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A New Approach for Fingerprint Classification based on Minutiae Distribution

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***Abstract*—**The paper describes a new approach for fingerprint classification, based on the distribution of local features (minute details or minutiae) of the fingerprints. The main advantage is that fingerprint classification provides an indexing scheme to facilitate efficient matching in a large fingerprint database. A set of rules based on heuristic approach has been proposed. The area around the core point is treated as the area of interest for extracting the minutiae features as there are substantial variations around the core point as compared to the areas away from the core point. The core point in a fingerprint has been located at a point where there is maximum curvature. The experimental results report an overall average accuracy of 86.57 % in fingerprint classification.

***Keywords*—**Minutiae distribution, Minutiae, Classification, Orientation, Heuristic.

I. Introduction

In many civilian and forensic applications, person identification is required rather than verification. Identification may take higher response time. A fingerprint has to be compared with all the fingerprint templates stored in a database, which is unacceptable. The response time can be reduced by reducing the number of comparisons. This is possible only if the fingerprints in the database are classified. The classification of fingerprints has been done based on their geometric features like core and delta point. The first in-depth scientific study on fingerprint classification was made by Galton [1]. Henry [2] further added two more number of classes to the total number of classes proposed by Galton. Galton - Henry classification scheme consists of classes arch, tented arch, left loop, right loop, and whorl as shown in the figures (Fig. 1 to Fig. 5).Minutiae features represents a fingerprint as an individual, they have been used for verification / identification. In this paper a methodology for fingerprint classification based on minutiae distribution has been proposed. Certain rules based on the probability distribution on minutiae for different fingerprint types have been formed. The minutiae information extracted for verification has been used for the classification.

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Fig. 1 Left loop

Fig. 2 Right loop

Fig. 3 Arch

Fig. 4 Tented Arch

Fig. 5 Whorl

Several methods for automatic fingerprint classification based on rule-based, syntactic, structural, statistical, neural network and multiple classifier approaches are in use; some of them are presented here. The Poincare index [3] is used to find type and position of singular points and a course classification has been derived in .A finer classification is obtained by tracing the ridge line flow. In Karu and Jain an iterative regularization [4] is carried out until a valid number of singular points are detected; this improves the classification accuracy. A more robust technique [5] was introduces by Hong and Jain in. They introduced a rule - based classification algorithm that uses the number of singularities together with the number of recurring ridges found in the image; the combination of these two distinct features leads to better performance. Cho presented a classification method [6] that uses only the loop points and classifies fingerprints according to the curvature and orientation of the fingerprint area near the loop. Jain and Minut proposed rule-base approaches [7], the classification is based on the geometrical shape of the ridges, for each class a fingerprint kernel is defined; the classification is then performed by finding the kernel that best fits the orientation field of a given fingerprint. Maio and Maltoni presented a structural approach [8] for classification. The orientation image is partitioned into regions by minimizing a cost function that takes into account the variance of the element orientations within each region. An inexact graph matching technique is then used to compare the relational graphs with class- prototype graphs. Chappelli proposed a template based matching [9] to guide the partitioning of the orientation image, the main advantage of the approach is that because it relies only on global structural information, it is able to deal with partial fingerprints, where sometimes, singular points are not available; it can also work on very noisy images. Senior suggested the hidden Markov model classifier for fingerprint classification [10].

II. Problem Definition

If two fingerprint images are the impressions of the same finger, then they must belong to the same category. Therefore, a query fingerprint needs to be compared only with the database fingerprints of the same category in the fingerprint matching process. Without an effective fingerprint classification scheme or some other indexing scheme, fingerprint identification involves an exhaustive matching of query fingerprint to all the fingerprint s in the database, which is computationally demanding [11].Due to large variations in the ridge pattern configuration, the definition of the global pattern features used to specify the classification criteria used by fingerprint experts is very complex and large. Fingerprint classification is intended for quickly providing an indexing mechanism and to give an indication of general pattern agreement. A central problem in designing such a classification scheme is to decide what features should be used to classify fingerprints and how categories are defined based on these features [12].

III. Proposed Methodology

A fingerprint image should be viewed as a flow pattern with a definite texture. The local features (minutiae) are extracted from the fingerprint image. The feature extraction stage applies a set of masks to the fingerprint image [13].The core point of the fingerprint image is located using the method described in [13].Minutiae distribution around the core point is examined to categorize the fingerprint image. The sequence is as shown in Fig. 6.

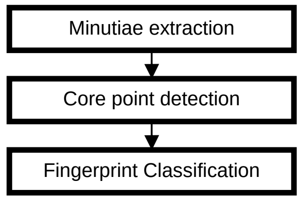


Fig. 6 The main steps in the proposed methodology

A. Minutiae Extraction

An orientation field for the flow texture is computed [13]. The input image is divided into equal sized blocks. Each block is processed independently. The gray level projection along a line perpendicular to the local orientation field provides the maximum variance. Locate the ridges using the peaks and the variance in this projection [14]. The ridges are thinned and the resulting skeleton image is enhanced using an adaptive morphological filter. The feature extraction stage applies a set of masks to the thinned and enhanced ridge image. The post processing stage deletes noisy feature points. The ‘salt and pepper’ noise present in a fingerprint image can be removed using median filter. The foreground regions correspond to the clear fingerprint area containing the ridges and valleys, which is the area of interest. The background corresponds to the regions outside the borders of the fingerprint area, which do not contain any valid fingerprint information. When minutiae extraction algorithms are applied to the background regions of an image, it results in the extraction of noisy and false minutiae. Thus, segmentation is employed to discard these background regions, which facilitates the reliable extraction of minutiae as described in [15].

The orientation image represents an intrinsic property of the fingerprint images and defines invariant coordinates for ridges and furrows in a local neighborhood as shown in Fig.7. By viewing a fingerprint image as an oriented texture, a number of methods have been proposed to estimate the orientation field of fingerprint images [16]. Given normalized image, N, the main steps for calculating dominant directions are as follows:

a. Divide N into blocks of size $w \times w$ (8×8).

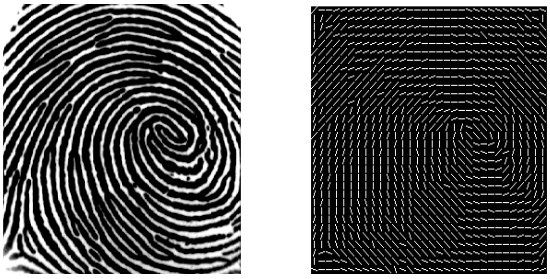
b. Compute the gradients $\partial_x(i, j)$ and $\partial_y(i, j)$ at each pixel. The gradient operators are simple Sobel operators.

c. Estimate the local orientation of each block centered at pixel *(i, j)* using (1),(2) and (3).

$$V_x(i, j) = \sum_{u=1}^{w} \sum_{v=1}^{w} 2\partial_x(u,v)\partial_y(u,v)\,, \tag{1}$$

$$V_y(i, j) = \sum_{u=1}^{w} \sum_{v=1}^{w} (\partial_x^2(u,v) - \partial_y^2(u,v)) \tag{2}$$

$$\theta(i,j) = \frac{1}{2}\tan^{-1}\frac{V_x(i,j)}{V_y(i,j)} \tag{3}$$



(a) (b)

Fig. 7 Calculation of dominant directions (a) Original fingerprint image (b) Orientation field of the fingerprint image

It is difficult to plot all the directions in each block, because of the number of pixels available for plotting directions. All dominant directions should be quantized into eight main directions. All possible directions should get converted into eight directions in the range of 90 degrees to -67.5 degrees. So we consider only 8 main directions. If some direction is in between two major values, it has to be assigned the nearest value.

A ridge center maps itself as a peak in the projection. The projection waveform facilitates the detection of ridge pixels. The method described in [14] has been used for locating ridges in the fingerprint image with the help of eight different masks. It is a process of making a binary image of ridges from the grayscale fingerprint image.

The most commonly employed method of minutiae extraction is the Crossing Number (CN) concept [16]. This method involves the use of the skeleton image where the ridge flow pattern is eight-connected. The minutiae are extracted by scanning the local neighborhood of each ridge pixel in the image using a 3x3 window.

False minutiae may be introduced into the image due to factors such as noisy images, and image artifacts created by the thinning process. Hence, after the minutiae are extracted, it is necessary to employ a post processing stage in order to validate the minutiae. Some examples of false minutiae include the spur, hole, triangle and spike structures [17]. A method based on certain heuristic rules is used to eliminate minutiae within certain threshold distance from each minutia to minimize the number of false minutiae. Furthermore, a boundary effect treatment is applied where the minutiae below a certain distance from the boundary of the foreground region are deleted. The effect of post processing is shown in Fig. 8.

(a) (b)

Fig. 8 Extracted minutiae points (a) after post processing (b) before post processing

B. Core Point Detection

The method described in [13] is used to detect the core point. A pixel wise adaptive 2D Gaussian low pass Wiener filter is applied to the fingerprint. The filter uses neighborhoods of size 5 x 5 to estimate the local gradient mean and standard deviation. This will help in reducing any noise that may cause spurious results in the gradient calculations. Divide the fingerprint into non overlapping blocks. Determine the gradients along X and Y directions, at each pixel in each block. With each block compute the slope perpendicular to the orientation of each block. Looking at blocks with slopes with values ranging from 0 to pi/2,trace the path down until we encounter a slope that is not ranging from 0 to pi/2.The block which has the highest number of mark contains the core point of the fingerprint as shown in Fig. 9.

Fig. 9 Core point in a fingerprint image (where there is maximum curvature)

C. Fingerprint Classification

Here a new approach for fingerprint classification has been presented. Minutiae are represented by means of their *x* and *y* coordinates and orientation as given in (4). The orientation of minutiae is the orientation of ridge on which the minutiae resides.

$$T = \{(x1, y1, \theta 1), (x2, y2, \theta 2), (xn, yn, \theta n)\} \tag{4}$$

The minutiae in 125 × 125 windows with the core point as the center are examined for the classification purpose. The main fingerprint classes according to Henry- Galton classification scheme are Arch, Tented arch, Right loop, Left loop and

Whorl. For each type of fingerprint image, the probability distribution of minutiae is distinct. For example in right loop the probability distribution of minutiae with pi/8, pi/4and3pi/8 is maximum .For each class, certain set of heuristics have been suggested for classification based on experimental conclusion.

Arch

The number of minutiae having angle' θ' should be more than 50 percentage of the number of minutiae having angle '-θ'.This condition should be satisfied for only one pair of angle (' θ' and '- θ') among (pi/8 and –pi/8) or (pi/4 and –pi/4).The majority of minutiae are distributed at the angles ' θ' and '-θ'. An example is shown in Table I for a typical fingerprint image. From the table It is clearly seen that the majority of minutiae are distributed at pi/8 and –pi/8.

TABLE I
THE MINUTIAE DISTRIBUTION OF A FINGERPRINT OF TYPE ARCH

Minutiae Angle	Number of Minutiae
0	2
pi/8	6
-pi/8	7
pi/4	0
-pi/4	1
3pi/8	0
-3pi/8	0
pi/2	0

Tented Arch

The number of minutiae having angle' θ' should be more than 50 percentage of the number of minutiae having angle '-θ'.This condition should be satisfied for at least two pairs of angle (' θ' and '- θ') and one of such pairs should be (3pi/8 ,and -3pi/8).An example is shown in Table 2 for a typical fingerprint image. From the table it is clearly seen that the heuristic condition is true for (pi/4 and –pi/4) and (3pi/8 and -3pi/8).

Right Loop

The minutiae distribution should be more than 60 percentage of the total number of minutiae for the angles pi/8, pi/4 and 3pi/8. An example is shown in Table III for a particular fingerprint image. From the table it is clearly seen that the heuristic condition is true for pi/8, pi/4and 3pi/8.

TABLE II
THE MINUTIAE DISTRIBUTION OF A FINGERPRINT OF TYPE TENTED ARCH

Minutiae Angle	Number of Minutiae
0	2
pi/8	3
-pi/8	8
pi/4	3
-pi/4	3
3pi/8	4
-3pi/8	3
pi/2	1

TABLE III
THE MINUTIAE DISTRIBUTION OF A FINGERPRINT OF TYPE RIGHT LOOP

Minutiae Angle	Number of Minutiae
0	2
pi/8	4
-pi/8	0
pi/4	3
-pi/4	1
3pi/8	3
-3pi/8	1
pi/2	1

Left Loop

The minutiae distribution should be more than 60 percentage of the total number of minutiae for the angles -pi/8, -pi/4 and -3pi/8. An example is shown in Table IV for a particular fingerprint image. From the table it is clearly seen that the heuristic condition is true for -pi/8, -pi/4and -3pi/8.

Whorl

There exist three different types of fingerprints of this category. They are as shown in the Fig. 10. A single condition is not enough for classifying fingerprint images of this category.

In the case of Type 1 the minutiae are uniformly distributed at the angles -pi/8, -pi/4 and -3pi/8 and more than 60 percentage of the total number of minutiae are distributed at the angles -pi/8, -pi/4 and -3pi/8 .The variance of minutiae distribution at the angles -pi/8, -pi/4 and -3pi/8 are computed. A threshold 'T' has been set for the variance and this threshold varies according to the occurrence of false minutiae during the feature extraction stage.

TABLE IV
THE MINUTIAE DISTRIBUTION OF A FINGERPRINT OF TYPE LEFT LOOP

Minutiae Angle	Number of Minutiae
0	0
pi/8	0
-pi/8	8
pi/4	1
-pi/4	3
3pi/8	0
-3pi/8	14
pi/2	2

(a) Type1 (b) Type2 (c) Type3

Fig. 10 Different types of fingerprints of whorl category

In Type 2 the minutiae are uniformly distributed at the angles 0, pi/2, and pi/4 and –pi/4 and more than 60% of the total number of minutiae are distributed at the angles 0, -pi/4, pi/4 and pi/2 The variance of minutiae distribution at the angles 0, -pi/4, pi/4 and pi/2 are computed. A threshold ‘T’ has been set for the variance.

In Type 3 the minutiae are uniformly distributed at the angles pi/8, pi/4 and 3pi/8 and more than 60% of the total number of minutiae is distributed at the angles pi/8, pi/4 and 3pi/8. The variance of minutiae distribution at the angles pi/8, pi/4 and 3pi/8 are computed. A threshold ‘T’ has been set for the variance. The examples are shown in Table V, Table VI and Table VII for three particular fingerprint images.

TABLE V
THE MINUTIAE DISTRIBUTION OF A FINGERPRINT OF TYPE 1

Minutiae Angle	Number of Minutiae
0	1
pi/8	0
-pi/8	4
pi/4	1
-pi/4	5
3pi/8	0
-3pi/8	3
pi/2	1

TABLE VI
THE MINUTIAE DISTRIBUTION OF A FINGERPRINT OF TYPE 2

Minutiae Angle	Number of Minutiae
0	4
pi/8	0
-pi/8	1
pi/4	2
-pi/4	5
3pi/8	1
-3pi/8	1
pi/2	3

TABLE VII
THE MINUTIAE DISTRIBUTION OF A FINGERPRINT OF TYPE 3

Minutiae Angle	Number of Minutiae
0	1
pi/8	0
-pi/8	4
pi/4	2
-pi/4	5
3pi/8	1
-3pi/8	4
pi/2	0

IV. Experimental Results

The algorithmic parameters such as the variance of the smoothing windows, and the number of directions in the orientation field were empirically determined by running the algorithm on a set of test images. The fingerprint classification algorithm described in this paper has been implemented and tested on a database of 350 fingerprints taken from 88 individuals (63-male,25-Female) in the age group of 20 to 30 with Hamster optical fingerprint scanner as the scanning device(25.3(W) x 40.7(L) x 67.7(H) mm,500 dpi). The probability distribution of minutiae has been checked in all the images. The size of the window around the core point is not fixed. It can be changed according to the size of the image. The accuracy of automatic detection of core point in case of whorl is low. The heuristic rules of classification have been applied on the corresponding minutiae distributions and tested. The performance of the algorithm has been checked with all fingerprint types. The results are observed as given in the Table VIII.

TABLE VIII
EXPERIMENTAL RESULTS

Fingerprint Type	Number of Images Tested	Classification Accuracy (Percentage)
Arch	20	90
Tented Arch	20	85
Right Loop	30	93.3
Left Loop	150	96.6
Whorl	130	73.1

V. Conclusion

A new method for fingerprint classification based on the probability distribution of minutiae has been developed with an average accuracy of 86.57%.The performance can be improved by minimizing the occurrence of false minutiae during the feature extraction. The input image quality adversely affects the performance of the classification algorithm. When the quality of the input fingerprint images is poor; the performance of the algorithm degrades rapidly

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