combined the results to make the final decision, the details are:

● Step1: for the first SP in SP_set1, calculating the euclidean distance with all same type SPs in SP_set2, SP_set3, if the distance within the predifined threshold, then averaging the corresponding SPs' coordinates as a true SP, meanwhile, removing the corresponding SPs from SP_set1, SP_set2, SP_set3 respectively;

● Step2: repeat step1 for the rest SPs in SP_set1;

● Step3: for each SP in SP_set2, the operations are almost the same with SPs in SP_set1, and we just need to validate each SP with SPs in SP_set3.

4. Experiments

In this experiment, this work will be compared with our previously proposed work[16] , and tested on FVC2002 DBA DB1,DB2,DB3, and for each DB, the top 20 group are selected (8*20=160 images).

The performance is evaluated with False Detecting Ratio (FDR), Missed Detecting Ratio (MDR), the detailed descriptions of FDR and MDR are as followed:

$$FDR = \frac{\text{the total number of false detected SPs}}{\text{the total number of genuine SPs}} \times 100\% \qquad (6)$$

$$MDR = \frac{\text{the total number of missed detected SPs}}{\text{the total number of genuine SPs}} \times 100\% \qquad (7)$$

Comparing results are shown in Table 1. From the results, we can conclude that: this method is more accuracy than the previous one.

Table 1. Comparing Results between this Method and Previously Proposed Method on FVC2002

FVC2002 DBA	**Previous method**		**This method**	
	FDR(%)	MDR(%)	FDR(%)	MDR(%)
DB1	0.41%	3.29%	0.41%	2.06%
DB2	4.13%	2.07%	2.89%	1.65%
DB3	1.99%	7.28%	1.99%	6.62%
Total	2.18%	4.21%	1.76%	3.44%

5. Conclusions

Based on experiments and analysis, we find that: in our previous work[16], different partition schemes may lead to different singular point extraction results, especially for poor fingerprint images. For eliminating the uncertainty, we employ three different partition schemes simultaneously, and combine the three extraction results to make the final decision. Experiment on FVC2002 DBA shows that: compared with the previous work, this work promotes the SPs extraction accuracy.

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