CORE POINT DETECTION USING FINE ORIENTATION FIELD ESTIMATION

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Abstract: Performance of Automatic Fingerprint Identification System(AFIS) is greatly influenced by the detection of core point. Extraction of best Region Of Interest(ROI) from image can play a vital role for core point detection. In this paper, we present an improved technique for fine orientation field estimation and core point detection. 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 in use for biometric recognition since long because of their high acceptability, immutability and individuality.

The probability that two fingerprints are alike is 1 in 1.9 x 10^{15}(W. F. Leung and Luk, 1991). These features make the use of fingerprints extremely effective in areas where the provision of a high degree of security is an issue.

Most Automatic Fingerprint Identification systems (AFIS) are based on local ridge features; ridge ending and ridge bifurcation, known as *minutiae*(A.K Jain and Boole, 1997). Core points and delta points are critical points in fingerprint. Core points are the points where the innermost ridge loops are at their steepest and delta points are points from which three patterns deviate (Anil Jain, 1998),(Zhang, 2000). Figure 1 shows the location of core point and delta point in a fingerprint image.

In AFIS, core point plays an important role (D. Maltoni and Prabhakar, 2003) and it is widely used for fingerprint matching (Anil Jain, 1998),(D. Maltoni and Prabhakar, 2003),(Maio and Maltoni, 1997) and classification (Wang and Wang., 2004),(A. K. Jain and Hong, 1999),(Sen Wang, 2002). The problem with applications related with fingerprint is how to fix the fingerprint with the help of a reference point so that it would be invariant to error generated by scanning process(Maio and Maltoni, 1997). This problem can be overcome by detecting core point accurately. Minutiae based fingerprint matching is widely used in AFIS (Maio and Maltoni, 1997),(Kalle Karu, 1996) where minutiae in neighbor of core point also plays an important role in frequency characteristic fingerprint matching (Maio and Maltoni, 1997).

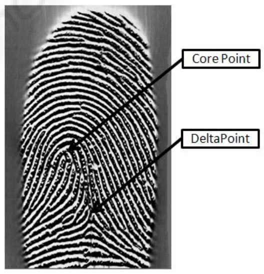

Figure 1: Core point and Delta point for a Fingerprint Image.

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

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0,$\pm$180 or $\pm$360 degrees(Kalle Karu, 1996). A.K. Jain, S. Prabhakar, L. Hong and S. Pankanti had used geometry of region technique in (Ani1 K. Jain and Pankanti, 2000) for reference point detection. Chul-Hyun Park, Joon-Jae Lee, Mark J.T. Smith and Kil-Houm Park 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 preprocessing of fingerprint image before locating the core point. Section 3 presents Poincare index, Geometry of Region Technique and Direction of Curvature technique while section 4 contains the proposed technique and its algorithm. Comparative analysis of experimental results of our technique with other techniques are presented and discussed in section 5 followed by conclusion in section 6.

2 FRONT-END PROCESSING

Core point detection process is greatly effected by quality of fingerprint image. Good image segmentation and orientation field estimation is required for optimal core point detection (Maio and Maltoni, 1997). Figure 2 shows the sequence of steps required for optimal core point detection.

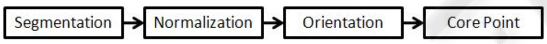

Figure 2: Sequential front-end processing for core point detection.

2.1 Image Segmentation

Segmentation is done to extract fingerprint image from background. In AFIS, the surrounding background in fingerprint image does not carry any information and therefore add to the processing time of all stages if included. The cutting and cropping out region containing fingerprint feature, commonly called Region of Interest(ROI), from the fingerprint image minimizes the computational time.

Steps for Mean and Variance Based fingerprint image segmentation technique (Maio and Maltoni, 1997) are summarized as follows:

1. Divide the input image I(i,j) into non-overlapping blocks with size w$\times$w.
2. Compute the mean value $M(I)$ for each block using equation 1.

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

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

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

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 Image Normalization

Normalization is performed to remove the effect of sensor noise and gray level background which are the consequence of difference in finger pressure applied at the scanner (Kawagoe and A.Tojo, 1984). Let $I(i,j)$ denotes the gray-level value at pixel (i,j). The normalized value $N(i,j)$ for pixel $(i,j)$is defined in equation 3 (Maio and Maltoni, 1997)

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

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 (Maio and Maltoni, 1997).

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

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

Where $I(i,j)$ represents the intensity of the pixel at ith row and jth column. The basic objective of normalization operation is to reduce the variations of gray-level values along the ridges and valleys (A.K Jain and Boole, 1997).

2.3 Orientation Field Estimation

Orientation or direction field estimation is not only used in core point detection but also in fingerprint matching (A.K Jain and Boole, 1997). The smoothed orientation field based on least mean square algorithm (A.K Jain and Boole, 1997)(Maio and Maltoni, 1997) 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.
3. Estimate the local orientation using the equations 6, 7 and 8 (Maio and Maltoni, 1997).

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

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

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

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 (Maio and Maltoni, 1997).

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

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

5. The two dimensional $w_\Phi w_\Phi$ 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 (Maio and Maltoni, 1997).

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

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

6. The smoothed orientation field at (i,j) is computed by equation 13 (Maio and Maltoni, 1997).

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

Figure 3 shows segmentation, normalization, orientation estimation and core point detection for a fingerprint image.

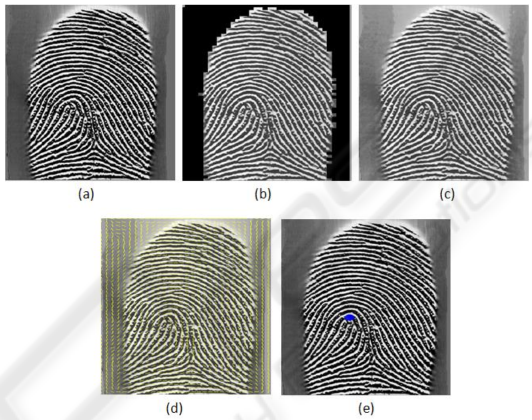

Figure 3: (a) Original image (b) Segmented image (c) Normalized image (d) Orientation estimation (e) Detected Core point.

3 CORE POINT DETECTION TECHNIQUES

The core point is used in both fingerprint classification and fingerprint matching using either spatial domain (A.K Jain and Boole, 1997)(Ani1 K. Jain and Pankanti, 2000) or transformed domain (Ani1 K. Jain and Pankanti, 2000). 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 (Maio and Maltoni, 1997).

The GR technique can be summarized as follows.

1. Compute the smoothed orientation field $\theta'(i,j)$by using equation 13 above.
2. Compute $\varepsilon(i,j)$ from equation 14 (Maio and Maltoni, 1997), which is the sine component of $\theta'(i,j)$

$$\varepsilon(i,j) = sin(\theta'(i,j)) \quad (14)$$

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 (Maio and Maltoni, 1997).

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

   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 (Kawagoe and A.Tojo, 1984). The PC technique can be summarized as follows (Maio and Maltoni, 1997),(Sen Wang, 2002).

1. Estimate the orientation field $\theta'(i,j)$ by using the least square orientation estimation algorithm given by equation 13 (Maio and Maltoni, 1997) 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 (Kawagoe and A.Tojo, 1984) where

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

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

   and

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

4. The core point should yield the Poincare index between 0.45-0.51 (Kawagoe and A.Tojo, 1984).
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 (Maio and Maltoni, 1997). The input block size is kxk = 3x3.
2. Smooth the orientation field $\theta'(i,j)$ by using equation 13 (Maio and Maltoni, 1997).
3. The difference of direction components is computed for every progressive block from equations 19 and 20.

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

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

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, segmentation and Normalization are done in the same way as described in section 2 while orientation field is estimated by new method as it greatly effects the core point detection.

4.1 Fine Orientation Field Estimation

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 21 and 22 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.

$$sobelHorizontal = \begin{pmatrix} -1 & 0 & 1 \\ 2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix} \qquad (21)$$

$$sobelVertical = \begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix} \qquad (22)$$

3. Estimate the local orientation using equations 23, 24 and 25 (Lim and S.Jae, 1990).

$$V_x(i,j) = \sum_{u=i-w/2}^{i+w/2} \sum_{v=j-w/2}^{j+w/2} (\partial_x(u,v))(\partial_y(u,v)) \tag{23}$$

$$V_y(i,j) = \sum_{u=i-w/2}^{i+w/2} \sum_{v=j-w/2}^{j+w/2} \partial_x^2(u,v) - \partial_y^2(u,v) \tag{24}$$

$$V_z(i,j) = \sum_{u=i-w/2}^{i+w/2} \sum_{v=j-w/2}^{j+w/2} (\partial_x(u,v) + \partial_y(u,v))^2 \tag{25}$$

4. Calculate background certainty and orientation field using equation 26 and 27 respectively (Zhongchao Shi and Xu, 2004).

$$coh = \sqrt{\frac{(V_x^2(i,j) + V_y^2(i,j))}{w^2 * V_z}} \tag{26}$$

if$coh > 10$then

$$\theta(i,j) = \frac{\pi}{2} + \frac{1}{2}\tan^{-1}\left(\frac{2V_x(i,j)}{V_y(i,j)}\right) \tag{27}$$

4.2 Optimal Core Point Detection

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

1. Compute the local orientation $\theta(i,j)$ by using equation (27) . 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
5. Find each connected component in A with pixel values 1. There is normally more than one objects. 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

The performance of our modification is tested on FVC2004 database(FVC, 2004).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. 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 1 and table 2.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 3 shows error performance 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 4.

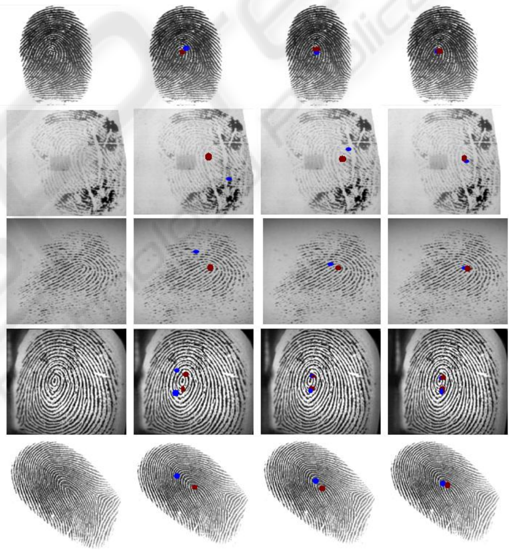

Figure 4: Pictorial comparison of proposed algorithm with traditional techniques. Ist column shows the original fingerprint images. 2nd and 3rd columns show the results of Poincare index and Detection of curvature techniques respectively. 4th column show the results of proposed algorithm.

Figure 4 shows the comparison of the proposed technique with the ones discussed in (Maio and Maltoni, 1997),(Maio and Maltoni, 1997),(Kawagoe and A.Tojo, 1984). Red dot shows the ideal core point location while the blue dot shows the detected core point. Figure 5 shows that proposed technique detects core point correctly even in case of very oily and dry fingerprint images.

Table 1: 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

Table 2: 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

Table 3: Error Performance Evaluation.

Techniques	Max Error	Min Error	Mean Error	Std 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 4: Evaluation of Computational Time.

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

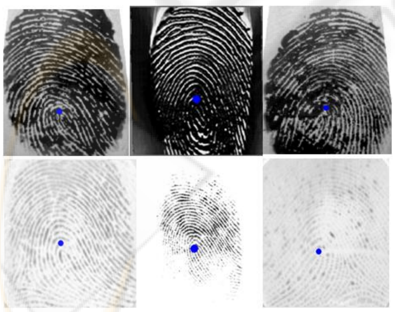

Figure 5: 1st row: Oily fingerprint images, 2nd row: Dry fingerprint images.

6 CONCLUSIONS

Our core point detection technique is useful as it detects the optimal core point with low computation and it requires simple field orientation. Optimal core point is detected using the fine orientation field estimation. 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.

REFERENCES

A. K. Jain, S. P. and Hong, L. (1999). A multichannel approach to fingerprint classification. In *IEEE Transactions on PAMI, Vol.21, No.4, pp. 348-359*.

A.K Jain, H. L. and Boole, R. (1997). One-line fingerprint verification. In *IEEE Trans. PAMI, Vol.19,No.4, pp.302-314*.

Ani1 K. Jain, Salil Prabhakar, L. H. and Pankanti, S. (2000). Filterbank-based fingerprint matching. In *IEEE Transactions on Image Processing, Vol. 9, No 5, pp. 846-859*.

Anil Jain, Ruud Bolle, S. P. (1998). Biometrics-personal identification in networked society. In *KluwerAcademic Publishers, pp 411*.

D. Maltoni, D. Maio, A. K. J. and Prabhakar, S. (2003). Handbook of fingerprint recognition. In *Springer-Verlag*.

FVC (2004). Finger print verification contest 2004. In *Available at (http://bias.csr.unibo.it/fvc2004.html)*.

Kalle Karu, A. J. (1996). Fingerprint classification. In *Pattern Recognition, vol. 18, No.3, pp.389-404*.

Kawagoe, M. and A.Tojo (1984). Fingerprint pattern classification. In *Pattern Recognition, Vol.17, pp.295-303*.

Lim and S.Jae (1990). *Two-Dimensional Signal Image Processing*.

Maio, D. and Maltoni, D. (Jan 1997). Direct gray-scale minutiae detection in fingerprints. In *IEEE Trans. on Pattern Analysis and Machine Inteligence, vol. 19, pp. 27-40*.

Sen Wang, Wei Wei Zhang, Y. S. W. (2002). Fingerprint classification by directional fields. In *Proceedings of the Fourth IEEE International Conference on Multimodal Interfaces (ICMI'02)*.

W. F. Leung, S. H. Leung, W. H. L. and Luk, A. (1991). Fingerprint recognition using neural network. In *Neural Networks For Signal Processing - Proceedings Of The 1991 IEEE Workshop*.

Wang, S. and Wang., Y. (2004). Fingerprint enhancement in the singular point area. In *IEEE signal processing letters, vol. 11, no. 1, pp. 16-19*.

Zhang, D. D. (2000). Automated biometrics technologies and systems. In *Kluwer Academic Publishers, pp.331*.

Zhongchao Shi, Yangsheng Wang, J. Q. and Xu, K. (2004). A new segmentation algorithm for low quality fingerprint image. In *IEEE Proceedings of the Third International Conference on Image and Graphics*.