Ridge-Based Fingerprint Recognition

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Abstract. A new fingerprint matching method is proposed in this paper, with which two fingerprint skeleton images are matched directly. In this method, an associate table is introduced to describe the relation of a ridge with its neighbor ridges, so the whole ridge pattern can be easily handed. In addition, two unique similarity measures, one for ridge curves, another for ridge patterns, are defined with the elastic distortion taken into account. Experiment results on several databases demonstrate the effectiveness and robustness of the proposed method.

Keywords: fingerprint recognition, point-pattern matching, ridge sampling, ridge matching.

1 Introduction

Minutiae (fingerprint ridges' bifurcations and ends) are commonly employed as the basic features in most fingerprint recognition algorithms. In such circumstances, fingerprint recognition can be regarded as a point-set matching problem, where the best match with the maximal number of corresponding point pairs in the two point sets is searched under certain error restriction. Many solutions have been proposed to solve this problem [1][2][3][4][5]. Most of the proposed methods are based on a rigid-body model, and do not have a proper way to handle the elastic distortion problem in fingerprint matching. In addition, there always exist some quality problems on fingerprint images collected, and fake minutiae may be generated during feature extraction process because of noise on fingerprint images. Most of the current algorithms could not do well at these circumstances.

In order to solve the problems mentioned above, in addition to minutiae, more fingerprint features such as global features (center and triangle points) or ridge features (ridge flow and ridges count between two minutiae) are introduced by some researchers to decrease the possibility of error occurred during matching. However, the features newly introduced also have elastic distortion, and thus these methods could not solve the problems ultimately. Looking for more robust and more efficient fingerprint matching algorithms is still a challenge problem.

Usually we can obtain skeleton images through enhancement, segmentation, binarization, and thinning stages of common fingerprint image preprocessing, and ridges in the skeleton image are single-pixel-wide curves. The skeleton image contains not only all of the minutiae information but also the whole ridge pattern. There has been few work on ridge-pattern-based fingerprint matching published in the literature. In this paper, we propose a novel fingerprint matching method with which two fingerprint ridge images are directly matched. The main

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contributions of this work are two folds: First, an associate table is introduced to describe the relation of a ridge with its neighbor ridges, and consequently the whole ridge pattern can be easily handled; secondly, by taking the elastic distortion into account, two unique similarity measures, one for ridge curves, another for ridge patterns, are defined. These make this algorithm effective and robust.

The rest of the paper is organized as follows: In section II, we introduce a way to obtain skeleton ridge images from the gray-scale fingerprint images; In section III, the proposed method is presented; Experiment results are given in section IV; Section V provides the conclusions and the future work.

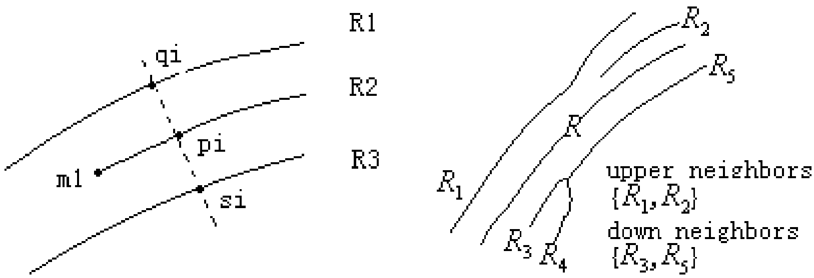
2 Fingerprint Skeleton Image

Fingerprint skeleton image can be obtained through the common preprocess procedure which includes segmentation, filtering, binarization and thinning stages. However, this preprocess procedure exists some problems when used for ridge extraction since it was tuned to minutiae extraction. Also the filtering stage are often time consuming.

Maio and Maltoni [6] presented a novel approach to extract minutiae directly from gray-level fingerprint images. With their algorithm ridges can be extracted by following the ridges until they terminate or intersect with other ridges. As the fingerprint image need not be filtered at every pixel, the computational complexity of the algorithm is low. We modified Maio's method in the following way to obtain skeleton images. First, ridges are extracted in high-quality image areas with Maio's method, and then more paths are searched and a strict stop criterion is adopted during ridge following in blurred image areas. Finally we employ the method proposed by Chen [7] to connect the broken ridges caused by scars, dryness or other reasons. A sample skeleton ridge image is shown in Fig. 1.

(a) Origin fingerprint image (b) Skeleton ridge image

Fig. 1. A skeleton image



(a) Associate points (b) Ridge neighbors

Fig. 2. The neighborhood of ridges

3 Ridge Matching

As shown in Fig.2(a), ridges $R1$ and $R3$ are neighbor ridges of ridge $R2$. A ridge curve may have more than one neighbor on its each side in the skeleton image. The neighborhood relationships among ridges are invariant during one's life time and are robust to elastic distortions of fingerprint images. These steady relationships make the base of the ridge-based fingerprint matching method proposed by us.

Define a direction for a ridge along which the ridge following procedure is performed. Then the left-hand-side neighbors of the ridge are called its upper neighbors and the right-hand-side neighbors are called its down neighbors (see Fig.2(b)). Suppose to draw a line at point p_i normal to ridge $R2$, the line intersects $R1$ at q_i and $R3$ at s_i, and q_i and s_i are called p_i 's associate points.

3.1 Similarity Measure of Two Ridge Curves

Suppose P_m and P_n are respectively the starting point and the ending point of ridge f , and P_m and P_n could be ridge end, ridge bifurcation or ridge broken points. The curvature γ of curve f is defined as:

$$\gamma = \int_{P_m}^{P_n} |d^2 f| \tag{1}$$

γ describes a curve's winding degree, and it's an invariant to image rotation and translation.

Suppose the lengths of two ridges f_1 and f_2 are d_1 and d_2 respectively, and the starting and ending points of f_1 and f_2 are not ridge broken points, we say these two ridges pre-matched to each other if the following conditions are satisfied:

$$\begin{cases} |(d_2 - d_1)/d_2| \leq th_1 \\ \varsigma = 1 - |(1-\kappa)/(1+\kappa)| \cdot |(\gamma_{f_1} - \gamma_{f_2})/(\gamma_{f_1} + \gamma_{f_2})| \geq th_2 \end{cases} \tag{2}$$

Where κ is the stretch factor of ridge f_1 and f_2, and is defined as:

$$\kappa = d_1/d_2 \tag{3}$$

Table 1. Associate table

Associate point(upper)	R_1	R_1	R_1	R_1	R_2	R_2	R_2	R_3	R_3	R_3	R_3	...
Sampling point	p_0	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	...
Associate point(down)	R_4	R_4	R_4	R_4	R_4	R_4	R_4	R_4	R_5	R_5	R_5	...

The above conditions can tolerate small elastic distortions, and ς gives the similarity measure of the two ridges.

3.2 Associate Table

As shown in Fig.2(b), there may exist more than one upper neighbor and down neighbor for one ridge. We will describe the relationships of a ridge with its neighbors by using a table, which is called associate table. The associate table is constructed with the following way.

We sample ridge R with interval d from its starting point to end point, and obtain one sampling point-set Θ and its associate point-sets Ψ_{up} and Ψ_{down}. All the points in Ψ_{up} and Ψ_{down} are labelled by their corresponding ridges (NULL for empty). The labels and the sampling point set Θ make up of ridge R's associate table. A typical ridge associate table is shown in table I.

Assume that the length of the shortest ridge is not less than 7 pixels in our system, and ridges shorter than 7 pixels are always generated by noise. Thus we choose the sampling interval of 7 pixels, although using dynamic sampling interval according to the ridge stretch factor can depict the neighborhood relationships of the ridge more accurate. The associate tables of all ridges contain all information and features the image has.

3.3 Ridge Matching Procedure

Ridge matching is performed by using ridge associate tables and travelling all the ridges. Suppose $R_{I_1} = \{r_i \,|i \leq M\}$ and $R_{I_2} = \{r_j \,|j \leq N\}$ are the skeleton ridge sets of fingerprint images I_1 and I_2 respectively. The procedure of matching I_1 and I_2 can be described as below:

1. Calculate each ridge's curvature in R_{I_1} and R_{I_2}, and compare ridge pairs which have the same type of starting and ending points. If the pair of ridges satisfies the conditions stated in section III part A, the pair of ridges is pre-matched. Arrange the matched ridge pairs in descending order according to their similarity measures. These pairs of ridges will be used as the initial pairs for matching. Multiple initial pairs may be needed for proper alignment of the two images.
2. Choose the first ridge pair of the initial set and record their starting points into the task queue.
3. Get one task point pair from the task queue, and sample the corresponding ridges (R_a and R_b).

4. Construct the associate tables of R_a and R_b, and put the associate points of the starting points of R_a and R_b into the task queue.
5. Check the associate tables of the two ridges and find the maximal matched length m of R_a and R_b. This is done in the following way. First set $m = 0$, and then:
   (a) Check the ridge labels of the consecutive upper associate points starting from the m^{th} sampling points of R_a and R_b. If the ridge labels of the upper associate points of the $(m+i)^{th}$ sampling point ($i \geq 3$) in either of the two tables is changed, update $m = m + i$ and $i = 0$; Put the starting point pair of the new neighbor ridges into the task queue, and go to (b);
   (b) Check the ridge labels of the consecutive down associate points starting from the m^{th} sampling point of R_a and R_b. If the ridge labels of the down associate points of the $(m+j)^{th}$ sampling point ($j \geq 3$) in either of the two tables is changed, update $m = m + j$ and $j = 0$; Put the starting point pair of the new neighbor ridge into the task queue, and go to (a);
   The above loop stops if no further match can be found.
6. According to the result obtained at step 5), we obtain the newly matched relation of Ra and Rb from the starting point to the m^{th} sampling point.
7. According to the result obtained at step 5), suppose ridge labels of the consecutive associate points do not have changes from i to j, $R^{'}$ and $R^{''}$ are ridges labels of the corresponding associate points respectively, we obtain the newly matched relation of $R^{'}$ and $R^{''}$ from sampling point i to j when $(j - i) \geq 3$ is satisfied.
8. If the newly matched ridges conflict with the previous matching results, i.e. if there already exists a ridge segment (longer than 3 times of sampling intervals) in R_{I_1} matched with the newly matched ridge segment in R_{I_2}, or vice versa, stop the matching procedure, and return to step 2) to restart the matching procedure by choosing a new initial ridge pair.
9. If there is no matching confliction, return to step 3). Matching goes on until the task queue is empty.
10. Calculate the matching score according to Eq.(4) presented in the next subsection. If the score is larger than a threshold, the whole matching procedure stops; if not, return to step 2) to restart the matching procedure by choosing a new initial ridge pair. The maximal matching score resulted from the different initial pairs gives the final result.

3.4 Similarity Measure of Two Ridge Patterns

The similarity measure of two fingerprints is defined as:

$$score = N/(C \times distortion) \tag{4}$$

Where N is the total length of all matched ridges, more ridges matched would achieve higher score; C is a scaling constant, and the distortion is defined as follows:

$$distortion = \sum_{i,j}^{|P|} |(|p_i p_j| - |q_i q_j|)|/(|P| \cdot (|P| - 1)) \tag{5}$$

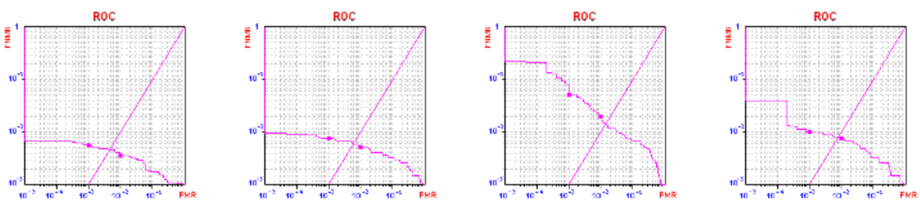
Where $p_i, p_j \in P$, $q_i, q_j \in Q$, P and Q are two point sets containing the termination points of all the matched ridge pairs, $|P|$ denotes the number of elements in P. The distortion describes the distortion between the ridge structures formed by matched ridge pairs, wrong matched ridge pair always leads to higher distortion value and lower score.

4 Experiment Results and Performance Evaluation

We tested our algorithm on the database of FVC2002[8], which contains 4 testing data sets and every set has 800 gray-level fingerprint images. The images in one set came from 100 different fingers with 8 sample images each. We matched every two fingerprints for each data set, which means 2800 times true matching and 36000 times false matching. The average matching time is 0.025s to 0.33s per

Table 2. Results on database of FVC2002

EER	DB1	DB2	DB3	DB4
Matching Ridges	0.35	0.63	1.45	0.7
Matching minutiae[9]	0.78	0.95	3.1	1.15



(a) ROC curve on DB1 (b) ROC curve on DB2 (c) ROC curve on DB3 (d) ROC curve on DB4

Fig. 3. ROC curves on FVC2002 databases

(a) Image I_1 of Sample A (b) Image I_2 of Sample A (c) Image I_1 of Sample B (d) Image I_2 of Sample B

Fig. 4. Ridge based fingerprint matching results

match by using a laptop with a PIII 866 CPU. Comparisons between this method and minutiae based method proposed in paper [9] on the four data sets are given in table II, The result shows that the algorithm has better performance than that in [9]. Fig.3 gives ROC curves on the four databases, and Fig.4 shows two examples of the matched images from the same finger. From figure 4, we can find that the method proposed in this paper not only handles the elastic distortion problem well but also helps to eliminate the matching uncertainty (such as caused by not having enough minutiae) since it fully utilizes the ridge information.

5 Summary and Future Work

In this paper, we have presented a novel fingerprint matching algorithm based on ridge structures. The method matches fingerprint skeleton images directly. Associate tables are introduced in this method to describe the neighborhood relations among ridge curves. Also two unique similarity measures, which properly handle the elastic distortions, are defined. Thus better performance is achieved by this method compared to minutiae-based matching method. However, future research is still needed on this method: match ridges more effectively, find fast ways to construct ridge associate tables, find more effective rules to follow matched or unmatched ridges. Blurred image area could generate fake ridges, and how to introduce fuzzy theory in ridge extraction stage is also important.

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