

COMBINING EXCLUSIVE AND CONTINUOUS FINGERPRINT CLASSIFICATION

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ABSTRACT

For efficient fingerprint matching, we propose to combine the advantage of exclusive and continuous fingerprint classification. We develop two combined fingerprint classification methods. The first method classifies a fingerprint into arch, left loop, right loop, tented arch, and whorl, then performs a continuous fingerprint classification in each class using the global rotation of the ridge flows or the distances between core points and delta points. The second method first classifies a fingerprint into arch, left loop, right loop, and whorl using the direction image around the reference point, and then performs a continuous fingerprint classification in each class using the FingerCode. Both methods can reduce fingerprint search time by nearly 95%.

1. INTRODUCTION

As one of the most mature biometric technologies, fingerprints have been used for personal identification for a long time. The purpose of fingerprint identification is to determine whether a query fingerprint is present in a fingerprint database. Whether the query fingerprint can be identified correctly or not is primarily dictated by the performance of the employed matching technique. However, it is very time consuming to match a query fingerprint with all the fingerprints in a large database. Researchers have proposed several fingerprint-indexing approaches to reduce the search time and computational complexity. The most popular method is fingerprint classification, including exclusive classification and continuous classification.

Most researchers use exclusive classification approaches, where fingerprints are partitioned into a number of pre-specified categories and a query fingerprint needs to be compared only with the fingerprints of the same category in the fingerprint matching process. Exclusive classification approaches can be categorized as: syntactic [9], singularities-based [10], structure-based [5][14], frequency-based [4], neural network-based [8][12][15], and hybrid [6][13] approaches. Their

performance strongly depends on the number of classes and on the distribution of fingerprints. Most exclusive classification approaches classify fingerprints into three to six subclasses of the six general classes: arch (A), tented arch (T), whorl (W), left loop (L), right loop (R), and twin loop. Twin loop is merged with the whorl class in a five-class fingerprint classification. Left loop, right loop, and tented arch are sometimes merged in some other cases. According to the fingerprint distribution (A = 3.7%, L = 33.8%, R = 31.7%, T = 2.9%, W = 27.9%), a common five-class fingerprint classification mechanism can cut down the search time by about 70 percent.

For continuous classification, a distance measure is usually defined for some special points in fingerprints [3][16][17]. Query fingerprints are compared only with those fingerprints whose distance measure is similar to the query fingerprint, i.e. the difference between the two is lower than a pre-specified threshold. The larger the threshold is, the more accurate the classification is, at the same time, the less time can be saved by the method.

In order to further reduce the fingerprint search time we propose a new method to combine the advantage of both approaches, by performing continuous classification after an exclusive classification step. In this paper, we will introduce two combined fingerprint classification methods. The first method classifies a fingerprint into arch, left loop, right loop, tented arch, and whorl, then performs a continuous fingerprint classification in each class using the global rotation of the ridge flows or the distances between core points and delta points. The second method first classify a fingerprint into arch, left loop, right loop, and whorl using the direction image around the reference point, and then performs a continuous fingerprint classification in each class with the FingerCode.

2. COMBINED CLASSIFICATION

2.1. Singularity-based approach

The singularity-based combined fingerprint classification approach is composed of an exclusive classification and a

further continuous classification. While the first exclusive classification step uses the locations of singular points (core and delta) to classify a fingerprint into five classes: arch, left loop, right loop, tented arch, and whorl, the second continuous classification step represents fingerprint in each subset as a value, describing the global rotation of the ridge flow for an arch-type fingerprint or the distance between the core point(s) and the delta point(s) for other-type fingerprints.

The exclusive classification can be summarized as follows:

1. Compute, smooth, and average the direction image using the same algorithm as in [1]. The direction image is tiled into windows of size 5×5 .
2. Compute the Poincare index for each sub window by summing up the direction changes of its 8-connected neighbors in the counterclockwise direction. Here the difference between two angles is normalized in $(-90^\circ, 90^\circ)$.
3. Locate all core and delta points and then classify the fingerprint image based on the number and locations of these points, as described in [10].

After exclusive classification, a further continuous classification is performed for each class. The maximum rotation C_R of the ridge flow is estimated for arch fingerprints, while the mean distance C_D between each core point and each delta point is computed for others. These C_R or C_D can be used to sort or index the fingerprints in the same category after the exclusive classification. Thus, search can be performed in a certain category and the query needs to be compared only with those fingerprints whose C_R or C_D are within a certain range centered at that of the query fingerprint. Figure 1 shows some fingerprint samples with different C_R or C_D .

According to the statistic on NIST-4 fingerprint database, C_R covers a wide range from 50° to 130° (See Figure 1.a), and C_D covers a wide range from 2 to 32 times of the mean ridge distance (See Figure 1.b-e). So we expect that the proposed approach can improve the performance.

Note that, the performance strongly depends on the veracity of the singular points location. It is not suitable for some live-scan fingerprint identification (with small size fingerprint sensors), since the singular points, especially delta points, maybe lost. In such case, FingerCode-based classification method may be a better alternative.

2.2. FingerCode-based approach

The FingerCode-based combined fingerprint classification approach is also composed of an exclusive classification

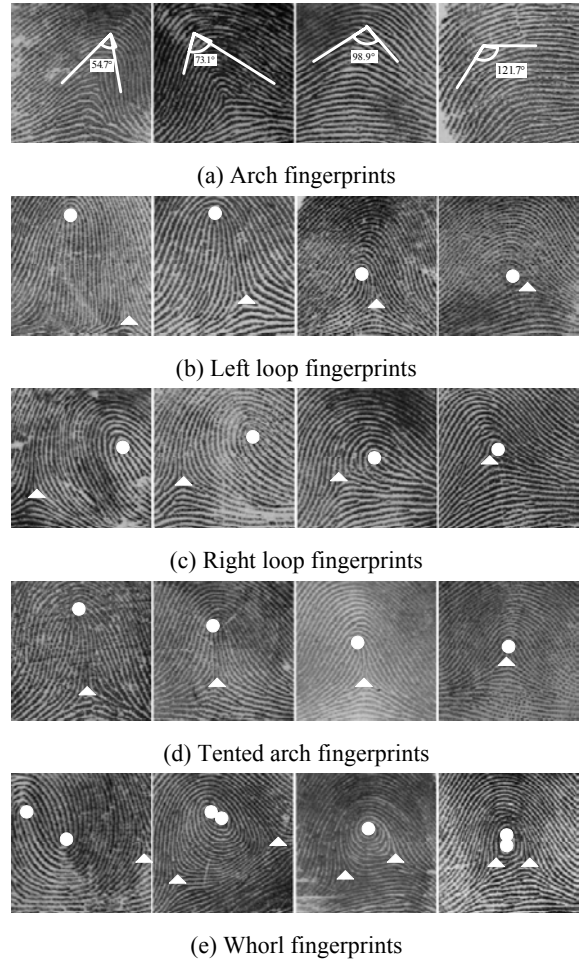


Figure 1 Fingerprints with different C_R or C_D values (● indicates core point, ▲ indicates delta point).

step and a continuous classification step. The exclusive step classifies a fingerprint into four classes: arch, left loop, ridge loop, and whorl, according to the summation of the direction changes around the reference point, and the continuous step represents the fingerprint as a quantity of the FingerCode.

2.2.1. FingerCode

FingerCode, introduced in [1], is a fixed length representation that can effectively capture both the local and global details in a fingerprint, with a bank of Gabor filters. The typical FingerCode generation process can be summarized in the following steps:

1. Locate the reference point and determine the region of interest for the fingerprint image.
2. Tessellate the region of interest, centered at the reference point, into a series of B ($=5$) concentric bands and each band is sub-divided into k ($=16$) sectors.

3. Normalize each sector to a specified constant mean M_0 (=100) and variance V_0 (=100).
4. Filter the region of interest in eight different directions using a bank of Gabor filters.
5. Compute the average absolute deviation from the mean (AAD) of gray values in each of the 80 sectors for every filtered image. The collection of all the AAD features in each filtered image is defined as FingerCode.

In this paper, we use the reference point location method we developed recently [11], which is robust and rotation-invariance. The average orientation of each sector is also computed.

2.2.2. FingerCode-based classification

For an arch fingerprint, the reference point is located at the point of maximum curvature of the concave ridges in the fingerprint image. For a loop (left loop, right loop, and tented arch) fingerprint, the reference will be located near the only one core point. For whorl (twin loop included) fingerprint, the reference point is near the center of the two core points. Thus, exclusive classification can be achieved by determine the direction change around the reference point. Based on this observation, we propose a new exclusive classification algorithm as follows:

1. Calculate the direction changes DC_i in each band.
2. If the maximum value DC of $\{DC_i\}_{i=1}^5$ is 2π , classify the fingerprint as whorl; otherwise go to step 3.
3. Compute the difference between the average orientations of each sector with the radial direction. Find two sub-divisions with local minimum difference summation along the radial direction.
4. For $DC = \pi$, if directions along the two sub-divisions, from the center to the outside, both show a typical “V” structure, classify the fingerprint as whorl; otherwise, the fingerprint is a loop fingerprint.
5. For $DC = 0$, if any one of the directions along the two sub-divisions presents a typical “V” structure, classify the fingerprint as loop; otherwise, the fingerprint is an arch fingerprint.
6. For loop fingerprints, find the sub-division with minimum difference summation along the radial direction. Classify the fingerprint as left loop if the average direction trend is a “)” structure, otherwise it is right loop.

After such exclusive classification, fingerprints are quantified with their FingerCode and then the fingerprint

database is sorted in every category. The quantification criterion can be defined as follows:

$$Q = \sum_{i=17}^{64} (\bar{V}_i^2 + \hat{V}_i^2)$$

Where \bar{V}_i and \hat{V}_i are the two corresponding FingerCode components in the tangent and normal directions in the i_{th} sector, and the most inner and outer bands are dropped because they are relatively unsteady when noise exists.

3. EXPERIMENTS

To evaluate the performance of the proposed algorithms, we conduct experiments on the standard fingerprint database, containing 4000 (2000 pairs) 256-graylevel fingerprints (512×480). For each pair of fingerprints, one image is put into the enrolled database, while the other one is put into the query queue. Every fingerprint image in the query queue will be identified in the enrolled database.

In the simulation of singularity-based approaches, considering that we aim to study the performance of continuous classification mechanism but not a simple existing five-class exclusive classification method, the singular points are located by hand for better accuracy. Figure 2 shows the overall performance. We find that in each fingerprint class, the continuous classification approach can achieve a similar performance with the previous continuous classification approaches [3][16][17]. Therefore, in addition to the 70% saving of exclusive classification, our second step continuous classification further reduces the search time by nearly 80%. So totally nearly 95% saving is achieved. We effectively combine the advantage of the exclusive classification and continuous classification.

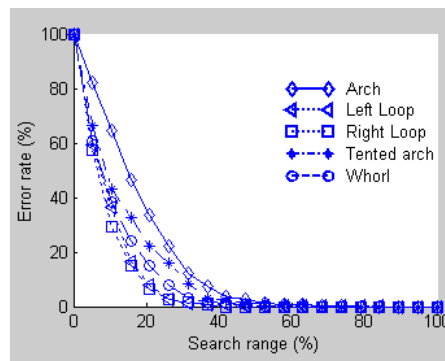


Figure 2. Error rate V.S. Search range graph of singularity-based continuous classification technique.

Table 1 shows the exclusive classification result of the new FingerCode-based classification approach, and Figure 3 shows the performance of its continuous classification technique. We can see that using the direction change can classify the fingerprint into four classes with high accuracy. We find that the FingerCode-based continuous

classification mechanism can further save the search time in each category by about 75~80%. So the total saving is again nearly 95%.

Table 1. Four-class classification result using the FingerCode-Based exclusive classification approach.

First fingerprint	Second fingerprint				Accuracy (%)
	Arch	Left loop	Right loop	Whorl	
Arch	501	13	11	0	95.42
Left loop	7	483	4	1	97.58
Right loop	14	9	521	3	95.25
Whorl	0	2	7	424	97.92

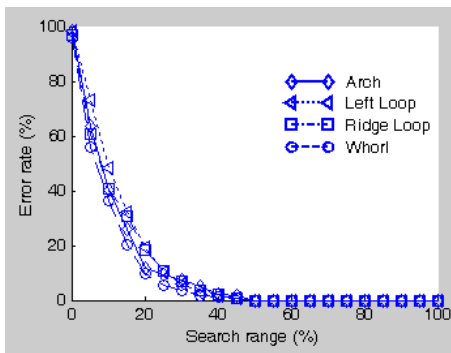


Figure 3. Error rate V.S. Search range graph of FingerCode-based continuous classification technique.

4. CONCLUSION

We have proposed two types of combined fingerprint classification schemes. They both contain an exclusive classification step and a following continuous classification step, based on singularities and FingerCode respectively. The exclusive classification approach can reduce the search time by about 70~75 percent, and the continuous classification approach can further reduce it by about 75~80 percent. Both methods effectively combine the advantage of the exclusive and continuous classification. In addition, the FingerCode-based method is suitable for live-scan fingerprint identification (with small size fingerprint sensors), where the singular points, especially delta points, may be lost.

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