Fingerprint Singular Point Detection Algorithm by Poincaré Index

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Abstract: - Fingerprint indexing is an efficient technique that greatly improves the performance of Automated Fingerprint Identification Systems. We propose a continuous fingerprint indexing method based on location, direction estimation and correlation of fingerprint singular points. There have been many approaches introduced in the design of feature extraction. Based on orientation field, Firstly, we divide it into blocks to compute the Poincaré Index. Then, the blocks which may have singularities are detected in the block images. Experiment show the present algorithm is robust than the traditional method on poor quality images.

Key-words: - Fingerprint Core Delta Point Orientation Poincaré Index

1 Introduction

Every person is believed to have unique fingerprints [1] .This makes fingerprint matching one of the most reliable methods for identifying people [2], Fingerprint matching is usually carried out at two different levels.At the coarse level, fingerprints can be classified into six main classes: arch, tented arch, right loop, left loop, whorl and twin loop, as shown in Fig.1. The fine-level matching is performed by extracting ridge endings and branching points, called minutiae [3], from a fingerprint image. The similarity between two fingerprints is determined by comparing the two sets of minutiae points. Although the coarse classification does not identify a fingerprint uniquely, it is helpful in determining when two fingerprints do not match. For example, a right loop image should be matched with only other right loop images in the database of fingerprints. When fingerprints from all the ten fingers are available, the coarse level classification of these ten prints drastically reduces the proportion of database images to be matched at the finer level. A human expert can perform coarse-level classification of fingerprints relatively easy. For an automatic system, the problem is much more difficult because the system must take into account the global directions of the ridges as well as their local connectivity to make its decision.

In recent years, fingerprints are most widely used for personal identification. Fingerprint images are direction oriented patterns formed by ridges and valleys. The singular point area is defined as a region where the ridge curvature is higher than normal and where the direction of the ridge changes rapidly. In most fingerprint identification algorithms and fingerprint classification algorithms, extracting the number and the precise location of SPs is of great importance.

Fingerprint classification is a coarse level partitioning of a large fingerprint database, where the class of the input fingerprint is first determined and subsequently, a search is conducted within the set of fingerprints belonging to the same class as the input fingerprint. In regard to fingerprint classification, only a portion of a fingerprint, called pattern area is of interest [4]. The pattern area of a fingerprint consists of those ridges encircled by typelines which is defined as the two innermost ridges that form a divergence tending to encircle or encompass the central portion of a fingerprint [5]. The pattern areas of loop or whorl types of fingerprints contain two types of singular points (core and delta). So it is very important to detect singular points accurately and reliably [6]. Nowadays, a practical method based on the Poincaré Index was always used for fingerprint singularities detection and a fingerprint has a well-defined orientation. The traditional detection based on the point orientation field can gain the accurate position of singularities, but the singular points are misjudged or not judged for the low quality image of the fingerprint sometimes and the

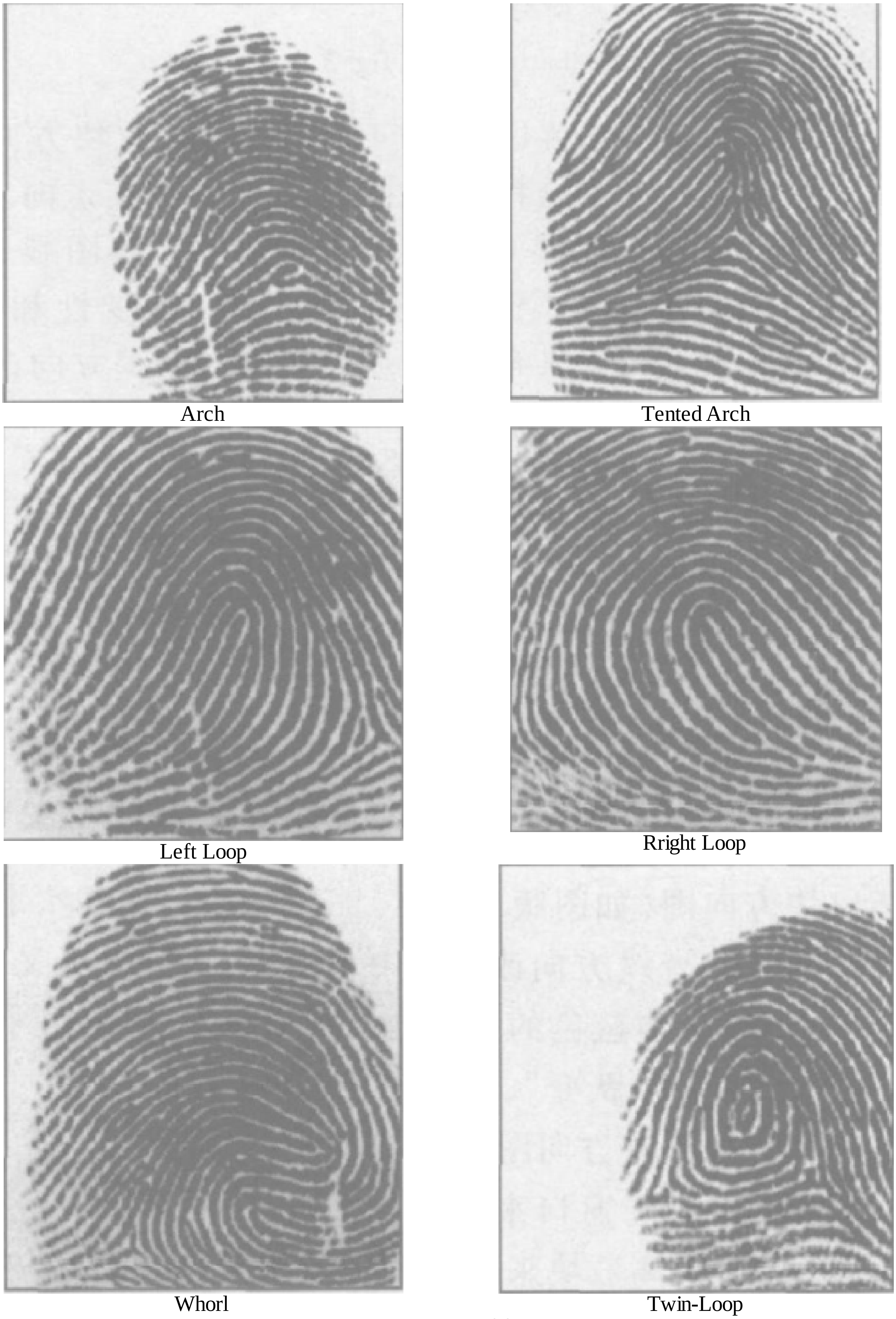


Fig. 1. Six classes of fingerprints

Algorithm has a high computational complexity. However, the traditional detection based on the block orientation field can detect the existence of all the singular points, but can not locate the positions accurately. The classical formula to compute the Poincaré Index can present only the rotation angles, but not the rotation direction of the vector in the vector field exactly.

We propose a multi-scale detection algorithm for singular points in fingerprint images based on both the continuous orientation field and the modified Poincaré Index. Firstly, the blocks which may contain singularities are detected by computing the Poincaré Index. Then, the singularities are detected in the block images accurately and reliably. So the new algorithm can locate the singularities at pixel level with an accuracy of only one pixel.

The main steps of our structural approach to fingerprints classification are as follows:

1) Computation of the directional image of the fringerprints. This directional image is a 28 × 30 matrix. Each matrix element represents the ridge orientation within a given block of the input image. The directional image was computed using the algorithm proposed in Ref. [7].

2) Segmentation of the directional image into regions containing ridges with similar orientations. To this end, the segmentation algorithm described in Ref. [8] was used.

2 Image segment

The boundary region, surrounding the actual fingerprint in the image, inherently contains discontinuities in the ridge pattern since beyond that boundary is background with relatively constant (but often noisy) pixel intensity. To address the border discontinuities, the fingerprint is segmented from the background.

We use the blockwise coherence to segment the images. The block is considered as foreground if its coherence of its direction field satisfy some predefined threshold, otherwise, the background. Then two iterations of dilation and erosion are used to remove holes resulting from inhomogenous regions. All the process discussed below is carried out on such foreground regions.

3 The coherence of Orientation field

Let I (i, j) denote the gray level of the pixel (i, j) in a M×N fingerprint image. Let θ' (x, y) represent the orientation of the anisotropy of the non-overlapping block centered at (x, y), and θ (x, y) the local dominant orientation (or flow direction). The local dominant orientation θ (x, y) equals θ' (x, y)+ $\pi/2$ since the flow orientation is perpendicular to the direction of anisotropy. For fingerprint images, in case the opposite directions cancel each other out, we define the range of the direction angles as (0, π). Let χ (x, y) represent the coherence of the flow directions.

Since the gradients of a Gaussian filter can give a good estimate of the underlying oriented pattern, we adopt its orientation as the local direction. First, the image is convolved with a Gaussian filter whose impulse response is given by

$$g_1(x, y) = e^{-(x^2+y^2)/2\sigma^2} \quad (1)$$

The filtered image is expressed as

$$G(i, j) = g_1(i, j) \times I(i, j) \quad (2)$$

Next, the optimal 3 by 3 operators [9] are used to obtain the gradients in horizontal and vertical directions as Gx (i, j) and Gy (i, j). Thus, the amplitude of the gradient is

$$|G_i(i, j)| = mag(\nabla G(i, j)) = \sqrt{G_x^2(i, j) + G_y^2(i, j)} \quad (3)$$

Let

$$\begin{cases} J_1(i, j) = 2G_x(i, j)G_y(i, j) \\ J_2(i, j) = G_x^2(i, j) - G_y^2(i, j) \\ J_3(i, j) = G_x^2(i, j) + G_y^2(i, j) \end{cases} \quad (4)$$

then, the anisotropy orientation estimate of the 8 by 8 block(x, y) is

$$\bar{\theta}(x, y) = \frac{1}{2}\tan^{-1}\left(\frac{\sum_{(i,j)\in\Phi_1} J_1(i, j)}{\sum_{(i,j)\in\Phi_1} J_2(i, j)}\right) \quad (5)$$

where Φ_1 is smoothing window centered on the block with the size of W1 by W1 [10,11]. For fingerprint images, the average width of the ridge or valley is five to eight pixels, so W1 = 16 gives a good orientation estimate and saves computational time. Furthermore,

$$\theta(x, y) = \bar{\theta}(x, y) + \frac{\pi}{2} \quad (6)$$

However, there are two reasons for failure of the orientation measure [11]. The neighborhood may contain a constant gray value area or an isotropic gray value structure without a preferred orientation. To distinguish these two cases we need to compare the magnitude of the orientation vector with the mean square magnitude of the gradient. As to fingerprint images, the background shows constant gray value, if we can distinguish between them, our segmentation will be ready. Therefore, we first set the threshold value G_{th} of the Gradient as

$$G_{th} = g_t * (|G_i|_{\max} - |G_i|_{\min}) + |G_i|_{\min} \qquad (7)$$

where $|G_i|_{\max}$ and $|G_i|_{\min}$ are supposed to be the global maximum and minimum g radient amplitude of the image respectively, and g_t is the threshold factor [12]. Smaller values of g_t will encourage weak edges to be identified, while larger values will favor noise suppression. For varied contrast fingerprint images, g_t is selected in the range of [0.05, 0.3]. In our work, $|G_i|_{\max}$ and $|G_i|_{\min}$ are adjusted in order to avoid the effect of asymmetry of the gradient distribution.

Therefore, the block coherence is defined as

$$\chi(x,y) = \begin{cases} -1, & if \ \dfrac{1}{w_1 * w_1} \sum_{(i,j)\in\phi_1} J_3(i,j) < G_{th} * G_{th} \\ \dfrac{\left(\left(\sum_{(i,j)\in\phi_1} J_1(i,j)\right)^2 + \left(\sum_{(i,j)\in\phi_1} J2(i,j)\right)^2\right)^{\frac{1}{2}}}{\sum_{(i,j)\in\phi_1} J_3(i,j)} & \end{cases} \qquad (8)$$

The block is regarded as a candidate for the background if the coherence is -1. The coherence ranges from 0 to 1. For ideal local orientation it is one, for an isotropic gray value structure without a preferred orientation it is zero which is correspondent to the noisy regions in the foreground or the regions near core or delta.

We then label all the connected regions whose coherence values are not 1, choose the one with the largest area as the supposed foreground print area. For the supposed background regions, if they are surrounded by the foreground, they are labeled as noisy regions or low contrast regions. Whose coherences are assigned a value of zero. That is

$$\chi'(x,y) = \begin{cases} -1 & \text{background} \\ 0 & \text{noisy} \\ \chi(x,y) & \text{forground} \end{cases} \qquad (9)$$

The average coherence of the foreground indicates the clarity of ridges, therefore, it can be used to control the reject rate if needed.

In this process, not only are the fingerprint ridge orientation and coherence attained, but the image is also segmented into noisy, background or foreground regions as a by-product. It is better than other methods as they treat all the blocks the same without separating the constant gray value area from the isotropic gray value structure without a preferred orientation.

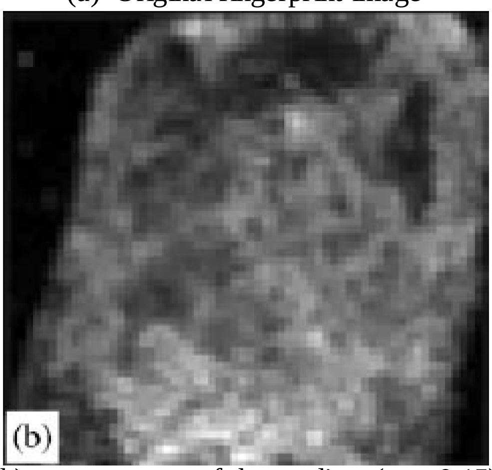
4 The eight direction field

A fingerprint has a well-defined direction field [13]. To compute the direction field, we define the ridge direction of a pixel as 8 directions. (at positions marked by numbers 1,..., 8).

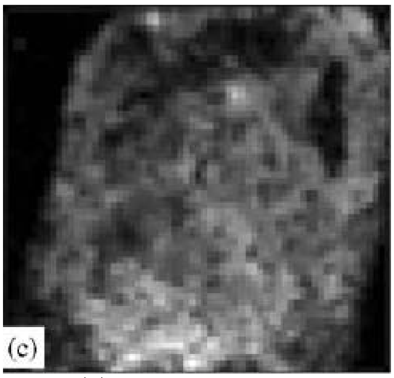
To decide the ridge direction of each pixel in the image, we compute the average grey value in direction i (i= 1,…,8 means one of the 8 directions) in a 9×9 window with the pixel as the centre. We compute the average grey value of the pixels labelled "i" and obtained G[i]. The 8 mean grey values are divided into 4 groups with the two directions in each group perpendicular to each other. Group j (j=1, 2, 3,4) contains direction j and j+4. The absolute value of the difference of the mean grey value is calculated in each group as:

$$G_{diff}[j] = |G_{mean}[j] - G_{mean}[j+4]| \quad (j=1, 2, 3,4) \qquad (10)$$

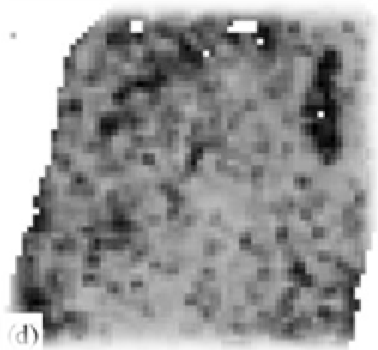
(a) Original fingerprint image



(b) mean-square of the gradient (gt = 0.15)



(c) orientation certainty



(d) coherence

(e) orientation overlaid on the segmented image

Fig. 2. Results of orientation field computation as well as image segmentation

7		6		5		4		3
8		7	6	5	4	3		2
		8				2		
1		1		*		1		1
		2				8		
2		3	4	5	6	7		8
3		4		5		6		7

Fig.3 eight direction

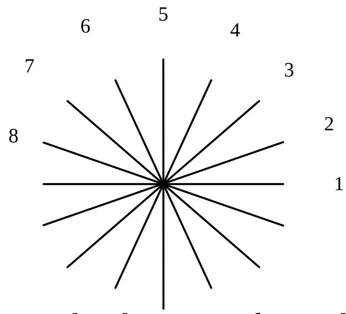


Fig.4 ridge directions of a pixel

Set the two directions in the group with the largest difference value as possible ridge direction. If

$$i_{\max} = \arg\left\{ \underset{i\in\{0,1,2,3\}}{Max}(G_{diff}(i)) \right\} \tag{11}$$

then i_{max} and i_{max+4} are possible ridge directions. The ridge direction in the pixel is decided by

$$o(x,y) = \begin{cases} i_{\max} & if\ |Grey - G[i\max]| \\ & <|Grey - G[i\max+4]| \\ i_{\max+4} & otherwise \end{cases} \tag{12}$$

Where *Grey* is the grey value at this pixel.

To reduce noise, the point direction field is smoothed. A local window of size 17×17 is taken around each pixel ,keeping it as the central of the window. We set the ridge direction of each pixel in the window as the direction of that pixel. That is, the mean direction of all the pixels in the window. To obtain the mean direction of a window, we calculate the number of pixels in the window where ridge direction is estimated as $i(i=1,\ldots,8)$ and set this number as $N[i]$. The mean direction of the block is:

$$O(x,y) = \arg\left\{ \underset{i=\{1,\ldots,8\}}{Max}(N[i]) \right\} \tag{13}$$

The smoothed point orientation field $O(x,y)$ is also called the continuous direction field [14].

We divided the continuous field into small blocks of size 9×9 and set the ridge direction of each pixels in the block as the mean direction of all the pixels in the block. To obtain the mean direction of a block, we calculate the number of pixels in the block where ridge direction is estimated as $i(i=1,\ldots,8)$ and set this number as Ni. The mean direction of the block is:

$$M(i,j) = \arg\left\{ \underset{i=\{1,\ldots,8\}}{Max}(Ni) \right\} \tag{14}$$

The block orientation field is a matrix and every pixel is estimated as $j(j=1,\ldots,8)$.

5 Direction estimation by least mean square

A number of methods have been developed to estimate the orientation field in a fingerprint [15]–[18]. The least mean square orientation estimation algorithm [19] has the following steps.

1) Divide I , the input image, into nonoverlapping blocks of size $w \times w$.

2) Compute the gradients $\partial x(i, j)$ and $\partial y(i, j)$ at each pixel (i, j) g_t . Depending on the computational requirement, the gradient operator may vary from the simple Sobel operator to the more complex Marr–Hildreth operator [20].

3) Estimate the local orientation of each block centered at pixel (i, j) using the following equations [18]:

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

$$v_y(i, j) = \sum_{u=i-w/2}^{i+w/2} \sum_{v=j-w/2}^{j+w/2} \left(\partial_x^2(u,v) - \partial_y^2(u,v)\right) \quad (15)$$

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

where $o(i, j)$ is the least square estimate of the local ridge orientation at the block centered at pixel (i, j) .Mathematically, it represents the direction that is orthogonal to the dominant direction of the Fourier spectrum of the $w \times w$ window.

A summary of our algorithm is presented below.

1) Estimate the orientation field o as described above using a window size of $w \times w$.

2) Smooth the orientation field in a local neighborhood. Let the smoothed orientation field be represented as o' . In order to perform smoothing (low-pass filtering), the orientation image needs to be converted into a continuous vector field, which is defined as follows:

$$\Phi_x(i, j) = \cos(2o(i, j)) \quad (16)$$

And

$$\Phi_y(i, j) = \sin(2o(i, j)) \quad (17)$$

Where Φx and Φy , are the components of the vector field, respectively. With the resulting vector field, the low-pass filtering can then be performed as follows:

$$\Phi_x^{'}(i, j) = \sum_{u=-w_\Phi/2}^{w_\Phi/2} \sum_{v=-w_\Phi/2}^{w_\Phi/2} w(u,v) \cdot \Phi_x(i-uw, j-vw) \quad (18)$$

And

$$\Phi_y^{'}(i, j) = \sum_{u=-w_\Phi/2}^{w_\Phi/2} \sum_{v=-w_\Phi/2}^{w_\Phi/2} W(u,v) \cdot \Phi_y(i-uw, j-vw) \quad (19)$$

W is a two-dimensional low-pass filter with unit integral and $w_\Phi \times w_\Phi$ specifies the size of the filter. Note that the smoothing operation is performed at the block level. For our experiments, we used a mean filter. The smoothed orientation field O' at (i, j) is computed as follows:

$$o'(i, j) = \frac{1}{2}\tan^{-1}\left(\frac{\Phi_y^{'}(i, j)}{\Phi_x^{'}(i, j)}\right) \quad (20)$$

6 Normalization

We normalize the region of interest to a constant mean and variance. Normalization is done to remove the effects of sensor noise and finger pressure differences. Let I(x, y) denote the gray value at pixel (x, y), Mi and Vi, the estimated mean and variance of each block. Ni(x, y), the normalized gray-level value at pixel (x, y). For all the pixels in each block, the normalized image is defined as:

$$N_i(x, y) = \begin{cases} M_0 + \sqrt{\dfrac{(V_0) \times \left(I(x,y) - M_i\right)^2}{V_i}}, \\ I(x,y) > M_i \\ M_0 - \sqrt{\dfrac{(V_0) \times \left(I(x,y) - M_i\right)^2}{V_i}}, \\ otherwise \end{cases} \quad (21)$$

where M_0 and V_0 are the desired mean and variance values, respectively. Normalization is a pixel-wise operation which does not change the clarity of the ridge and furrow structures. If normalization is done on the entire image, then it cannot compensate for the intensity variations in the different parts of the finger due to finger pressure differences. Normalization of each block separately alleviates this problem.

7 The poincare index value

Many methods have been proposed to detect the singular points in fingerprint images, while the Poincare index which is derived from continuous curves is the most popular one. As for digital fingerprint images, a double core point has a Poincare index valued as1, a core point as 1/2 and a delta point as −1/2 .

Let $\theta(x,y)$ denote the direction of the pixel (x,y) in an $M\times N$ fingerprint image. The Poincaré Index at pixel (x,y) which is enclosed by a digital curve (with N points) can be computed as follows:

$$Poincare(x,y)=\frac{1}{2\pi}\sum_{k=0}^{N-1}\Delta(k) \qquad (22)$$

Where

$$\Delta(k)=\begin{cases}\delta(k) & |\delta(k)|<\frac{\pi}{2}\\ \delta(k)+\pi & \delta(k)\le-\frac{\pi}{2}\\ \pi-\delta(k) & \delta(k)\ge\frac{\pi}{2}\end{cases} \qquad (23)$$

$$\delta(k)=\theta(x_{(k+1)\bmod N},y_{(k+1)\bmod N})-\theta(x_k,y_k). \qquad (24)$$

and it goes in a counter-clockwise direction from 0 to N-1.For our method, N is 4 (Fig.6).

$(x-1,y)$	$(x-1,y+1)$
(x, y)	$(x,y+1)$

Fig.6. The mask of detecting singular points

We compute the Poincaré Index at pixel in the (i,j) by the modified version of Poincaré Index(9), and the corresponding value is $Poincare(i,j)$. The modified version of Poincaré Index can present not only the rotation angles, but also the rotation direction of the vector in the vector field, exactly. For our method, the closed digital curve is selected as 4 pixels. In order to calculate simply, the direction yards from 0 to 7 is used to compute the Poincaré Index.

$$\Delta(k)=\begin{cases}\delta(k) & |\delta(k)|<\frac{\pi}{2}\\ \delta(k)+\pi & \delta(k)\le-\frac{\pi}{2}\\ \delta(k)-\pi & \delta(k)\ge\frac{\pi}{2}\end{cases} \qquad (25)$$

8 Singular point detection

If $Poincare(i,j)=0.5$, the block $M(i,j)$ may contain a core point;If $Poincare(i,j)=-0.5$, the block $M(i,j)$ may contain a delta point;Otherwise, the block $M(i,j)$ doesn't contain singular points.

The blocks which may contain singularities are detected by our method. Then the Poincaré Index at pixel (x,y) which is enclosed by a digital curve of 4 pixels can be compute in the detected blocks(Fig.7), and the corresponding value is $Poincare1(x,y)$. The direction yards from 0 to 7 is also used for computing the Poincaré Index.

If $Poincare1(x,y)=+0.5$, the point is a core point;
If $Poincare1(x,y)=-0.5$, the point is a delta point;
Otherwise, the point is not a singularity.

If the number of core points Nc is more than 2 or the number of delta points Nd is more than 2, we smooth the continuous orientation field until the number of core points or delta points is lesser than 2

The singularity detection algorithm described above has been tested on the fingerprint images in the FVC2002 database. We choose the typical fingerprint image which is shown in Fig.7. In Fig.11,the white blocks contains the core points and the black blocks contains the delta points.

Fig.7. The original fingerprint images

Fig.8The segmented fingerprint image

Fig.9. The continuous orientation field of fingerprint image

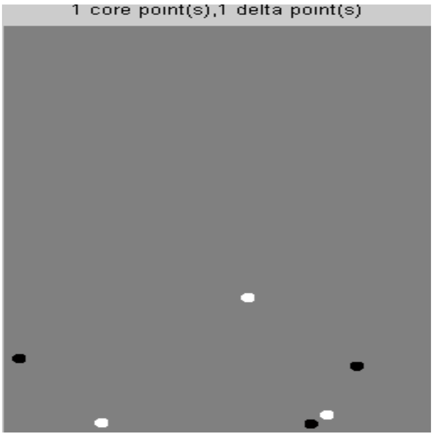


Fig.10. The blocks which may contain singularities:

Fig.11. Singular points found

9 Conclusion

The fingerprints have been traditionally classified into categories based on information in the global patterns of ridges. In large scale fingerprint identification systems, elaborate methods of manual fingerprint classification systems were developed to index individuals into bins based on classification of their fingerprints; these methods of binning eliminate the need to match an input fingerprint to the entire fingerprint database in identification applications and significantly reduce the computing requirements .Efforts in automatic fingerprint classification have been exclusively directed at replicating the manual fingerprint classification system. A fingerprint classification system should be invariant to rotation, ranslation, and elastic distortion of the frictional skin. Although fingerprint landmarks provide very effective fingerprint class clues, methods relying on the fingerprint landmarks alone may not be very successful due to lack of availability of such information in many fingerprint images and due to the difficulty in extracting the landmark information from the noisy fingerprint images. As a result,the most successful approaches need to (I) supplement the orientation field information with ridge information; （II） use fingerprint landmark information when available but devise alternative schemes when such information cannot be extracted from the input fingerprint images; and (III) use reliable structural/syntactic pattern recognition methods in addition to statistical methods.

Fingerprint identification in a large dataset is a very time consuming task. Fingerprint indexing can evidently reduce the number of comparisons. SPs can be robustly identified and contain fingerprint intrinsic features.

Several approaches have been developed for automatic fingerprint classification. These approaches can be broadly categorized into four main categories:

1)_ model-based,
2)_ structure-based,
3)_ frequency-based, and
4)_ syntactic.

The model-based fingerprint classification technique usesthe locations of singular points (core and delta) to classify a fingerprint into the five above-mentioned classes A model-based approach tries to capture the knowledge of a human expert by deriving rules for each category by hand constructing the models and therefore, does not require training.

In this paper, a novel method based on the point orientation field and the block orientation field is presented with a higher accuracy to overcome the shortcoming of the traditional methods. The main benefit of this algorithm is its fast running speed, because we don't have to calculate the Poincaré Index value at every pixel and only detect the singularities in the effective region. Experimental results for real fingerprint images shows that the proposed method provides accurate results, which would facilitate fingerprint identification and fingerprint classification afterwards.

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