FINGERPRINT MATCHING INCORPORATING RIDGE FEATURES USING WAVELET TRANSFORM

D.Chelladurachi*

S.Muthukumar**

Abstract:

Next to DNA, fingerprint is the unique feature which identifies the individual. Due to distortions such as skin elasticity, non uniform pressure applied by the subject, different finger placement with the sensor and deformations in the skin, the fingerprint is difficult to match in the conventional minutiae only approach. But when ridge features are incorporated with minutiae features (minutiae type, orientation and position) more topological information is obtained. And also ridges are invariant to transformations such as rotation and translation. Ridge based coordinate system is used to extract the ridge features such as ridge length, ridge count, ridge type and curvature direction in the skeletonized image. Breadth First Search is used to traverse the graph formed using the minutiae as the node and the ridge vector formed using the ridge features as the edge. The proposed ridge feature gives additional information for fingerprint matching with little increment in template size and can be used along with the existing minutiae features to increase the accuracy and robustness of fingerprint recognition systems.

Index Terms— Breadth first search, ridge features, ridge-based coordinate system, ridge vector.

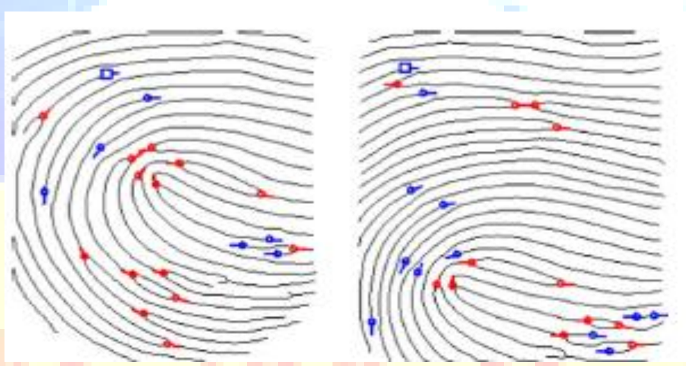
* Student, M.TECH(Information Technology), PSN College of Engineering And Technology.

** Assistant professor(dept of IT), M.TECH(Information Technology), PSN College of Engineering And Technology.

I. INTRODUCTION:

FINGERPRINT recognition has been widely adopted for user identification due to its reliable performance, usability, and low cost compared with other biometrics such as iris, signature, face, and gait recognition. It is used in a wide range of forensic and commercial applications, e.g., criminal investigation, e-commerce, and electronic personal ID cards.

Although significant improvement in fingerprint recognition has been achieved, many challenging tasks still remain. Among them, nonlinear distortions, presented in touch-based fingerprint sensing, make fingerprint matching more difficult. As shown in Fig. 1, even though these two fingerprint images are from the same individual, the relative positions of the minutiae are very different due to skin distortions. This distortion is an inevitable problem since it is usually associated with several parameters [6], [3], including skin elasticity, non uniform pressure applied by the subject, different finger placement with the sensor, etc.



(a) (b)

Fig. 1. Example of skin distortions.

To deal with the distortions in fingerprint images and improve the matching performance, various methods have been proposed by many researchers. These can be roughly classified into several groups: modeling the distortion of fingerprints [6], [9]; detecting the distortions using special hardware or video sequences allowing some amount of distortion in the minutiae matching stages [8].

Luo *et al.* [8] used changeable tolerance boxes in the minutiae matching process. The size of the tolerance boxes is incrementally increased, moving from the center towards the borders of the fingerprint area, to deal with the effect of distortion. Although many fingerprint matching methods have been developed to cope with distortions, most of them are minutiae-based. Thus, they cannot use more topological

information (such as ridge shape) covering the entire fingerprint image and the limitation of information still exists. In addition, these methods use complex data structures and many parameters for fingerprint matching. Accordingly, it is hard to understand and implement these methods accurately. Considering the facts mentioned above, instead of developing complex distortion models or elaborate minutiae alignment algorithms, a new and simple matching scheme by incorporating conventional minutiae features and additional ridge features associated with corresponding minutiae sets is proposed. To extract the ridge features, a ridge-based coordinate system is also defined. The ridge features consist of four elements: ridge count (rc), ridge length (rl), ridge curvature direction (rcd), and ridge type (rt).

These features are invariant to any geometric transformations (rotation, translation) of the fingerprints and concisely represent the relationships between the minutiae since the maintenance of ridge structures is robust to distortions.

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II. FINGERPRINT PREPROCESSING AND RIDGE FEATURE EXTRACTION:

A. Fingerprint Preprocessing

Before extracting the proposed ridge features, we need to perform some preprocessing steps (see Fig. 2). These steps include typical feature extraction procedures as well as additional procedures for quality estimation and circular variance estimation. First the image is divided into 8× 8 pixel blocks. Then, the mean and variance values of each block are calculated to segment the fingerprint regions in the image.

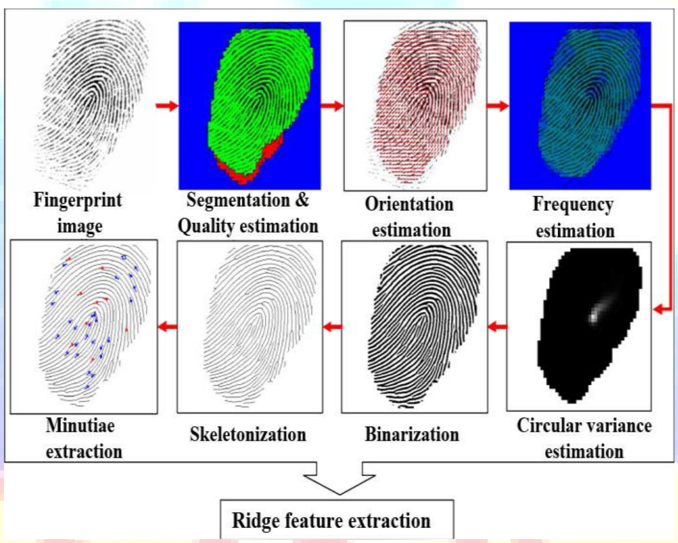


Fig. 2. Overall Preprocessing Steps

Adaptive binarization is applied which selects varying threshold based on the intensity of pixels in each block. The orientation of ridges is estimated using the formula given below. Apply least square approximation for all the pixels in each block.

$$tg2ß = 2 \sum \sum (g_x * g_y) / \sum \sum (g_x^2 - g_y^2) \qquad (1)$$

where g_x and g_y gradients taken along x and y axis respectively.

After finished with the estimation of each block direction, those blocks without significant information on ridges and furrows are discarded based on the following formula,

$$E= \{ 2\sum\sum(g_x*g_y)+(((gx2-gy2)\}/W*W*(((gx2+gy2) \quad (2)$$

For each block, if its certainty level E is below a threshold, then the block is regarded as a background block

Histogram equalization is applied to enhance the image and to improve the contrast in the image. It also connects the false broken points when the input is taken through the sensors. Finally a skeletonized ridge image is obtained by the process of thinning and other morphological operations. Then, the minutiae (end points and bifurcations) are detected in the skeletonized image. The quality estimation procedure [11] is performed in order to avoid extracting false minutiae from poor quality regions and to enhance the confidence level of the extracted minutiae set.

B. *Ridge Feature Extraction*

1) Proposed Ridge-Based Coordinate System

After performing the preprocessing steps, the skeletonized ridges and minutiae information is obtained from the fingerprint image. The ridge coordinates are defined to extract ridge features between two minutiae. The ridge-based

coordinate system is defined by considering a minutia (called origin) and vertical and horizontal axes starting from the origin minutia. First, the vertical axis is defined by drawing a line passing through the origin and orthogonal to the orientation of the origin. The axis also traverses the ridge flows orthogonally. In addition, to define the sign of the vertical axis according to the origin, the cross product between the orientation of the origin and the vector pointing from the origin to the side of the vertical axis is calculated.

In the ridge-based coordinate system, the ridge features that describe the relationship between the origin and an arbitrary minutiae is given as follows.

$$\vec{V} = (\text{rc, rl, rcd, rt}) \qquad (3)$$

where rc is the ridge count, rl is the ridge length, rcd is the ridge curvature direction and rt is the ridge type. These four components form a ridge-based feature vector between two minutiae and this feature vector is used in the matching process.

2) Ridge Feature Extraction

In the general ridge count methods [7], [10], the number of ridges that intersect the straight line between two minutiae in the spatial domain is counted. However, when the ridge counting line is parallel to the ridge structures, the line may meet the same ridge at one point, at more than two points, or at no point, due to skin deformation Therefore, unlike existing ridge-counting methods, here, the ridge count (rc) is calculated by counting the number of ridges along the vertical axis until the axis meets the ridge attached to the neighboring minutia. The vertical axis is perpendicular to the ridge structures. Thus, the counted numbers are less affected by skin deformation than in the results of the general ridge counting methods. The ridge count feature is more robust to skin deformation. Furthermore, to increase the discriminating power of the ridge count (rc) feature, the direction of the ridge count line is also considered. The ridge count (rc) is not always a positive number and the sign of the ridge count follows the sign of the vertical axis. If two minutiae are directly connected by the same ridge, the ridge count would be zero.

The ridge length (rl) is the distance on the horizontal axis from the intersection of the vertical and horizontal axis to a minutia. The ridge length value also has a sign and follows the sign of the related horizontal axis to improve the discriminating power. The probability distribution of the absolute difference of the ridge length elements are mostly less than 16 pixels.

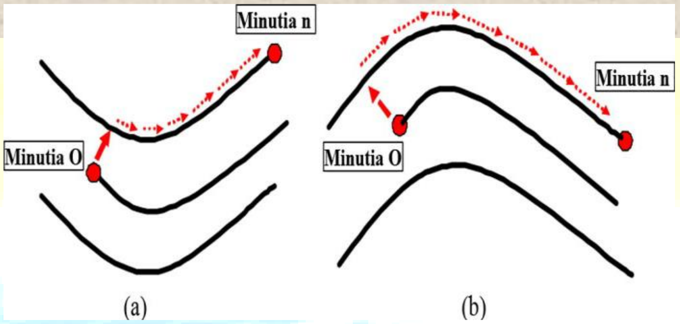


Fig. 3. Ridge curvature direction. (a) Concave shape. (b) Convex shape.

To use more topology information in ridge patterns for matching, the ridge curvature direction is also considered. As shown in Fig. 3, even though the ridge count and ridge length values are very similar, the shapes of the ridge patterns may be different [concave shape—Fig. 3(a); convex shape—Fig. 3(b)].

The ridge curvature direction is defined as follows:

$$rcd = \text{sign}\left(\sum_{i=1}^{N} \vec{v}_i * \vec{v}_{i-1}\right) \qquad (4)$$

where v_i represents the i^{th} vector between the sampling points along the horizontal axis from the intersection of the vertical and horizontal axes to the minutia n and N represents the number of sampling points.

Due to the feature extraction error, skin condition changes, and different finger pressures, end points may appear as bifurcations and vice versa. Therefore, considering these facts and to further improve the discriminating power of ridge features, the ridge type (rt) is used as one of the ridge features instead of a minutia type. To determine the ridge type (rt), each minutia is classified as an end point or a bifurcation. If a minutia is an end point, there is only one ridge belonging to the minutia. If a minutia is a bifurcation, there are three ridges connected to the minutiae.

The overall procedure for extracting ridge features is as follows:

1) Perform preprocessing steps and extract a ridge image from a fingerprint.

2) Traverse the ridge-valley structures along the vertical axis from each minutia origin.

a) If the vertical axis intersects with the ridges attached to a minutia, extract ridge features (ridge count, ridge length, ridge curvature direction, and ridge type) from the origin to the minutia and form a ridge feature vector between the origin and the minutiae.

b) Keep traversing all the ridges until one of three terminating conditions is satisfied.

3) If all minutiae are used as the origin minutiae, terminate the procedure. Otherwise, return to step 2).

The termination conditions include the following three cases:

1) The vertical axis reaches a background region in the fingerprint image.

2) The vertical axis reaches a poor quality region in the fingerprint image.

3) The vertical axis reaches a high circular variance region in the fingerprint image.

III. FINGERPRINT MATCHING:

The ridge feature vectors between the minutiae in the ridge coordinate system can be expressed as a directional graph whose nodes are minutiae and whose edges are ridge feature vectors. The graph matching methods are adopted to utilize the ridge feature vectors in fingerprint matching. Chikkerur *et al.* [12] proposed a graph-based fingerprint minutiae matching method in a Euclidean space. They first defined the local neighborhood of each minutia, called K-plet, which consists of the K –nearest minutiae from a center minutia. The comparison of two K–plets is performed by computing the distance between the two strings obtained by concatenating the K neighboring minutiae, sorted by their radial distance with respect to the center minutia. Neighborhoods are matched by dynamic programming and a match of local neighborhoods is propagated with a breadth-first fashion. Thus, we apply this matching scheme to our ridge-based coordinate system, since the ridge-based coordinate system can be represented as a graph and each coordinate system makes a local neighborhood.

The overall flow of the proposed fingerprint matching algorithm is as follows:

1) Initially match any pair of ridge-based coordinate systems extracted from the enrolled fingerprint image and the input fingerprint image using dynamic programming.

2) Select the top degree of matched ridge-based coordinate pairs.

3) For every initially matched pair, a breadth-first search (BFS) is performed to detect the matched ridge- based coordinate pairs incrementally.

4) Check the validity of the matched coordinate pairs using the relative position and orientation of the minutiae and count the number of matched minutiae.

5) Iterate steps 3) and 4) N times and return the maximum number of matched minutiae.

6) Compute the matching score.

Dynamic programming is applied to find the optimal solution in matching two string sequences in the enrolled and input ridge-based coordinates. The ridge feature vectors in a ridge-based coordinate system are arranged in the order of their ridge count feature component (rc), then the order is invariant intrinsically. Therefore, the feature vectors in a ridge-based coordinate system can be stored as the elements of an ordered sequence. Thus, all the enrolled and input ridge-based coordinates are compared one by one and a similarity score is computed for the dynamic programming.

The similarity score is calculated as follows:

$$\begin{cases} \text{score} = P\left(\frac{w_1}{X}\right), & \text{when} \quad P\left(\frac{w_1}{X}\right) > P\left(\frac{w_2}{X}\right) \\ \text{score} = 0, & \text{otherwise} \end{cases} \qquad (5)$$

where X is the absolute difference between two feature vectors, w_1 is the correctly matched class, and w_2 is the incorrectly matched class.

For the ridge feature vector, the three feature elements (ridge count, ridge length, and ridge curvature direction) are used to calculate the scores and the ridge type feature is used to check the validity of the candidate pairs. The validity of the matched coordinate pairs using the relative position and orientation of the minutiae used in conventional minutiae-based matching. If the relative position and orientation of the minutiae in the coordinate pair are also matched, then it can be sure that these minutiae are correctly matched. Then the number of matched minutiae are counted and stored. Finally, after the execution of the BFS procedure for every initial matched pair, the maximum number of matched minutiae between two fingerprints is found.

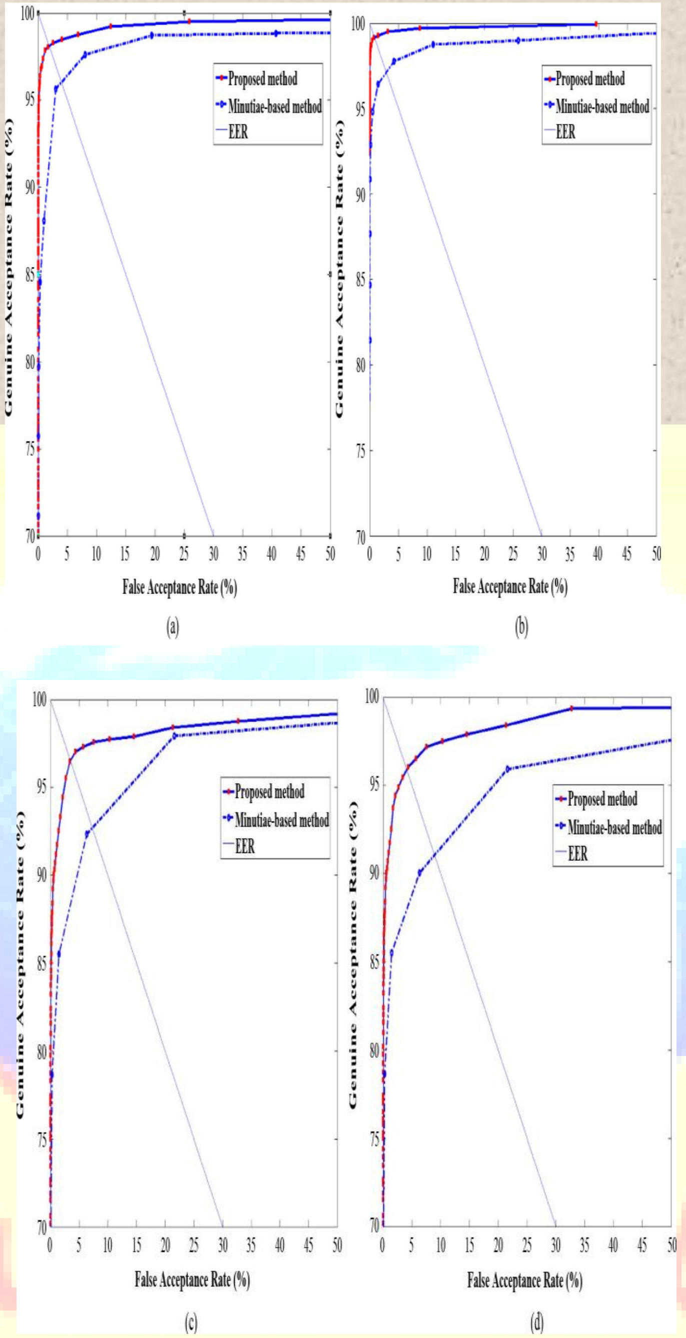
To compute the matching score, we must consider both the degree of overlap between two impressions and the degree of similarity of the overlapped region. Thus, the matching score can be computed as follows:

$$S_m = \frac{L*L}{m0*n0} * \frac{L*L}{N1*N2} \qquad (6)$$

where L, N_1 , and N_2 are the number of matched minutiae, the number of minutiae in an input image, and the number of minutiae in a template image, respectively. m_0 and n_0 are the number of minutiae in the overlapping regions of the query and template images, respectively. The overlapped regions are where two fingerprints intersect after the linear transformation (translation and rotation) using the matched minutiae.

IV. EXPERIMENTAL RESULTS AND ANALYSIS:

The recognition performances of two algorithms (the conventional minutiae-based matching method [13] and the proposed method) is compared. To demonstrate the effect of the proposed ridge features more generally, the conventional minutiae-based method, which is based on popular minutiae features such as minutiae position, minutiae orientation, and minutiae type [13] is chosen instead of the state-of-the-art minutiae-based algorithms which use additional specific matching techniques. The conventional method utilizes several reference points for local alignment and an adaptive tolerance box is used to calculate the number of matched minutiae. For genuine matches, each impression of each finger is compared with other impressions of the same finger.



Experimental Results.

V. SUMMARY AND FUTURE WORK:

Unlike existing ridge-counting methods, in ridge based coordinate system, the ridge count (rc) is calculated by counting the number of ridges along the vertical axis until the axis meets the ridge attached to the neighboring minutia. The vertical axis is perpendicular to the ridge structures. Thus, the counted numbers are less affected by skin deformation than in the results of the general ridge counting methods. Ridge count feature is more robust to skin deformation. Furthermore, to increase the discriminating power of the ridge count (rc) feature, the direction of the ridge count line is also considered. The ridge length value also has a sign and follows the sign of the related horizontal axis to improve the discriminating power. With this approach , no complex data structure is involved and no minutiae alignment algorithm is used. The proposed ridge features are invariant to any transform, thus they can be used in addition to conventional alignment-free features in the fingerprint identification or cancellable fingerprint area and gives additional information for fingerprint matching with little increment of template size.

The proposed fingerprint matching method can be applied to images with small foreground area and images with low quality which contains very less number of minutiae points than required.

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