7-8 April, 2012 Proceedings published by International Journal of Computer Applications® (IJCA)ISSN: 0975 - 8887

Fingerprint Features Extraction and matching

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ABSTRACT
The proposed ridge features are composed of four elements: ridge count, ridge length, ridge curvature direction, and ridge type. For extracting ridge features, we also define the ridge-based coordinate system in a skeletonized image With the proposed ridge features and conventional minutiae features(minutiae type, orientation, and position), we propose a novel matching scheme using a breadth-first search to detect the matched minutiae pairs incrementally. proposed ridge feature gives additional information for fingerprint matching with little increment in template size and can be used in conjunction with existing minutiae features to increase the accuracy and robustness of fingerprint recognition systems**.**

Keywords
Ridges count, minutiae feature, Matching**.**.

1. INTRODUCTION
F INGERPRINT recognition has been widely adopted for user identification due to its reliable performance, usability, and low cost compared with other biometrics such as signature, iris, face, and gait recognition [1]. 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. even though these two fingerprint images are from the same individual, the relative positions of the minutiae are very different due to skin distortions.
Instead of developing complex distortion models or elaborate minutiae alignment algorithms, we propose a new and simple matching scheme by incorporating conventional minutiae features and additional ridge features associated with corresponding minutiae sets. 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. Moreover, since the correlation between the proposed ridge features and conventional minutiae features is low, combining these features leads to an improvement in the overall recognition performance with a small increment in template size. Our ridge features require only 5 bytes (ridge count—1 byte; ridge length—2 bytes; ridge curvature direction—1 byte; and ridge type—1 byte) for each minutiae pair.

2. FINGERPRINT PREPROCESSING AND RIDGE FEATURE EXTRACTION
2.1 Fingerprint Preprocessing
we need to perform some preprocessing steps (see Fig. 1). These steps include typical feature extraction procedures as well as additional procedures for quality estimation and circular variance estimation. We first divide the image into 8 8 pixel blocks. Then, themean and variance values of each block are calculated to segment the fingerprint regions in the image. We then apply the method described in [6] to estimate the ridge orientation and the ridge frequency is calculated using the method presented . The Gabor filter [6] is applied to enhance the image and obtain a skeletonized ridge image. Then, theminutiae (end points and bifurcations) are detected in the skeletonized image. The quality estimation procedure is performed in order to avoid extracting false minutiae from poor quality regions and to enhance the confidence level of the extracted minutiae set.
postprocessing steps [to remove falsely extracted ridges, such as short ridges and bridges. We can then extract the ridge structures consistently against various noise sources.

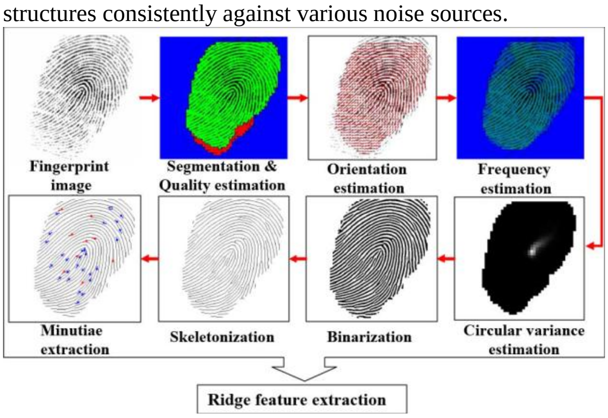


Fig. 1. Overall preprocessing steps

2.2 Ridge Feature Extraction
2.2.1 **Proposed** *Ridge-Based Coordinate System*
we obtain the skeletonized ridges and minutiae information from the fingerprint image.
We can then define ridge coordinates and extract ridge features between two minutiae. As shown in Fig. 2, each ridge-based coordinate system is defined by 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 accordingto 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. rc, rl, rcd, and rt represent the ridge count, ridge length, ridge curvature direction, and ridge type, respectively. These four components form a ridge-based feature vector between two minutiae and this feature vector is used in the matching process.

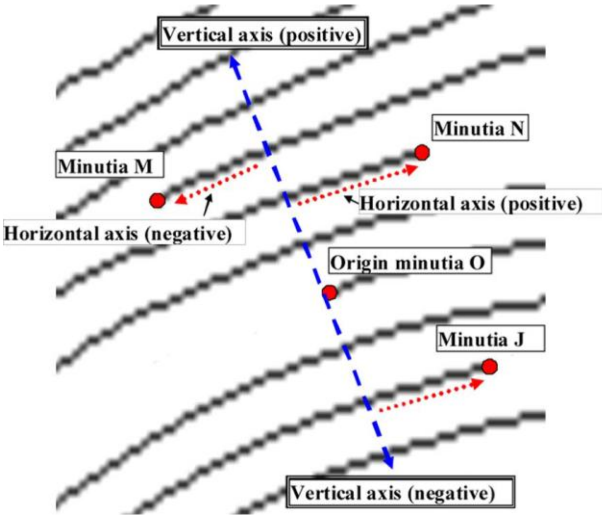


Fig. 2. Ridge-based coordinate system

2.2.2 Ridge Feature Extraction

In the general ridge count methods [2], [3], 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. In order to prove the effectiveness of the proposed ridge counting method, we used 50 fingers from FVC 2002 DB1. Furthermore, to increase the discriminating power of the ridge count (rc) feature, we also consider the direction of the ridge count line. 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. To prove the usefulness of the ridge length feature, we conducted an experiment similar to the analysis of the ridge count feature. Fig. 3 shows the probability distribution of the absolute difference of the ridge length feature. As shown in the figure, the absolute differences of ridge length elements are mostly less than 16 pixels. Therefore, we can set the threshold of the ridge length feature to determine the same fingerprint as 16 pixels. The ridge length value also has a sign and follows the sign of the related horizontal axis to improve the discriminating power.

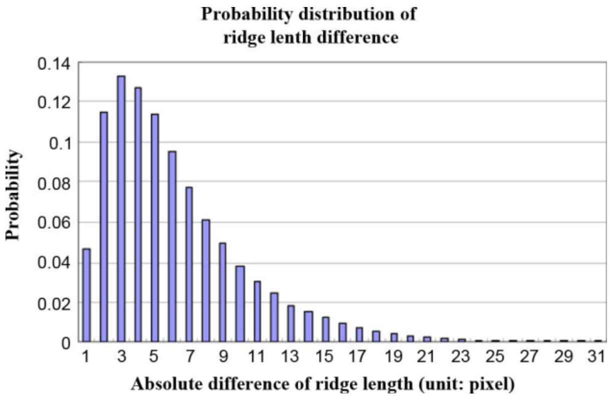


Fig. 3. Probability distribution of the absolute difference of ridge length.

To use more topology information in ridge patterns for matching, the ridge curvature direction is also considered. As shown in Fig. 4, even though the ridge count and ridge length values are very similar, the shapes of the ridge patterns may be different [concave shape—Fig. 4(a); convex shape—Fig. 4(b)].

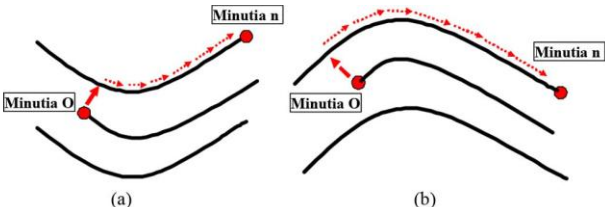
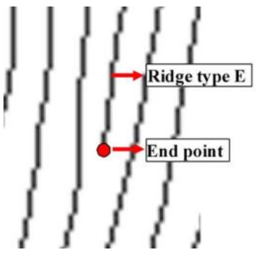


Fig. 4. Ridge curvature direction. (a) Concave shape. (b) Convex shape

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 first 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. Next, the type of ridge associated with the minutia is determined as one of four types according to the type of the minutia and the relative position of the ridges. As shown in Fig. 5, if a minutia is an end point, the ridge type is defined as E . In a bifurcation case, the three ridges are labeled by checking



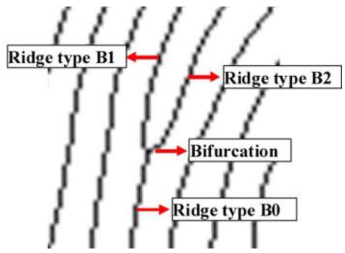


Fig. 5. Examples of ridge types.

the angle between each ridge and the minutia orientation. A triangle is created by three points on the ridges (equidistant from the bifurcation). If the vertex of the triangle is not on the shortest side of the triangle, then the ridge belongs to the vertex and is defined as type B0 . The other two ridges are classified as type B1 andB2 , moving in a clockwise direction from B0 Generally speaking, ridge type E can change only into ridge type B1 or B2 . However, type E cannot be converted into type B0 Therefore, we use this information in the fingerprint matching.

3. 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. Thus, we can adopt graph matching methods to utilize the ridge feature vectors in fingerprint matching. Chikkerur *et al.* [7] 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 cente rminutia. 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. Moreover, the data structure of the ridge-based coordinate system is very similar to the K-plet structure proposed in [7]. 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 based on the *Bayesian* decision rule. 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. After that, we select the top N degree of matched ridge-based coordinate pairs. In this paper, we set the value N as 10. For every initially matched pair, we perform a BFS to increment the match for other neighboring ridge-coordinate systems. However, there is not always a path for every minutiae pair because we do not extract ridge features in the fingerprint regions which have low quality or a high curvature. Therefore, we find a detour path to perform the BFS . We check 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, we can be sure that these minutiae are correctly matched. We then count the number of matched minutiae and store them. Finally, after the execution of the BFS procedure for every initial matched pair, we find the maximum number of matched minutiae between two fingerprints. Fig. 6 shows an example of matched minutiae using the proposed method. As shown in the figure, even if two impressions of the same finger are different due to skin distortion, many minutiae are matched correctly.

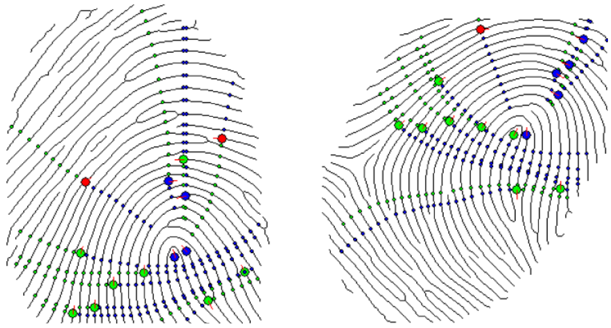


Fig. 6. Example of matched minutiae using the proposed ridge feature vectors (solid circles represent matched minutiae and dotted lines represent the vertical axis of each minutia).

4. EXPERIMENTAL RESULTS AND ANALYSIS

We compared the recognition performances of two algorithms (the conventional minutiae-based matching method [2] and the proposed method). To demonstrate the effect of the proposed ridge features more generally, we chose the conventional minutiae-based method, which is based on popular minutiae features such as minutiae position, minutiae orientation, and minutiae type [2] 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 the experiments, we used the databases FVC 2002 DB1, DB2, DB3, and FVC 2004 DB1, released on theWeb [22], [23]. Regarding fingerprint quality, FVC 2002 DB3 and FVC 2004 DB1 have lower quality fingerprints than other databases because the users were explicitly requested to exaggerate distortions [1]. Therefore, it is reasonable to analyze the robustness of the proposed method against skin distortions by using these databases. Each database is composed of 800 fingerprint images from 100 different fingers (eight impressions per finger). For genuine matches, each impression of each finger is compared with other impressions of the same finger. Therefore, 2800 genuine matches were executed in each database. For imposter matches, each impression of each finger is compared with all impressions of the different fingers. Therefore, 316 800 imposter matches were conducted in each database. Table I shows the equal error rate (EER) comparisons of two matching methods on the FVC databases and Fig. 8 shows the ROC curves on each database.

Table 1. EER comparisons of two matching methods on FVC databases

Database	EER(%)	
	Proposed method	Conventional minutiae-based method
FVC 2002 DB1	1.8	4
FVC 2002 DB2	0.8	2.9
FVC 2002 DB3	3.5	7.3
FVC 2004 DB1	4.3	8.9

From the experimental results, we can see that the proposed method is superior to the conventional minutiae-based one for all the databases. Even though the performances for FVC 2002 DB3 and FVC 2004 DB1 are lower than those for FVC 2002 DB1 and DB2, we can maintain that our ridge features can support the minutiae features when they are used together in the matching stage.

5. CONCLUSIONS AND FOR FUTURE WORKS

In this paper, we proposed a novel fingerprint matching algorithm using both ridge features and the minutiae. The ridge features consist of four elements (ridge count, ridge length, ridge curvature direction, and ridge type) that describe the relationship between the minutiae. With the proposed ridge features and conventional minutiae features (minutiae type, orientation, and position), we proposed a novel matching scheme using a BFS to detect the matched minutiae pairs. The experimental results show that the proposed method gives higher matching scores compared to the conventional minutiae-based one. Hence we can conclude that the proposed ridge features give additional information for fingerprint matching with little increment of template size. And, for future work, we will try to incorporate these features into the state-of-the-art minutiae-based matchers for further improvement of the matching performance. Also, our matching method needs to be improved for images with small foreground area and those of low quality. Therefore, in future work, we will develop the use of global knowledge of fingerprints, such as singular point position, to enhance the matching accuracy. We will also develop a robust preprocessing method to reduce enhancement errors. Moreover, our ridge features can be used in other applications. In the area of fingerprint identification, it is important to be able to extract alignment-free features since it needs no time to align a query feature set with the N enrolled feature sets one by one . In cancellable fingerprints, without a fiducial corresponding pair such as a core point, it is difficult to align a transformed feature set with an enrolled one . 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

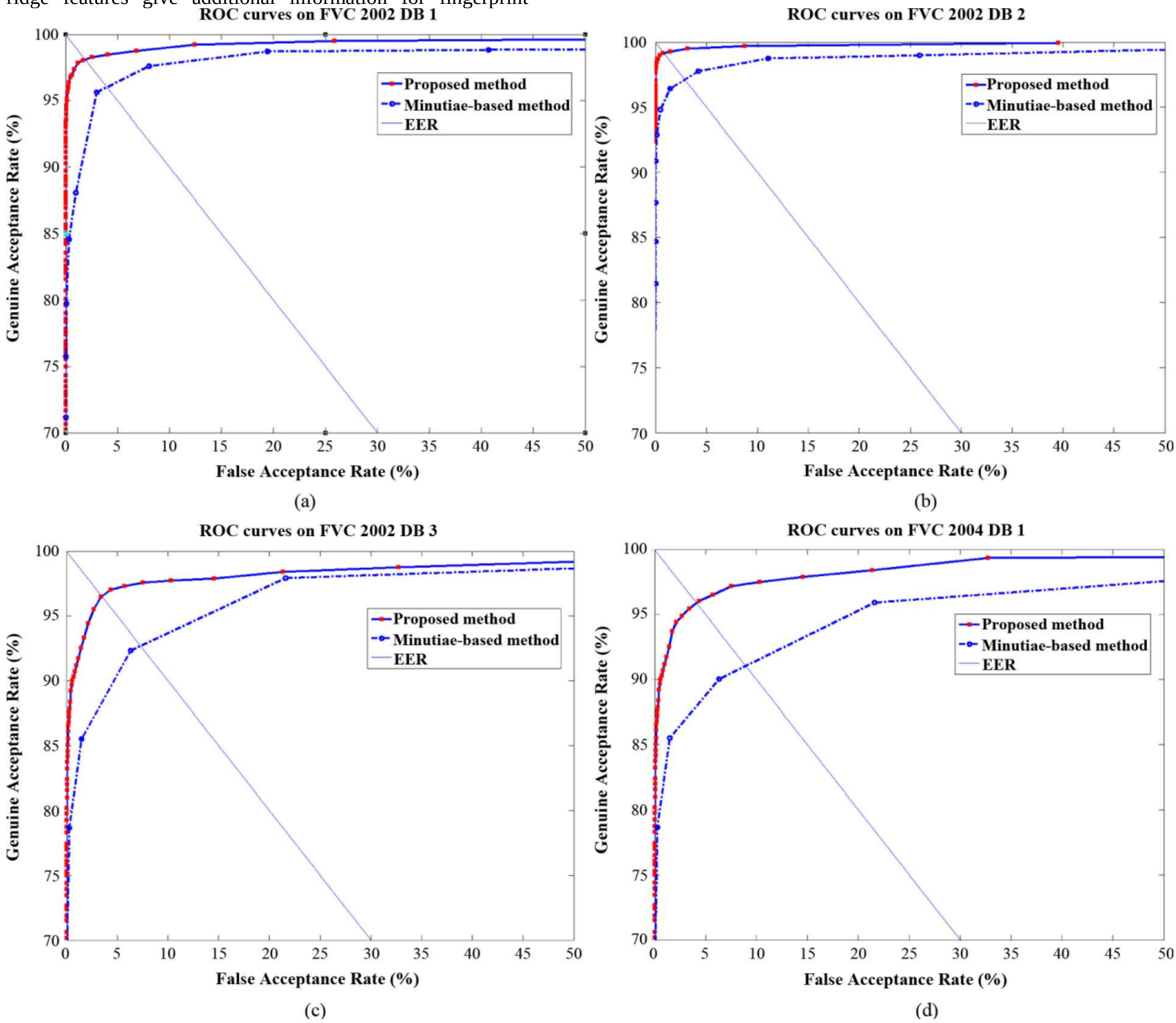


Fig. 8. ROC curves on each database

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