Fingerprint Classification Method Based on Analysis of Singularities and Geometric Framework

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Abstract. According to the former contributions, the authors present a novel fingerprint classification method based on analysis of singularities and geometric framework. First, a robust pseudoridges extraction algorithm on fingerprints is adopted to extract the global geometric shape of fingerprint ridges of pattern area. Then, by use of the detected singularities and with the help of the analysis of the global geometric shape of fingerprint ridges of pattern area, the fingerprint image is classified into different pre-specified classes. This algorithm has been tested on the NJU fingerprint database which contains 2500 images. For the 1000 images in this database, the classification accuracy is 92.2%.

Keywords: fingerprint classification, global geometric shape, singularity.

1 Introduction

Nowadays, automatic fingerprint identification is one of the most reliable and important biometric technology. However, automatic fingerprint identification is computationally demanding especially for a large database. So an effective fingerprint indexing scheme can greatly help facilitate efficient matching for large fingerprint database. Fingerprint classification, which classifies fingerprint images into a number of pre-defined categories, provides an indexing scheme to improve the efficiency of the matching task [1~2, 22].

Over the past few decades, a significant number of approaches have been developed for the purpose of fingerprint classification. The methods of fingerprint classification can fall into the following categories:(i) the knowledge-based approach[1, 3~4], (ii) the structural approach[5~9], (iii) the frequency-based approach[10],(iv) the syntactic approach[11~13], and (v) the artificial neural network approach[14~17]. Furthermore, the hybrid approach[1~2] that combines two or more of the foregoing approaches are combined, is used to accomplish the classification task.

Most of the approaches mentioned above are subjected to one kind of disadvantage. One apparent weakness of these approaches is that they are not able to deal with the usual noisy characteristic of fingerprint images well. For instance, due to the core and delta points used in classification might be uncertain in noisy images or be dropped in non-whole images, only using the singularities for fingerprint classification might not be viable. Many approaches may be susceptible to the large variations of ridge orientation within the patterns of the same class, or they would only work

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within a fixed state of orientation and position. In a fingerprint image, the local ridge features carry the individuality information about the fingerprints and the global pattern configurations, which form special patterns of ridges and furrows in the central region of the fingerprint, carry information about the fingerprint class. Therefore, the global pattern configurations should be used for fingerprint classification. Generally, global fingerprint features can be derived from the orientation field and global ridge geometric framework. The orientation field of a fingerprint consists of the ridge orientation tendency in local neighborhoods, and it is highly structured and can be roughly approximated by a core-delta model[2]. Therefore, singularities and their relationship can be used for fingerprint classification. On the other hand, the global ridge geometric framework also provides important clues as to the global pattern configuration of a fingerprint image [4].

This paper presents a fingerprint classification method based on the analysis of singularities and geometric framework. First, a robust pseudoridges extraction algorithm on fingerprints is adopted to extract the global geometric shape of fingerprint ridges of the pattern area. Then, by using the singularities and the global geometric shape features, the fingerprint image is classified into six classes (arch, tented arch, left loop, right loop, whorl and twin). Because it is difficult to get the correct and complete information of singularities used in the other classification method, this method is not merely based on the singularities and thus improves the classification accuracy. The global geometric shape of fingerprint ridges is extracted by directly tracing the orientation field, the traced orientation field is smoothed locally, and the global ridge geometric framework traced remains constant under large variations of local ridge orientation, Therefore, the fingerprint classification algorithm is robust. Moreover, our algorithm is invariant under transition and rotation.

In the following sections, the paper presents the details of our fingerprint classification method. In section 2, the global geometric shape extraction method is introduced. Section 3 presents our classification scheme. Experimental results and conclusions are given in section 4.

2 Global Geometric Shape Extraction

In our fingerprint classification scheme, the feature information such as the global ridge geometric framework, fingerprint singularities and the symmetrical axis of the core point will be used for fingerprint classification, but the methods for getting these features are not the emphasis of this paper, which have been reported in our other papers[18] [21]. The essential ideas for above several features extraction are given the brief introduction as follows:

2.1 Fingerprint Pseudoridge Tracing

According to the method presented in [18], the pseudoridge tracing is started from the core point and only uses the flow field information, avoiding complicated computation of thinned ridges, minutia and other trivial processing. Because the fingerprint is flow-modal, the flow field reflects the global tendency of fingerprint ridges and is continuous except in the individual singularity[19], as is different from the gray ridges, some of which are conjoint, some disconnected and other furcated. Besides the ridge structures in poor quality fingerprint images are not robust. Hence, it is more reasonable to trace the flow field than to trace the ridges directly. In order to make the traced pseudoridges more accurate, the paper suggests a skillful and effective method for the orientation field estimate. On only the exact points traced but not the whole fingerprint image, orientation field estimates are performed, the operation time will be reduced as a result. The paper also exploits a method of adaptive tracing, in which if the variation of flow field is dull, the tracing step is large, otherwise (for example, near the core points), the tracing step is small. This characteristic is useful in checking the singularities. Moreover, our algorithm operation is invariant under transition and rotation for it is irrelative with a fixed state of orientation and position.

In paper [18], an effective point direction estimatation approach is also proposed. The approach utilizes the ridge orientations around an aim point to smooth the aim point direction skillfully, which reflects the general orientations of the neighbor ridges and alleviates the local noises accordingly. Thus, the proposed point direction estimatation approach ensures the pseudoridge tracing algorithm is robust to the noise images. The specific idea is as follows:

The point direction of a point is usually specified for a region (block) that centered at this point. In this paper, the 16×16 pixels region is used to compute the point directions. To get a more reasonable point direction of an aim point, a smoothing technology should be introduced to alleviate the effect of noise. The directions of the points, which are located in the neighborhood of every 8 pixels along X and Y coordinates of aim points, are used to smooth the aim point direction, and the mask size for smoothing point directions is 5×5. Thus, the smoothing area is more reasonable, the smoothing degree is stronger, and the result is better.

2.2 Symmetrical Axis of the Core Estimation

In addition, the orientation θ_c of the symmetrical axis of the region near the core is one of the main features of modal area. It can be used for fingerprint classification and taken into account for fingerprint matching in which the rotation angle is adjusted between the input image and the template image. Therefore, it is an important issue to compute the symmetrical axis of the region near the core reliably. Some literatures only discuss the case that the core point is in the upper section of the image, so it is variational under rotation. In this paper, the idea of V. S. Srinivasan et al.[20] is adopted and improved to compute the more accurate consecutive orientation rather than the coarser disperse orientation. The key idea is that the orientation θ_c is the statistical dominant direction among a coarsely chosen disperse orientations in the region of core point.

Based on the methods presented above, figure 1 shows some examples of pseudoridges extraction for typical fingerprints, and figure 2 shows some examples of symmetrical axis of the core estimation. In figure 1, the different color lines denote the results gained by different tracing ways (clockwise tracing or anti-clockwise tracing). And in figure 2, the black-white line denotes the correct orientation θ_c of the symmetrical axis of the region near the core, and the green line denotes the orientation which is determined by other factors (for example, the second maximum of the percentage for every template).

3 Fingerprint Classification Scheme

The Detection of singular points which is used in fingerprint classification has been reported in literature [21]. In this section, a refined fingerprint classification scheme is introduce as follows:

For the purpose of classification, the utilization of a global geometric feature to describe uniquely the general shape of fingerprint ridges within a particular class has been proposed. That each fingerprint class possesses a distinct geometric feature which is descriptive of the class' global ridge shape has been discovered. However, it is also observed that this global geometric feature of a particular class might also exist in another class. Nevertheless, it has been made a conjecture that this is due to a progression of the class ridge patterns from the simple to the complicated in which a distinct feature of a complicated or high class would not be found in a simple or lower class. Therefore, based on this understanding, in order to resolve the above feature ambiguity problem, operation in a top-down manner must be adopted [8], namely, the complicated or high class is determined in advance, secondly, the simple or lower class is determined. So, the order for fingerprint classification proposed in this paper is that the global geometric feature of the twin class is extracted firstly, and secondly the whorl class' is detected, then the other classes. The specific steps are as follows:

Firstly, the potential turns which are near the core points are found out from a set of the traced pseudoridges points above. The method is that the region, around which the distances between every vertices gained by tracing pseudoridges are very small and the number of vertices is considerable, is found out and the center point of this region is treated as the turn point.

Secondly, the global geometric framework (pseudoridge) traced is smoothed. The control vertices between which the distance is less than a threshold value are incorporated. Further, the above processed control vertices which are in a line on the whole and also in a predefined range are incorporated. After smoothing processing, the fake turning points would be reduced enormously and the subsequent computation is also cut down.

Finally, a set of vertices vectors which forms the turned ridges is found out from the set of vertices vectors in which the pseudoridge' corresponding control vertices are re-employed as approximating tangent vectors with each pair of vertices representing a vector in the direction of increasing indices. Assuming V to be the set of vertices vectors, a turn is made if

$$CosValue < -0.908 \tag{1}$$

where,

$$CosValue = v_i \cdot v_j / |v_i| \cdot |v_j| \qquad v_i, v_j \in V \qquad and \qquad i \neq j \tag{2}$$

Then, the vertices vectors which make up the turns should be signed and used for the following fingerprint classification.

(1). Classification of the twin type

The twin type should be determined by the unique feature that the twin type takes the shape of two non-monotonic turns or turns with opposite signs. See Fig. 3, if the number of the detected turns is two or more than two and there is a set of sequence vertices vectors which make up the turns: Va, Vb and Vc, where, Vc is the joint vector of two turns, and where the angle between the line from the center point of Vc to the center point of Va and the line from the central point of Vc to the central point of Vb is an obtuse angle, then the fingerprint is classified as a twin type. Otherwise, the next step should be carried through.

(2). Classification of the whorl type

In contrast with the twin type, a whorl ridge exhibits a spiral-like shape and takes the form of at least two monotonic turns or turns with similar signs. See figure 4, similarly, if the number of the detected turns is also two or more than two and there is a set of sequence vertices vectors which make up the turns: Va, Vb and Vc, where, Vc is the joint vector of two turns, and where the angle between the line from the central point of Vc to the central point of Va and the line from the central point of Vc to the central point of Vb is an acute angle, then the fingerprint is classified as a whorl type. Otherwise, the next step should be carried through.

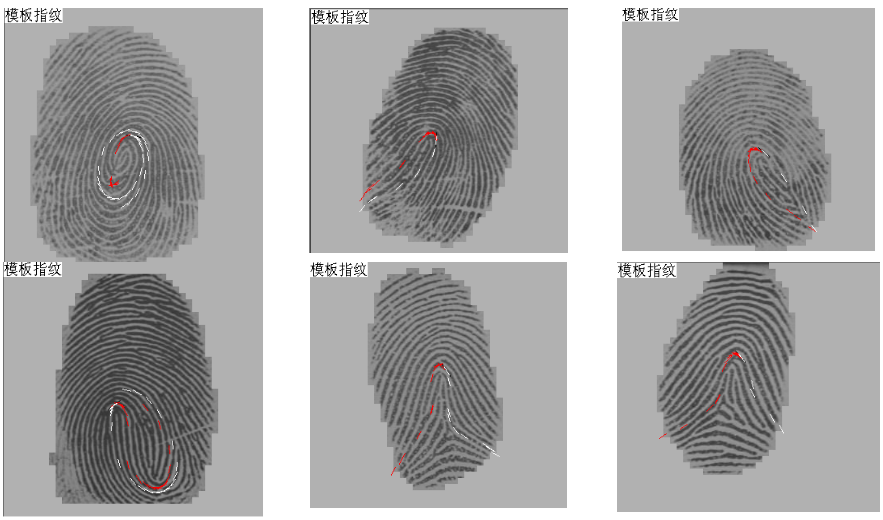

Fig. 1. Examples of pseudoridges extraction for typical fingerprints

(3). Classification of the loop type

If the number of turn is only one, then the core point should be checked by the turn point computed above. Namely, if the core point is near the turn point, then the core point is true, otherwise, the turn point replaces the core point. Subsequently, using the method presented above, the symmetrical axis of the region near the core is estimated. The position interrelation between the traced pseudoridge and the symmetrical axis of the core is determined. If the start point and the end point of pseudoridge are all on the left of the symmetrical axis, then the fingerprint is classified as a left loop type, if the start point and the end point of pseudoridge are all on the right of the symmetrical axis, then the fingerprint is classified as a right loop type.

In order to examine the case in which the pseudoridge's end point terminates on a side of the symmetrical axis (left or right) and forms another side's (right loop or left loop) trend, if the two end points are on each side of the symmetrical axis respectively, then the direction angle between the vector with the start point as well as its neighborhood point of pseudoridge and the symmetrical axis, and the direction angle between the vector with the end point as well as its neighborhood point of pseudoridge and the symmetrical axis, are both computed. If both position relations constituted by this two direction angles form the left loop trend and the direction angles are larger than a threshold value, then the fingerprint is classified as a left loop type. Or if both position relations constituted by this two direction angles form the right loop trend and the direction angles are larger than a threshold value, then the fingerprint is classified as a right loop type. Otherwise, the fingerprint is classified as a tented arch type.

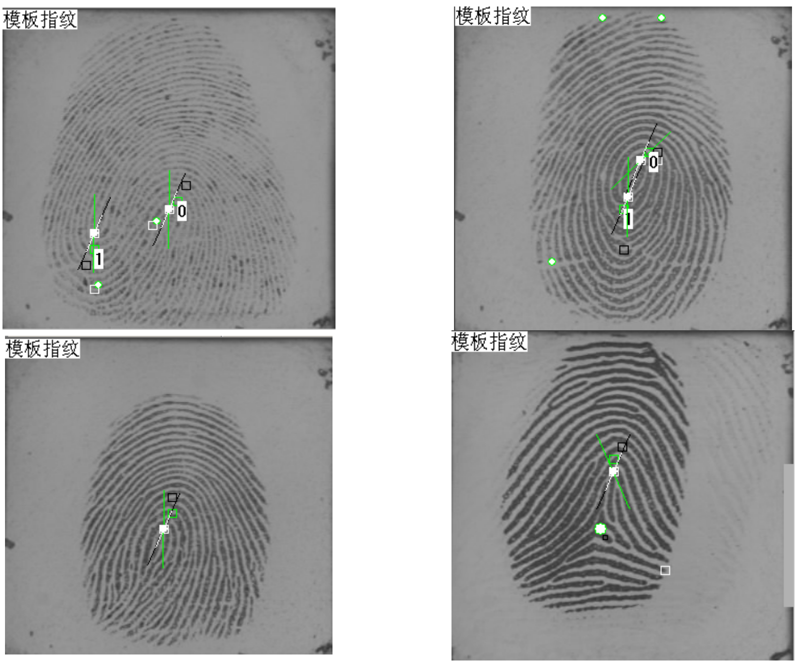

Fig. 2. Examples of the symmetrical axis of core

(4). Classification for the other cases

In other situations, the following cases should be considered:

A. If there are two core points or more than two core points, then a whorl type is assigned;

B. If there are a core point and a delta point, then judge the following conditions.

(i) If the angle, α, between the line segment from the core to the delta and the symmetric axis is less than a predefined threshold value, θthreshold, then a tented arch type is identified;

(ii) If α is more than θthreshold and the delta point is on the left of the core's symmetric axis, then the fingerprint is classified as a right loop type;

(iii) If α is more than θthreshold and the delta point is on the right of the core's symmetric axis, then the fingerprint is classified as a left loop type

C. If there are no core points and no delta points, or no turns in the traced pseudoridge, then a arch type is identified.

If the conclusion in the step (3) and the conclusion in the step B of (4) are same, then this conclusion is reserved, otherwise, the following steps should be carried through.

If the traced pseudoridge is mostly on the right of the line segment from the core to the delta, then the fingerprint is classified as a right loop type;

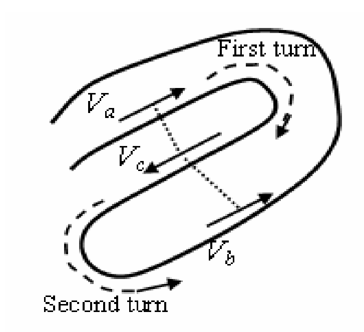

Fig. 3. Global geometric shape feature of the twin type

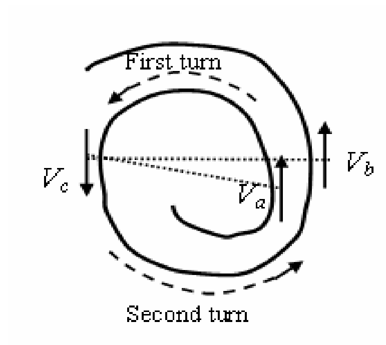

Fig. 4. Global geometric shape feature of the whorl type

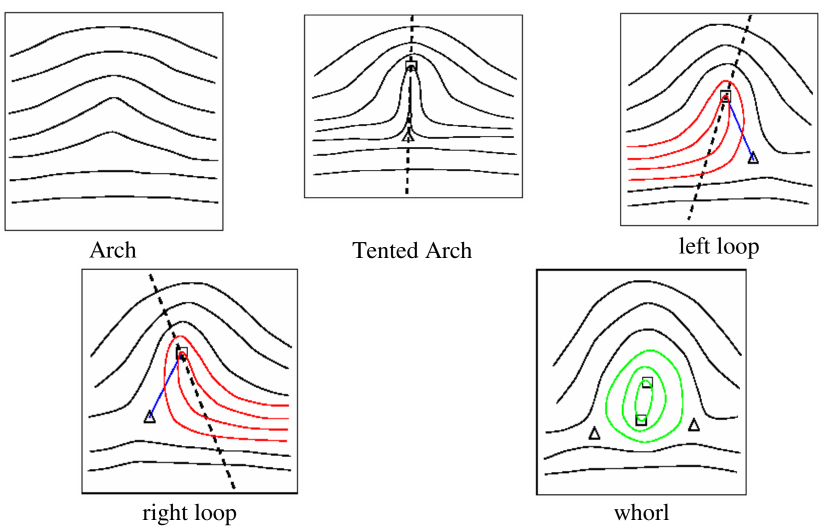

Fig. 5. Sketch maps of some fingerprint classes

If the traced pseudoridge is mostly on the left of the line segment from the core to the delta, then the fingerprint is classified as a left loop type;

Otherwise, the fingerprint is classified as a tented arch type.

If the conclusion in the step (2) and the conclusion in the step A of (4) are same, then this conclusion is reserved, otherwise, the conclusion in the step A of (4) is preferential.

Lastly, if none of the above conditions is satisfied, then the fingerprint is rejected.

4 Experimental Results and Conclusions

The classification algorithm described above has been tested on the 1000 typical fingerprints of NJU fingerprint database which contains 2500 images taken from 250 different fingers, 10 images per finger, and these fingerprint images are of varying quality in order to provide a realistic situation. The results are shown in table 1. The first column shows the class index, and the first row gives the assigned class using the current approach. The class index of one fingerprint in the database does not necessarily belong to only one class. According to the experimental results, the accuracy is 87% without rejection, if the tented arch and the arch are combined into one class, the accuracy rises to 92.2%. And a lower error rate can be achieved by adding the reject option based on the quality of the images.

Table 1. Experiment results tested on NJU fingerprint database

True Class	**Assigned Class**					
	Left loop	Right loop	Whorl	Tented Arch	Arch	Twin loop
Left loop	244	2	9	3	18	1
Right loop	3	259	7	1	11	2
Whorl	3	2	180	0	1	5
Tented Arch	4	5	1	96	45	0
Arch	0	2	1	2	69	0
Twin loop	2	0	8	0	0	78

The causes of mistake classification are that some images are of low quality due to noises, or that fingerprint images collection is not in its integrity, or that traced pseudoridges is wrong due to the geometric framework being around the central area where the modal area varies complicatedly. Meanwhile, our fingerprint database is not a special fingerprint classification database, so, our method should be tested and improved on the normal database for fingerprint classification (NIST-4 database) and that of the latent fingerprints.

At first glance, the fingerprint classification problem appears to be rather simple. But because of large intraclass and small interclass variations in global pattern configuration and poor quality of input images, the issue of fingerprint classification is still a real challenge.

Since the framework makes use of a global shape feature, it is less susceptible to the image noise, and combines but not completely uses the local feature such as core and delta points, the classification algorithm proposed in this paper also works well when false singular points exist or true singularities are missing. Moreover, our algorithm operation is irrelative to a fixed state of orientation and position, so it is invariant under transition and rotation. In the future, the focus will be put on improving the algorithm and investigating a practical fingerprint classification scheme which is based on the pattern similarity.

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