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Fingerprint Image Classification using Singular Points and Orientation Information

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ABSTRACT

The fingerprint classification process is an essential task that reduces fingerprint matching time of an Automatic fingerprint identification system, where a large database is used. It is still a challenging task. The proposed work classifies the fingerprints by using singular points and orientation information below the core point. As the first step of proposed work, features like orientation field and singular points are extracted. Orientation field is estimated using multi-scale principal component analysis and singular points are detected using shape analysis of binary candidate region image. To speed up the classification process, rules based on location of singular points and orientation information below upper core point are used for classification. The proposed work is tested on most popular public NIST special database 4 and experimental results show that classification accuracy is 92.2 % for five-class problem and 97.35% for four-class problem without rejection. Also, the proposed work classifies more accurately the ambiguous fingerprint images into its primary as well as secondary class.

Keywords: Fingerprint classification, Orientation field, Principal component analysis, Multi-scale pyramid decomposition, Homogeneous zone division, Binary candidate region image, Singular point, Upper core point, Lower core point, Delta point.

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I. INTRODUCTION

Fingerprints are used in civilian, commercial and forensic applications for person identification because of its uniqueness, reliability and ease of use. Most of the commercial systems are embedded with fingerprints and for these applications voluminous fingerprints are collected and stored in large databases. In Automatic fingerprint identification system (AFIS) the input fingerprint is compared with all fingerprints stored in the database for a match, which is a time consuming process for large database. Hence, to reduce the number of comparisons, an AFIS needs classification process where fingerprint images in a large database are grouped into subsets of predefined classes according to the various features of fingerprints. After classification process in AFIS, the type of fingerprint is identified and then input fingerprint is compared with a subset of the database corresponding to that fingerprint type for exact matching.

According to Galton-Henry classification, fingerprints are classified into five types such as left loop, right loop, whorl, arch and tented arch [1] as shown in Fig. 1. Loop has one core point and one delta point. Arches do not have any core point or delta point. A tented arch fingerprint is with one core point and one delta point both aligned vertically. A whorl contains two core points and two delta points [2]. Orientation field and singular points are the most important features in classifying fingerprints.

a b c d e

Fig. 1. Fingerprint images (a) left loop (b) right loop (c) whorl (d) arch (e) tented arch

Jain et al. [3] have used a novel feature vector called FingerCode which is the collection of all the features defined for each sector in each filtered image and have classified based on a two-stage classifier which uses a K-nearest neighbor classifier in the first stage and a set of neural networks in the second stage with 32.5 % rejection ratio. Yao et al. [4] have presented a new fingerprint classification algorithm based on two machine learning approaches called support vector machines (SVM) and recursive neural networks (RNN) with 20 % rejection rate. They have used SVM for extracting fingerprint features and RNN for classification. Zhang et al. [5] have proposed the fingerprint classification based on both singularities and traced pseudoridge analysis. Park et al. [6] have proposed a fingerprint classification based on discrete Fourier transform (DFT) and nonlinear discriminant analysis (NDA) where DFT and directional filters are used to extract directional image and NDA is used to extract discriminant features and to reduce the dimensions of the extracted features. Wang et al. [7] have proposed a fingerprint classification method using the location of singular points where singular points are detected based on the distribution of Gaussian–Hermite moments. Li et al. [8] have proposed an algorithm based on the interactive validation of singular points and the constrained nonlinear orientation model for fingerprint classification. Hong et al. [9] have proposed a fingerprint classification algorithm with an improved feature type of recurring ridges. Liu et al. [10] have presented a fingerprint classification algorithm that uses adaboost learning method to model multiple types of singularity features and to design a classifier for classification. Cao et al. [11] have presented a regularized orientation diffusion model for fingerprint orientation extraction and a hierarchical classifier for fingerprint classification with no rejection. Jung et al. [12] have proposed a Noisy and incomplete fingerprint classification algorithm which is carried out by using the regional local models. Hong et al. [13] have proposed a novel method in which the SVMs are generated with the one-vs-all scheme and dynamically ordered with naïve Bayes classifiers. A rule-based fingerprint classification method is proposed by Guo et al. [14] wherein the two features, namely the types of singular points and the number of each type of point are adopted to distinguish different fingerprints.

Even though more and more fingerprint classification methods have been proposed, some improvement is needed in terms of speed and accuracy. Some of the existing algorithms [3 – 5] were tested on NIST databases with certain percentage of rejection rate.

In the proposed method, orientation field for the segmented fingerprint image is estimated based on PCA and multi-scale pyramid decomposition. Estimated oriented image is divided into homogeneous zones. From homogeneously divided orientation image, binary candidate region image for upper and lower core points ($BCRI_U$ and $BCRI_L$) are constructed. Then upper and lower core points are identified by shape analysis of $BCRI_U$ and $BCRI_L$ respectively. Next, classification process is carried out based on location of core point, delta point and orientation information below the upper core point. This paper is organized as follows: stages of fingerprint image classification are elaborated in section 2 and experimental results are discussed in section 3.

II. FINGERPRINT IMAGE CLASSIFICATION

2.1 Preprocessing

As the first step of preprocessing, image resizing is done to maintain uniformity. Next segmentation is done to separate the area of interest, ridge and valley area from un-recoverable non-ridge and non-valley area. The method of Chikkerur et al. [26] is adopted for isolating ridge and valley area from the background by generating mask on resized fingerprint image using morphological operation – 'erode', contrast enhancement, Otsu's thresholding [15] followed by morphological operation – 'open'. Fingerprint images before segmentation and after segmentation are shown in Fig. 2.

Fig. 2. Fingerprint image before (a) and after (b) segmentation

2.2 Feature Extraction

Fingerprint type is determined by the features such as number of singular points i.e. core and delta points and their location relativity. In a fingerprint image, the singular points are localized with the help of orientation image. Hence, at first, fingerprint orientation image have to be estimated. From the estimated orientation image singular points are detected. In this work fingerprint orientation image is estimated using multi-scale PCA [17] and is divided homogeneously. Next BCRIs are constructed from homogeneously divided orientation image and positions of core points are located by analyzing BCRI for the cup and cap like shapes.

2.2.1 Orientation Field Estimation

This work adopts multi-scale PCA proposed by Feng and Milanfar [17] which yields accurate local dominant orientation even for the noisy fingerprint images. Fig.3 shows various fingerprint images and their corresponding orientation images estimated using the following procedure [17]:

Step 1: Construct gradient pyramid with n layers by smoothening the fingerprint image using mean filter followed by down-sampling.

Step 2: For the fingerprint image of n^{th} layer do the following:

i. Form local blocks with 1 pixel overlapping on the gradient image of the layer.
ii. Estimate dominant orientation of each block as follows:
a. Group the gradient of each block into a matrix G of size N×2 where N is a number of pixels in a block.
b. Compute SVD for the matrix G, G = USV^T.

where U is a orthogonal matrix of order N×N, representing each vector's contribution to the corresponding singular vector; S is N × 2, representing the energy in the dominant directions; and V is orthogonal of order 2 × 2, in which the first column v_1 represents the dominant orientation of the gradient field.

c. Obtain the local dominant orientation of the image block $O_n(i,j)$ by rotating v_1 by 90˚.
d. Find energy rate of the image block as $ER_n(i,j)= \frac{s_1-s_2}{s_1+s_2}$ where s_1 and s_2 are singular values of S.

Step 3: Do the following task from $(n–1)^{th}$ layer to 1^{st} layer.

i. Form local blocks with 1 pixel overlapping on the gradient image of the layer.
ii. Estimate dominant orientation of each block as follows:
a. Group the gradient of each block into a matrix G of size N×2 where N is a number of pixels in a block.
b. Compute SVD for the matrix G, G = USV^T.

where U is a orthogonal matrix of order N×N, representing each vector's contribution to the corresponding singular vector; S is N×2, representing the energy in the dominant directions; and V is orthogonal of order 2×2, in which the first column v_1 represents the dominant orientation of the gradient field.

c. Obtain the local dominant orientation of the image block of parent layer $O_p(i,j)$ by rotating v_1 by 90˚.
d. Find energy rate of the image block of parent layer as $ER_p(i,j)= \frac{s_1-s_2}{s_1+s_2}$ where s_1 and s_2 are singular values of S.
e. Up-sample the child layer's orientation image O_c and energy rate ER_c by 2.
f. If $ER_p(i,j) > ER_c(i,j))$ then update energy rate ER_p and orientation image O_p as:

$$O_p(i,j) = \frac{(O_p(i,j) \times ER_p(i,j)) + (O_c(i,j) \times ER_c(i,j))}{ER_p(i,j) + ER_c(i,j)}$$

$$ER_p(i,j) = \frac{ER_p^2(i,j) + ER_c^2(i,j)}{ER_p(i,j) - ER_c(i,j)}$$

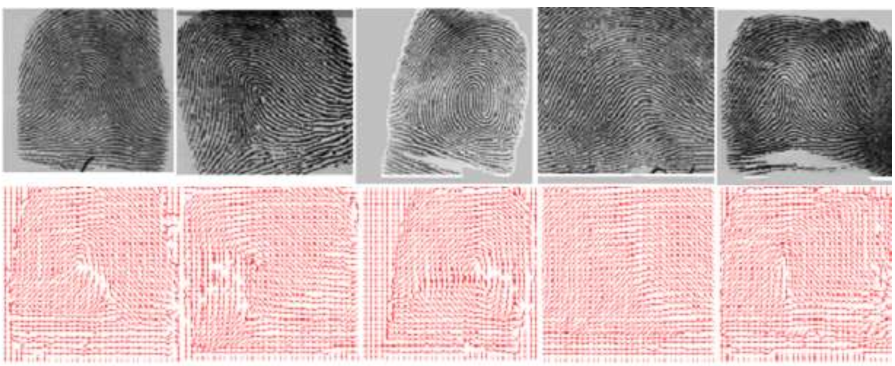

Fig.3. Various fingerprint images(top) and corresponding orientation images (bottom)

2.2.1.1 Homogeneous Zones Division (HZD)

Blocks having similar orientation in an orientation image form a homogeneous zone [18]. HZD is a process of dividing orientation image into homogeneous zones and follows as:

H^k be the label of the orientation of k^{th} homogeneous zone.

$$H^k = \frac{(k-1)\pi}{n} \ if \left(\frac{(k-1)}{n}\pi - \omega_0 \le O(i,j) < \frac{(k-1)}{n}\pi + \omega_0\right). \quad (1)$$

where $\omega_0 = \frac{\pi}{2n}$ and $O(i,j)$ is the orientation of block(i,j).

Assign a label for each homogeneous zone as follows.

Homogeneous zone
$$H^1 = 0 \quad if\ (-\omega_0 \leq O(i,j) < \ \omega_0) \quad . \quad (2)$$

Homogeneous zone
$$H^2 = \frac{\pi}{n} \quad if\ \left(\frac{\pi}{n} - \omega_0 \leq O(i,j) < \ \frac{\pi}{n} + \omega_0\right) \quad . \quad (3)$$

Homogeneous zone
$$H^3 = \frac{2\pi}{n} \quad if\ \left(\frac{2\pi}{n} - \omega_0 \leq O(i,j) < \ \frac{2\pi}{n} + \omega_0\right) \quad . \quad (4)$$

⋮

Homogeneous zone
$$H^n = \frac{(n-1)\pi}{n}\ if\ \left(\frac{(n-1)}{n}\pi - \omega_0 \leq O(i,j) < \ \frac{(n-1)}{n}\pi + \omega_0\right) \quad . \quad (5)$$

In a fingerprint image core point is always at the point where different homogeneous areas in the quantized orientation image are met. Hence orientation image is divided into homogeneous zones by the above mentioned procedure to detect core point location. The homogeneously divided orientation images for the samples of five different fingerprint types are shown in Fig. 4.

Fig. 4. Homogeneously divided orientation images of different fingerprint types

2.2.2 Core Point Localization

Poincare index (PI) method is used by method [19] for core point detection in which PI for each block of orientation image is calculated using digital curve around the block, considering the surrounding orientations as vectors. Some other approaches are used complex filters [20], directional mask [21] to detect core point. Most of the core point detection algorithms can efficiently detect the core point when the image quality is fine. When the image quality is poor, the core point detection rate is decreased [22].

On the observation it is identified that the region of the ridges that contains core point called candidate region, has the shape similar to symbol cap (∩) in the upper core point and/or cup (∪) in the lower core point and the orientation values of 8 neighboring blocks of the core point are in non decreasing values from 0 to π which occur in clockwise direction.

The proposed method constructs two different BCRIs: $BCRI_U$ and $BCRI_L$ which is a binary image to detect singular points. The binary value 1 in a BCRI represents that the corresponding region is a candidate region for core point. $BCRI_U$ for cap shaped candidate region is constructed by finding difference between the orientation of every block, θ_L and its right block, θ_R and assign a binary value based on the equation(6)[23].

$$BCRI_U\ (\theta_L) = \begin{cases} 1 & \text{if } -\frac{3\pi}{4} \leq (\theta_L - \theta_R) \leq -\frac{\pi}{4} \text{ and } \theta_L \neq 0° \text{ and } \theta_R \neq 0° \\ & \text{or} \\ & -\frac{3\pi}{4} \leq (\theta_L - \theta_R) \leq -\frac{\pi}{2} \text{ and } \theta_L = 0° \\ & \text{or} \\ & \frac{\pi}{4} \leq (\theta_L - \theta_R) \leq \frac{\pi}{2} \text{ and d } \theta_R = 0° \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

Similarly, $BCRI_L$ for cup shaped candidate region is constructed using the equation(7)[23].

$$BCRI_L\ ((\theta_L) = \begin{cases} 1 & \text{if } \frac{\pi}{4} \leq (\theta_L - \theta_R) \leq -\frac{3\pi}{4} \text{ and } \theta_L \neq 0° \text{ and } \theta_R \neq 0° \\ & \text{or} \\ & -\frac{\pi}{2} \leq (\theta_L - \theta_R) \leq -\frac{\pi}{4} \text{ and } \theta_L = 0° \\ & \text{or} \\ & \frac{\pi}{2} \leq (\theta_L - \theta_R) \leq \frac{3\pi}{4} \text{ and d } \theta_R = 0° \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

Candidate region is connected when adjacent vertical positions in $BCRI_U$ have the value 1. Upper core point is located by finding the orientation values of 8 neighboring blocks around the bottom most of each connected candidate region is checked with the following conditions.

Condition 1: Orientation values are in non decreasing order vary from 0 to π in clockwise direction.
Condition 2: At least 4 different homogeneous zones are there.

If the conditions satisfy then the corresponding candidate region is the location of the upper core point. If more than one candidate region satisfy the conditions then the location of the upper core point is calculated by averaging x coordinates and y coordinates.

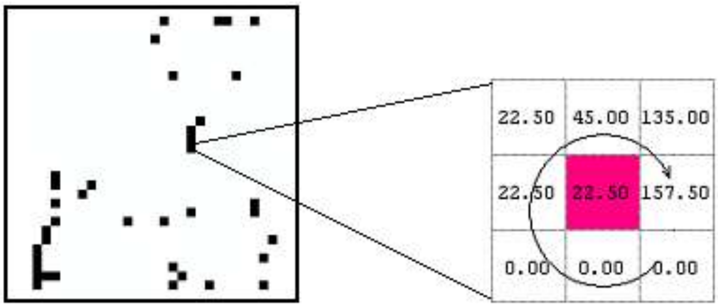

Fig. 5. BCRI$_U$ and neighboring pixels around upper core point

Similarly lower core point is identified by applying the above said procedure by considering the top most candidate region instead of bottom most of the connected candidate region. At the end of this procedure C core points (0, 1 or 2 – upper and lower) are identified for a fingerprint image. Fig. 5 and Fig. 6 show the BCRI$_U$ and BCRI$_L$ and their neighboring pixels around upper and lower core points respectively.

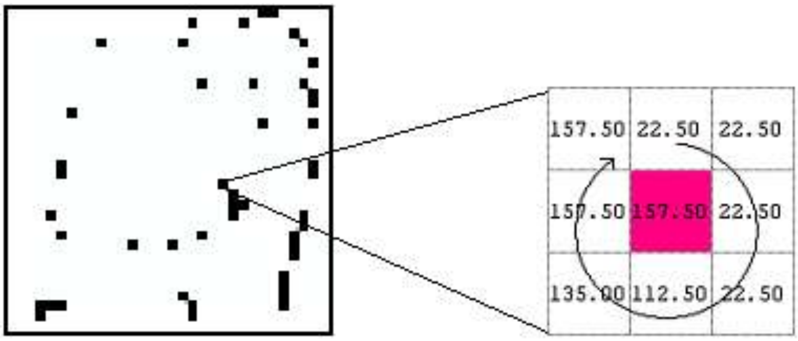

Fig. 6. BCRI$_L$ and neighboring pixels around lower core point

2.2.3 Delta Point Localization

Delta point is identified using BCRI$_U$ as the procedure followed in core point detection with the following changes:

1. Top most of each connected candidate region is considered.
2. Condition 1 is reversed i.e. orientation values are in non decreasing order vary from 0 to π in anti-clockwise direction.

Fig. 7 shows the delta point locations and their neighboring pixels for a whorl type fingerprint image.

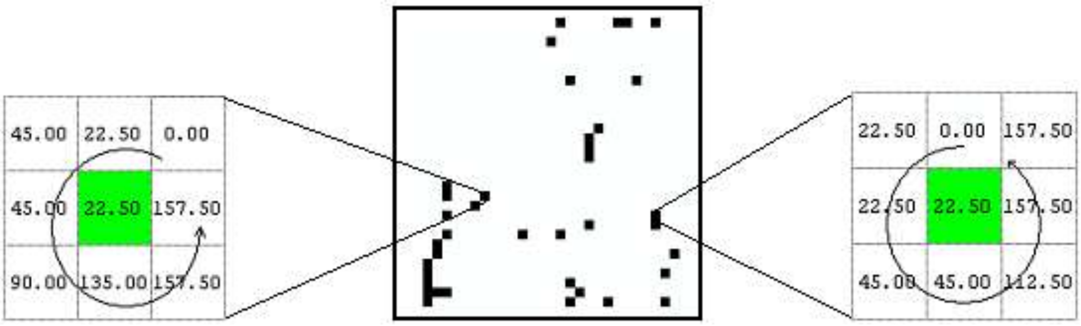

Fig. 7. BCRI$_U$ and neighboring pixels around delta points

In the proposed method delta point localization procedure is not used for all fingerprint images. It is used only when it detects only one core point.

2.3 Fingerprint Classification

Fingerprint classification is a process of assigning a fingerprint into one of the several predefined types such as left loop, right loop, whorl, arch and tented arch which can provide an indexing mechanism for an AFIS [3]. Features like orientation image, singular points and number of core points are extracted in the feature extraction phase. The proposed method classifies a fingerprint images based on number of core points (NC), the locations of upper core point and delta, and orientation values below the upper core point. The classification procedure is as follows:

Procedure

Step 1: Separate ridge & valley area from non-valley area, non-ridge, and
unrecoverable area of the fingerprint image.

Step 2: Estimate orientation field for segmented fingerprint.

Step 3: Divide orientation image into 8 homogeneous zones.

Step 4: Construct $BCRI_U$ using (6) and $BCRI_L$ using (7).

Step 5: Identify connected candidate region and do the following:

(a) Locate bottommost block of connected candidate region.

(b) Check whether orientation values of 8 neighbors are in non-decreasing order in clockwise direction.

(c) Check whether four unique homogeneous zones are in neighboring blocks.

(d) If (b) & (c) satisfies, the candidate region is upper core point location.

Step 6: If more than one upper core points are identified then average the coordinates of the located blocks to locate exact upper core point.

Step 7: Perform steps 5 and 6 to find lower core point, but in step 5(a) locate topmost block of connected candidate region instead of bottommost block.

where NC – number of core points; Steps 8 – 10 are the proposed rules for classification

Step 8: If NC = 0 then fingerprint type (FT) is arch.

Step 9: If NC = 2 then FT is whorl.

Step 10: If NC = 1 then

- Call delta localization procedure that returns number of delta points (ND) and delta location ($D_{x,y}$)
- If ND = 0 then fingerprint does not have delta. Count the blocks that having 45˚(RC) and 135˚ (LC) only by considering five rows of blocks below the core point location.
  - If RC>LC then FT is right loop
    else FT is left loop.
- If ND = 1 and C & D are aligned vertically (ie. $D_x = C_x$) then FT is tented arch.
- If ND = 1 and $D_x < C_x$
  - If $|D_x – C_x| <= 2$ and $|D_y – C_y| <= 3$ then primary class of FT is tented and secondary class is right loop else right loop.
- If ND = 1 and Dx > Cx
  - If $|D_x – C_x| <= 2$ and $|D_y – C_y| <= 3$ then primary class of FT is tented and secondary class is left loop else left loop.
- If ND=2 then the FT is whorl.

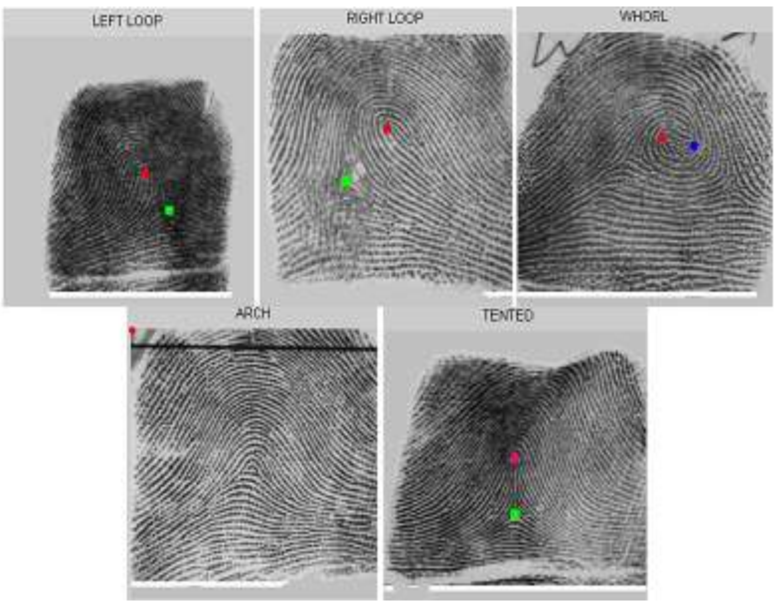

Fig. 8. Classification results by the proposed method

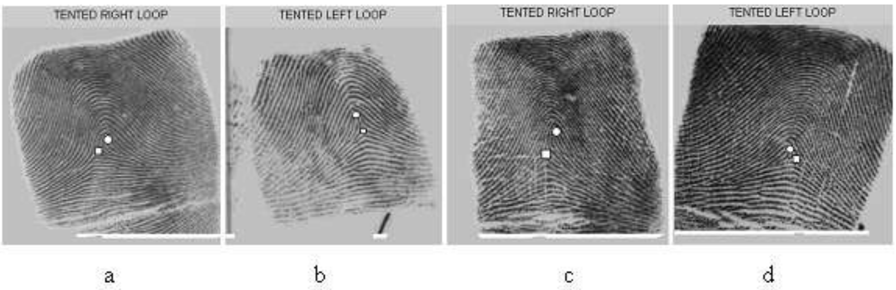

Fig. 9. Classification results of Cross-referenced fingerprints

III. RESULTS AND DISCUSSION

The performance of the proposed algorithm is tested with the help of the public fingerprint databases NIST special database 4 [25] and implemented in MATLAB 2013a. NIST special database 4 has 2000 8-bit gray scale fingerprint image pairs. Each of the fingerprint pairs are two completely different rolling of the same fingerprint of 512 ×512 pixels with 32 rows of white space at the bottom and of 19.7 pixels per millimeter resolution. The database is evenly distributed over each of the five classifications with 800 fingerprint images from each class. In the NIST special database 4, seven hundred fingerprint images out of 4000 fingerprint images are assigned two class labels (primary and secondary class labels) due to a variety of ambiguities such as a scar in the fingerprints, the print rolling quality, and the fingerprint having a ridge structure of two different classes [24]. The distribution of fingerprint images in NIST special database 4 according to the classification based on primary class label and within each row, fingerprints that are cross referenced to the secondary class label are shown in table 1 and the example of a cross referenced fingerprint image is shown in Fig. 10. Hence the classification result of proposed method is considered to be correct if it matches either the first class label or second class label. This consideration is adopted by the researchers [7].

Table 1. The Distribution of fingerprint images in NIST Special Database 4

Class	L	R	W	A	T	Total
L	756	0	2	0	42	800
R	0	746	4	0	50	800
W	2	6	792	0	0	800
A	0	2	0	760	38	800
T	166	238	0	150	246	800

Zhang et al. [5] have classified the fingerprints with 11.8% rejection rate by analysis of singularities and pseudo ridges and produced 94% accuracy for 4 – class problem and 85.6% accuracy for 5 – class problem. Without rejection, method of [5] have been produced 91.9% accuracy for 4 – class classification and 84.3% accuracy for 5 – class problem. They have used Poincare index to detect singular points and classification is done by analysis of pseudo ridge tracing. Their classification result is shown in Table 2. Wang et al. [7] have also used Poincare index to detect singular points and they have classified fingerprint images using Gaussian – Hermite Moments (GHM) and singular points. Method [7] yields improved classification accuracy for tented arch than Zhang et al. [5]. From Table 3 it is found that their classification accuracy is 88.6% for 5 – class and 92.5% for 4 – class without rejection. Chua et. al. [27] have used edge-trace-cum-core-delta-pairing and merging-and-pruning heuristic for finding optimal singular points. The classification of method of [27] is based on simple rule-based method and its result is shown in Table 4.

Table 2. 5-Class experimental results of Zhang Yan et al. [5] with 11.8% rejection rate

True Class	Assigned Class L	R	W	A	T	Accuracy (%)	Overall Accuracy (%)
L	746	3	16	39	3	92.4	
R	5	644	28	48	3	88.5	
W	12	13	624	3	1	95.6	85.6
A	3	2	1	889	1	99.2	
T	25	4	8	307	220	39	

In the proposed method, after completing the preprocessing, orientation field is estimated using multi-scale PCA which produces accurate orientation even for the noisy fingerprint images and then singular points are detected using shape analysis of orientation image. Without rejection our proposed method yields 92.2% of accuracy for 5 – class classification and 97.35% for 4 – class classification shown in Table 5 and Table 6 respectively. Classification accuracy for 4 – class of methods and the proposed method is shown in Table 7. The proposed method also classifies ambiguous fingerprints into their primary and secondary fingerprint type. In the proposed method, delta localization procedure is not needed for arch and whorl type fingerprints because arch and whorl fingerprint type can be determined only by number of core points. Hence time is saved while a large database is classified. Fig.8 shows the result of the proposed classification.

Table 3. 5-Class experimental results of Wang Dai et al. [7]

True Class	Assigned Class						Accuracy (%)	Overall Accuracy (%)
	L	R	W	A	T	Unknown		
L	739	5	25	33	0	2	91.9	88.6
R	14	721	24	39	3	4	89.6	
W	27	26	727	3	5	7	91.4	
A	4	4	3	848	17	0	96.8	
T	34	14	19	141	507	5	70.4	

Table 4. 4-Class experimental results of Chua et. al. [27]

True Class	Assigned Class				Accuracy (%)	Overall Accuracy (%)
	L	R	W	A		
L	731	5	29	63	88.29	92.15
R	12	716	20	78	86.68	
W	17	12	754	13	94.72	
A	34	25	6	1485	95.81	

Table 5. 5-Class experimental results of proposed method

True Class	Assigned Class					Accuracy (%)	Overall Accuracy (%)
	L	R	W	A	T		
L	773	21	1	3	2	96.63	92.2
R	68	729	0	3	0	91.13	
W	2	0	794	4	0	99.23	
A	2	0	0	798	0	99.75	
T	0	0	0	206	594	74.25	

Table 6. 4-Class experimental results of proposed method

True Class	Assigned Class				Accuracy (%)	Overall Accuracy (%)
	L	R	W	A		
L	773	21	1	5	96.63	97.35
R	68	729	0	3	91.13	
W	2	0	794	4	99.25	
A	2	0	0	1598	99.88	

Another key success of proposed method is that it can classify the ambiguous fingerprint images which are cross referenced in the NIST special database 4, are classified into their primary and secondary types. Fig. 9 shows the primary and secondary types of some of cross-referenced fingerprints by the proposed method.

Table 7. Classification Accuracy of various methods

Method	4 – Class (%)
Zhang et al. (2004) [5]	91.9
Park and Park (2005) [6]	94
Hsieh et. al. (2005) [28]	93.1
Wang et al. (2007)	92.5
Li et al. (2008) [8]	94.9

Liu et al. (2010) [10]	96
Cao et al. (2013) [14]	97.2
Chua et. al. (2015) [27]	92.15
Wang et. al. (2016) [29]	91.4
Michelsanti et. al. (2017) [30]	94.4
Michelsanti et. al. (2017) [30]	95.05
Proposed method	**97.35**

IV. CONCLUSION

Fingerprint image classification mainly depends on proper orientation image and accurate location of singular points. The proposed method estimates proper orientation image using multi-scale PCA and detects the exact singular point location by shape analysis of BCRI. Then the classification becomes easier using rules based on location of singular points and orientation information below upper core point and yields accuracy of 92.2 % for five-class problem and 97.35% for four-class problem without rejection. Also, the proposed work classifies more accurately the ambiguous fingerprint images into its primary as well as secondary class.

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