Core Point Detection using Improved Segmentation and Orientation

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Abstract

Core point detection is very important in fingerprint classification and matching process. Usually fingerprint images have noisy background and the local orientation field also changes very rapidly in the singular point area. It is difficult to locate the singular point precisely. In this paper, we present a new algorithm for optimal core point detection using improved segmentation and orientation. In our technique detects core point accurately by extracting best region of interest(ROI) from image and using fine orientation field estimation. We present a modified technique for extracting ROI and fine orientation field. The distinct feature of our technique is that it gives high detection percentage of core point even in case of low quality fingerprint images. The proposed algorithm is applied on FVC2004 database. Results of experiments demonstrate improved performance for detecting core point.

1. Introduction

Fingerprints have been used as a method of identifying individuals due to the favorable characteristics such as "unchange ability" and "uniqueness" in an individual's lifetime. In recent years, as the importance of information security is highly demanded, fingerprints are utilized for the applications related to user identification and authentication [1]. Most Automatic Fingerprint Identification systems (AFIS) are based on local ridge features; ridge ending and ridge bifurcation, known as $minutiae$ [2].

Core points and delta points are critical points in fingerprint. A core is defined as a point in the orientation filed where the orientation in a small local neighborhood around the point presents semi-circular tendency [3]. Core points are the points where the innermost ridge loops are at their steepest and delta points are points from which three patterns deviate [3,4]. Fingerprint image shown in Figure 1 has both core point and delta point in its singular region.

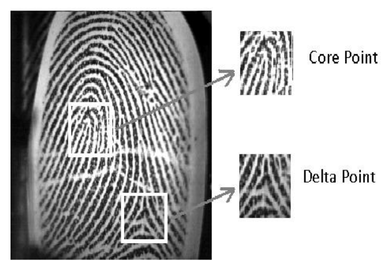

Figure 1. Fingerprint Image with its singular points

In AFIS, core point plays an important role [5] and it is widely used for fingerprint matching [2,6,7] and classification [7,8,9]. The problem with applications related with fingerprint is that how to fix the fingerprint with the help of a reference point so that it would be invariant to error generated by scanning process [7]. This can be avoided by detecting core point accurately. Minutiae based fingerprint matching is widely used in AFIS [6,10] and minutiae in neighbor of core point also plays an important role in frequency characteristic fingerprint matching [7].

A number of algorithms have been proposed for optimal core point detection and most of them are based on ridge orientation estimation techniques. A common method used for core point detection is Poincare index in which point in the ridge orientation field is classified as singular point if orientation along a small closed curve around that point changes 0, ±180 or ±360 degrees [10]. [7] had used geometry of region technique for reference point detection. [16] had proposed a method for reference point detection especially for arch-type fingerprint.

This paper is organized in six sections. Section 2 deals with the flow of processes applied on a fingerprint image before locating the core point. Section 3 presents Poincare index, geometry of region technique and Detection of Curvature technique while section 4 contains the proposed technique and its algorithm. Experiment results of our technique compared with other techniques are discussed in section 5 followed by conclusion in section 6.

2. Preprocessing for Core point Detection

Fingerprint images have various resolution and normally 500 dpi fingerprint images are used. Generally scanned fingerprint image includes noisy background, distortion and includes even scanner boundary reflection , which may cause problem in detecting the reference point. So, some preprocessing is required to locate core point correctly [11]. Figure 2 shows the flow diagram of fingerprint core point detection.

2.1. Segmentation

Fingerprint image segmentation requires extracting fingerprint image from background. In AFIS, the processing of the surrounding background in fingerprint image is not necessary and consumes more processing time in all stages. Cutting or cropping out the region that contains the fingerprint feature(ROI) minimizes the number of operations on the fingerprint image.

Mean and variance based method [5] is commonly used for fingerprint image segmentation but it fails when the background is much distorted.

Steps for Mean and Variance Based fingerprint image segmentation [5] are summarized as follows:

1. Divide the input image I(i, j) into non-overlapping blocks with size w×w.

2. Compute the mean value $M(I)$ for each block using equation 1.

$$M(I) = \frac{1}{w^2} \sum_{i=-w/2}^{w/2} \sum_{j=-w/2}^{w/2} I(i,j) \tag{1}$$

3. Use the mean value computed in step 2 to compute the standard deviation value $std(I)$ from equation 2

$$std(I) = \sqrt{\frac{1}{w^2} \sum_{i=-w/2}^{w/2} \sum_{j=-w/2}^{w/2} (I(i,j) - M(I))^2} \tag{2}$$

4. Select a threshold value empirically. If the $std(I)$ is greater than threshold value, the block is considered as foreground otherwise it belongs to background.

2.2. Normalization

Normalization is performed to remove the effect of sensor noise and gray level background which are the consequence of difference in finger pressure [11]. Let $I(i, j)$ denotes the gray-level value at pixel (i,j). The normalized value $N(i, j)$ is defined in equation 3 [5] as

$$N(i,j) = \begin{cases} M_o + \sqrt{\frac{(V_o(I(i,j)) - M_i)^2}{V_i}} & \text{if } I(i,j) > M \\ M_o - \sqrt{\frac{(V_o(I(i,j)) - M_i)^2}{V_i}} & otherwise \end{cases} \tag{3}$$

Here M_0 and V_0 are the desired mean and variance respectively. The mean $M(I)$ and variance $V(I)$ of a gray-level fingerprint image with the dimension of $M \times N$ pixels, are defined using equation 4 and 5 respectively [5].

$$M(I) = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} I(i,j) \tag{4}$$

$$V(I) = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (I(i,j) - M(I))^2 \tag{5}$$

Where $I(i, j)$ represents the intensity of the pixel at ith row and jth column. The main purpose of the normalization operation is to reduce the variations of gray-level values along the ridges and valleys [2].

2.3. Orientation Field Estimation

Orientation or direction field estimation is not only used in core point detection but also in fingerprint matching [2]. The smoothed orientation field based on least mean square algorithm [2,7] is summarized as follows:

1. Divide the input image $I(i, j)$ into non-overlapping blocks with size w x w.

2. Compute the gradients $\partial_x(i, j)$ and $\partial_y(i, j)$ at the center of the block.

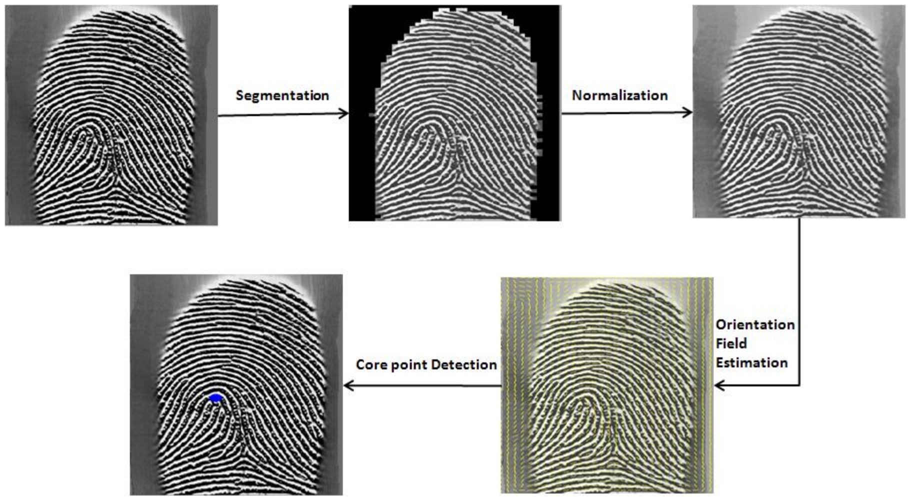

Figure 2. Flow Diagram for Core Point Detection

3. Estimate the local orientation using the equations 6, 7 and 8 [7].

$$V_x(i,j) = \sum_{u=i-w/2}^{i+w/2} \sum_{v=j-w/2}^{j+w/2} 2\partial_x(u,v)\partial_y(u,v) \quad (6)$$

$$V_y(i,j) = \sum_{u=i-w/2}^{i+w/2} \sum_{v=j-w/2}^{j+w/2} \partial_x^2(u,v)\partial_y^2(u,v) \quad (7)$$

$$\theta(i,j) = \frac{1}{2}\tan^{-1}\left(\frac{V_y(i,j)}{V_x(i,j)}\right) \quad (8)$$

Here $\theta(i,j)$ is the least square estimate of the local ridge orientation at the block centered at pixel (i,j).

4. The local ridge orientation varies slowly in a local neighborhood where no core point appears. The discontinuity in ridge and valley due to noise can be reduced by applying a low pass filter. However, to apply a low pass filter the orientation image must first be converted to a Continuous Vector Field (CFV). The continuous vector field is defined by the x-component Φ_x and the y-component Φ_y computed using equation 9 and 10 respectively [7].

$$\Phi_x(i,j) = cos(2\theta(i,j)) \quad (9)$$

$$\Phi_y(i,j) = sin(2\theta(i,j)) \quad (10)$$

5. The two dimensional $w_\Phi \times w_\Phi$ low-pass filter G with unit integral is applied to the resultant CFV. The filtered x-component and y-component of the CFV are obtained by equations 11 and 12 respectively [7].

$$\Phi'_x(i,j) = \sum_{u=-w_\Phi/2}^{w_\Phi/2} \sum_{v=-w_\Phi/2}^{w_\Phi/2} G(u,v)\Phi_x(i-uw, j-vw) \quad (11)$$

$$\Phi'_y(i,j) = \sum_{u=-w_\Phi/2}^{w_\Phi/2} \sum_{v=-w_\Phi/2}^{w_\Phi/2} G(u,v)\Phi_y(i-uw, j-vw) \quad (12)$$

6. The smoothed orientation field at (i,j) is computed by equation 13 [7].

$$\theta'(i,j) = \frac{1}{2}\tan^{-1}\left(\frac{\Phi'_y(i,j)}{\Phi'_x(i,j)}\right) \quad (13)$$

2.4. Core Point

In many fingerprint related applications one has a problem of how to fix the fingerprint image with the help of a reference point [12], so that it would be invariant to evident spatial error originated from the scanning process. Using singular points one has the means to do this, since the fingerprints contain only a very limited number of singular points, usually from two to four. A whorl type fingerprint image has two core points. For fingerprints that do not contain loop or whorl singularities, the core is usually associated with the point of maximum ridge line curvature [5].

Singular points have also a very important role on the coarse level classification diminishing the number of images to go through before the time consuming minutiae classification [10].

3. Core point Detection Techniques

The core point is used in both fingerprint classification and fingerprint matching using either spatial domain [2] or transformed domain [7]. This section details different techniques for core point detection.

3.1. Geometry of Region technique (GR)

It is very important to find the geometry of region to detect core point as the ridge line curvature varies sharply near core point region [5].

The GR technique can be summarized as follows.

1. Compute the smoothed orientation field $\theta'(i,j)$by using equation 13 above.

2. Compute $\epsilon(i,j)$ from equation 14 [7], which is the sine component of $\theta'(i,j)$

$$\epsilon(i,j) = sin(\theta'(i,j)) \tag{14}$$

3. Initialize a label image A which is used to indicate the core point.

4. Assign the corresponding pixel in the value of the difference in integrated pixel intensity of each region A from equation 15 [7].

$$A(i,j) = \sum_{R_1} \epsilon(i,j) - \sum_{R_2} \epsilon(i,j) \tag{15}$$

   The regions R1 and R2 are determined empirically and also their geometry are designed to capture the maximum curvature in concave ridges and should cover at least one ridge.

5. Find pixel (i,j) that have maximum value in A and assign it as the core point.

6. If the core point still cannot be located, the steps (1-5) could be iterated for a number of times while decreasing the window size used in step 1) above.

3.2. Poincare Index

An elegant and practical method based on the Poincare index was proposed in [13]. The PC technique can be summarized as follows [5,9].

1. Estimate the orientation field $\theta'(i,j)$ by using the least square orientation estimation algorithm given by equation 13 [7] above.

2. Initialize a label image A which is used to indicate the core point.

3. For each pixel, compute Poincare index, $PC(i,j)$ from 16, 17 and 18 [13] where

$$PC(i,j) = \frac{1}{2\pi} \sum_{k=0}^{N_p-1} \Delta(k) \tag{16}$$

$$\Delta(k) = \begin{cases} \delta(k) & \text{if } \delta(k) < \pi/2 \\ \pi + \delta(k) & \text{if } \delta(k) \leq -\pi/2 \\ \pi - \delta(k) & otherwise \end{cases} \tag{17}$$

   and

$$\delta(k) = \epsilon(x_{(k+1)_{modN_p}}, y_{(k+1)_{modN_p}}) - \epsilon(x_k, y_k) \tag{18}$$

4. The core point should yield the Poincare index between 0.45-0.51 [13].

5. The center of the block with the value of one is considered to be a core point. However if there are more than one block with that values, the average calculation is applicable.

3.3. Detection of Curvature Technique

1. Compute the local orientation $\theta(i,j)$ by using equation 8 [7]. The input block size is kxk = 3x3.

2. Smooth the orientation field $\theta'(i,j)$ by using equation 13 [7].

3. The difference of direction components is computed for every progressive block from equations 19 and 20.

$$DiffY = \sum_{k=1}^{3} sin2\theta(k,3) - \sum_{k=1}^{3} sin2\theta(k,1) \tag{19}$$

$$DiffX = \sum_{k=1}^{3} cos2\theta(3,k) - \sum_{k=1}^{3} cos2\theta(1,k) \tag{20}$$

4. The core point could be located at the corresponding (i,j) where $DiffX$ and $DiffY$ are negative.

4. Proposed Technique

In our proposed method new modified technique is used for segmentation. Normalization is done in the same way as described in 2.2 while orientation field is estimated by new method as it greatly effects the core point detection.

4.1. Modified Gradient based Segmentation

In this section , we present a new Modified Gradient Based Method for fingerprint segmentation. In this method, we compute the local gradient values for fingerprint images which detect sharp change in the gray level value of background. This technique segments the fingerprint images accurately especially very dry and wet fingerprint images are segmented in an accurate manner. Steps for our method are summarized as follows:

1. Divide the input image I(i,j) into non-overlapping blocks with size w x w. In our case w = 8.
2. Use histogram equalization to enhance the contrast between background and foreground.
3. Use a 3x3 median filter to reduce the noise in background of the image[14].
4. Compute the gradients $\partial_x(i,j)$ and $\partial_y(i,j)$ at each pixel (i,j)which is the center of the block.
5. Compute the mean values M_x and M_y for x and y component of the gradient using equations 21 and 22 respectively

$$M_x = \frac{1}{w^2}\sum_{i=-w/2}^{w/2}\sum_{j=-w/2}^{w/2}\partial_x(i,j) \tag{21}$$

$$M_y = \frac{1}{w^2}\sum_{i=-w/2}^{w/2}\sum_{j=-w/2}^{w/2}\partial_y(i,j) \tag{22}$$

6. Compute standard deviation for both M_x and M_y using equations 23 and 24

$$std_x = \sqrt{\frac{1}{w^2}\sum_{i=-w/2}^{w/2}\sum_{j=-w/2}^{w/2}(\partial_x(i,j) - M_x(I))^2} \tag{23}$$

$$std_y = \sqrt{\frac{1}{w^2}\sum_{i=-w/2}^{w/2}\sum_{j=-w/2}^{w/2}(\partial_y(i,j) - M_y(I))^2} \tag{24}$$

7. Compute the gradient deviation using equation 25

$$grddev = std_x + std_y \tag{25}$$

8. Select a threshold value empirically. If $grddev$ is greater than threshold value, the block is considered as foreground otherwise it belongs to background.

   Figure 3 shows the segmented images based on gradient based method. Images in 2nd row show that this method is good for dark background.

Figure 3. 1st Row:Fingerprint Images from FVC2004 database, 2nd Row: Gradient Based Segmented Images

4.2. Fine Orientation Field Estimation

Fine Orientation field estimation is very vital for fingerprint recognition. It is a complicated and challenging task to extract the fine and exact orientation field for low quality fingerprints but our proposed technique is suitable for low quality fingerprint images also. Further more experimental results also show that it performs much better than previous works.

The steps for proposed technique are summarized as follows:

1. Divide the input image I(i,j) into non-overlapping blocks with size w x w. In our case w = 16.
2. Use 3x3 sobel vertical and horizontal masks from equations 26 and 27 to compute the gradients $\partial_x(i,j)$ and $\partial_y(i,j)$ at each pixel (i,j) respectively which is the center of the block. Sobel masks are used because of their simplicity and efficiency. Sobel operator performs a 2D spatial gradient measurement on a fingerprint image.

$$sobelVertical = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix} \tag{26}$$

$$sobelHorizontal = \begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix} \quad (27)$$

3. Estimate the local orientation using equations 28, 29 and 30 [15].

$$V_x(i,j) = \sum_{u=i-w/2}^{i+w/2} \sum_{v=j-w/2}^{j+w/2} (\partial_x(u,v))(\partial_y(u,v)) \quad (28)$$

$$V_y(i,j) = \sum_{u=i-w/2}^{i+w/2} \sum_{v=j-w/2}^{j+w/2} \partial_x^2(u,v) - \partial_y^2(u,v) \quad (29)$$

$$V_z(i,j) = \sum_{u=i-w/2}^{i+w/2} \sum_{v=j-w/2}^{j+w/2} (\partial_x(u,v) + \partial_y(u,v))^2 \quad (30)$$

4. Calculate background certainty of an image using equation 31 [16].

$$coh = \sqrt{\frac{(V_x^2(i,j) + V_y^2(i,j))}{w^2 * V_z}} \quad (31)$$

5. If coh > 10 (empirically calculated) in above equation 31 then calculate the orientation field using equation 32 [16]

$$\theta(i,j) = \frac{\pi}{2} + \frac{1}{2}\tan^{-1}\left(\frac{2V_x(i,j)}{V_y(i,j)}\right) \quad (32)$$

Otherwise calculating the orientation field is unnecessary.

4.3. Optimal Core Point Detection

In the our proposed technique, we have also used Poincare index, but in a little bit different way, and by applying some changes to it.

Steps for our core point detection technique are summarized as follows:

1. Compute the local orientation $\theta(i,j)$ by using equation 32 . The input block size is kxk = 3x3.

2. Locate the region of interest (ROI) based on background certainty

3. Initialize a label image A which is used to indicate the core point.

4. Apply steps 3 and 4 on ROI from Poincare Index technique

Table 1. Segmentation Results

Approaches	Accurately Segmented (Numbers)	Accurately Segmented (%)	Poorly Segmented (Numbers)	Poorly Segmented (%)
Mean and Variance Based Segmentation	213	66.5	107	33.5
Modified Gradient Based Segmentation	303	94.6	17	5.4

5. Find each connected component in A with pixel values 1. There is normally more than one object. Core Point object will always have the largest area. So we first figure out the object having the largest area.

6. Then we calculate the centroid of the selected object. This centroid gives us the location of core point.

5. Experimental Results

Our modification is tested on FVC2004 [17] database. The database contains 40 different fingers and 8 impressions of each finger (40x8=320 fingerprints). The images in DB1, DB2, DB3 and DB4 are 640×480, 328×364, 300×480 and 288×384 respectively and each having a resolution of 500 dpi. Segmentation results of our modified gradient based method compared with Mean and Variance based method are shown in table 1. For all fingerprint images core points are detected ideally. Euclidian distances between ideally detected core points and core points detected from discussed techniques are calculated. The core point detection results are compared and they are summarized in table 2 and table 3. The decision for accepted location (Accepted Core Point, ACP) and false location (False Core Point, FCP) is based on euclidian distances. For all methods maximum, minimum,mean and standard deviation of error is calculated. Table 4 shows error performance of different techniques and are defined in terms of number of pixels. For above mentioned techniques ,a comparative analysis of the computation time, with AMD, 801 MHz, and 1 GB RAM, is summarized in table 5. Figure 4 shows that our technique detects core point correctly even in case of very oily and dry fingerprint images. Figure 5 shows the comparison of the proposed technique with the ones discussed in [5,7,13]. Red dot shows the ideal core point location while the blue dot shows the detected core point.

6. Conclusion

Extracting best region of interest (ROI) and using fine orientation filed estimation, core point s are detected with great accuracy. Our core point detection technique is useful as it detects the optimal core point with low computation .

Table 2. Evaluation Core Point Detection for FVC2004

Approaches	ACP (Numbers)	ACP (%)	FCP (Numbers)	FCP (%)
Poincare Index	191	59.68	129	40.32
Detection of Curvature	263	82.18	57	17.82
Optimal Core Point	293	91.56	27	8.44

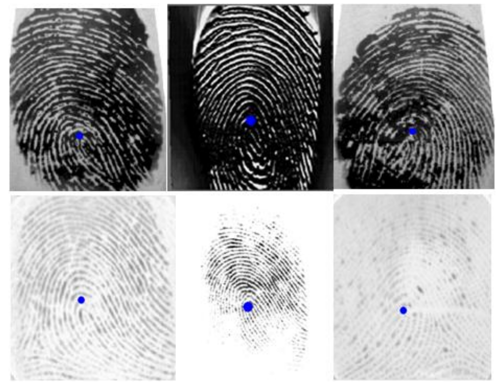

Figure 4. 1st row: Oily fingerprint images, 2nd row: Dry fingerprint images.

Table 3. Performance Evaluation of Core Point Detection for Different Quality Images

Fingerprint Image Quality	Poincare Index (%)	Detection of Curvature (%)	Optimal Core Point (%)
Good Quality	90.3	94.8	98.7
Low Quality	50.1	63.4	82.3
Rotated Images	57.8	71.2	87.1

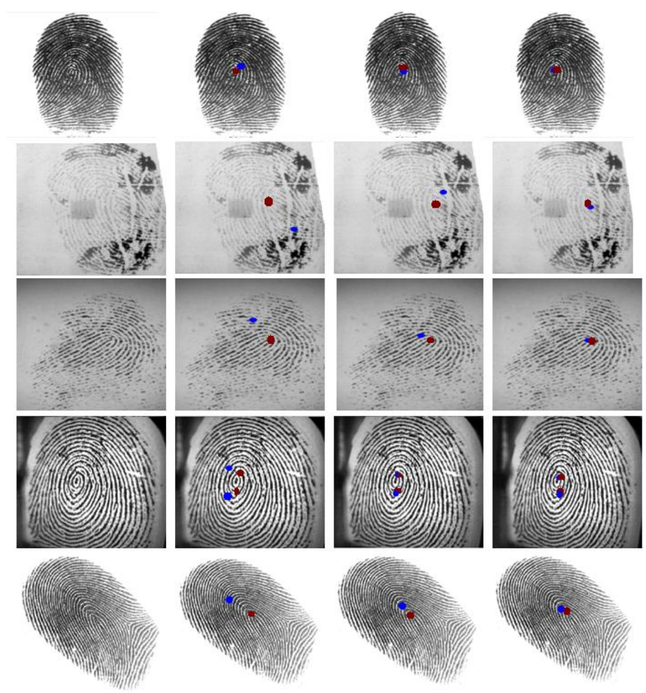

Figure 5. Pictorial comparison of proposed algorithm with traditional techniques. Ist column shows the original fingerprint images. 2nd and 3rd columns show the results of Poincare index and Detection of curvature techniques respectively. 4th column show the results of proposed algorithm.

Table 4. Error Performance Evaluation

Techniques	Maximum Error	Minimum Error	Mean Error	Standard Deviation
Poincare Index	240.98	0	25.51	37.75
Detection of Curvature	240.98	0	22.73	36.01
Optimal Core Point	240.98	0	14.75	34.39

Table 5. Evaluation of Computational Time

Techniques	Processing Time Seconds
Poincare Index	0.45
Detection of Curvature	0.25
Optimal Core Point	0.18

Our segmentation technique detects ROI by computing the mean and standard deviation of gradient of the image. The segmentation results show that our proposed algorithm performs better than the Mean and Variance based segmentation technique. Optimal core point is detected using the fine orientation field estimation which is proposed in this paper. The performance of the proposed technique is better than the Poincare index and Detection of Curvature technique. Moreover the proposed technique gives better results even in case of oily and dry images.

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