Fingerprint Identification Based on Frequency Texture Analysis

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Abstract

Nowadays the AFIS (Automatic fingerprint Identification system) plays more and more important roles in various applications such as access control, ATM card verification and criminal identification. The most wildly used fingerprint identification algorithm today is based on spatial minutia detection and matching, which needs a time consuming revision during the matching phase. The proposed frequency-based algorithm uses Fourier Transform to code an enhanced fingerprint image into a series of float numbers namely feature sector, where the minutia and the ridge information are fused together in the fingerprint enhancing phase. The matching is simply to calculate the absolute distance between the two feature sectors. Because the use of FFT and the concentric circle sampling method, our algorithm achieves the geometric distortion invariant ability and a high matching speed. The experiment results prove the feasibility of our algorithm, and our future research work to improve the performance is presented finally.

1. Introduction

Fingerprint as a part of Biometrics, has grown significantly in the past decade. Lots of outstanding algorithms have been proposed, and some of them have already been used in industry[1]. In a fingerprint identification system, one’s fingerprint is sampled and compared with a pre-built fingerprint database to identify his/her identity. The most widely used Fingerprint identification algorithm today, is based on spatial minutia extracting and matching, which mainly relies on the local spatial information namely minutiae. Although the minutia based algorithm has achieved a high accuracy, other useful discriminatory information is despised in the feature extraction. Furthermore, in the matching step of the minutia-based algorithm, minutiae need to be revised according to the template to conquer the translation and the rotational distortion of the fingerprint images[1], which is time consuming, and make the fingerprint identification system unpractical on large fingerprint databases. A new approach based on the spatial ridge texture was proposed in [3]. In which, the raw fingerprint image was firstly filtered in eight different directions using a bank of Gabor filters, and then the standard deviation of the gray values in the sectors around the central point were computed to generate a feature vector, based on which the fingerprint was matched. Although the ridge information has been made used in [3] and the matching time cost is greatly reduced, the information provided by the minutiae is ignored, and the algorithm is not rotational invariant. Another method based on the Fourier transform has been put forward in [4], in which it achieves an acceptable balance between the accuracy and the speed, but the minutiae information is disregarded also. Though the minutiae and the ridges information are used together in [5], it is in the matching phase but not in the feature extracting phase that the two discriminating features are fused, which equals to matching the fingerprint twice to improve the discriminating ability.

In this paper, a novel fingerprint identification algorithm based on the frequency texture is proposed, and four sections are presented to depict it. The algorithm and the implementation are described in Section 2. The experiment results are analyzed in Section 3. The conclusion and the future work are presented in Section 4.

2. Algorithm and implementation

2.1. Basic idea

The fingerprint image is usually translationally and rotationally distorted during its collection. In
traditional ways, the time consuming revision is used before matching to conquer the distortion, and it slows down the identification speed greatly. The Fourier Transform changes every pixel of the image into a set of frequency value together with their associated amplitudes and phases. The spatial information of the original image is contained only in the phases, and is got rid of in the amplitudes. If the amplitude value of the frequency image is sampled by concentric circles, the extracted feature would be both translational and rotational invariant. Furthermore, if the information provided by the minutiae is used to enhance the input image of the Fourier Transform, the minutiae and the ridge information can be integrated together in the feature extracting phase.

In our algorithm, the raw fingerprint image is firstly enhanced, and then transformed into the frequency domain by FFT. The feature vector is generated by sampling the FFT frequency image using the concentric circles, and the matching is simply carried out by calculating the absolute distance of the feature vectors.

2.2. Enhancement

Because the varieties of the collection condition, the fingerprint wetness, and the fingerprint abrasion, the raw fingerprint image varies in quality. The enhancement is necessary for fingerprint images before the feature extraction. We use the enhancement algorithm based on the Gabor filter proposed in [7] to enhance the raw fingerprint image as shown in Figure 1. Afterward, since in FFT, the pixel with larger value contains more energy, the image is thresholded and the pixels’ grey value is reversed to make it more appropriate for FFT (see Figure 2).

2.3. The energy distribution enhancement of the inter-process image

The fingerprint is comprised chiefly by the minutiae and the ridges, all of which are considered important discriminating features of fingerprints. There is little algorithm before can fuse the two features together in one match, and the combination of the two features may leads to a higher identification rate. In our algorithm, the location information provided by the minutiae is used to enhance the energy distribution of the input image for FFT. As the ridges near the minutiae should be considered more important, it is reasonable to enhance the energy distribution of the fingerprint image according to the distribution of the minutiae. Namely, the pixels’ value around the minutiae will be increased to amplify the influence of the area around the minutiae, and the grey value of the pixels far away from the minutiae should be decreased accordingly. (see Figure 3) It is decided by the quality of the fingerprint images for how much the pixels’ value should be changed. If the fingerprint image quality is good, there are more minutiae can be extracted right, so the area around the minutiae should occupy more energy.

2.4. FFT-based feature extraction

After the enhancement of the energy distribution, the inter-process image is transformed into frequency domain by FFT and sampled by concentric circles. (see Figure 4). For each circle, the frequency values on it are added together to form the float type finger code of this circle, the array of different finger codes on respective circles is the matching feature vector for the fingerprint at last. The size of the feature vector is decided by the number of the sampling concentric circles, which is decided by the size of the fingerprint image. The larger the fingerprint image is, the larger
the feature vector size should be. In the experiment of this paper, the feature vector size \( L \) is 120.

Figure 4. Sample the FFT image

2.5. Matching

The matching is quite simple for our algorithm. Let \( V_{f1} = (a_1, a_2, \ldots, a_n) \) and \( V_{f2} = (b_1, b_2, \ldots, b_n) \) denote the feature vectors of the two fingerprints to be matched, \( T_m \) denote the thresholds used in the matching process. The absolute difference vector \( V_d \) of the two fingerprint feature vectors is calculated by:

\[
V_d = \left( \frac{|a_1 - b_1|}{\max(a_1, b_1)}, \frac{|a_2 - b_2|}{\max(a_2, b_2)}, \ldots, \frac{|a_n - b_n|}{\max(a_n, b_n)} \right)
\]

Define the absolute distance of the two matching factors[6]:

\[
R_m = \sum_{i=1}^{n} \frac{|a_i - b_i|}{\max(a_i, b_i)}
\]

Then the matching result is:

\[
\begin{cases}
\text{Success} & \text{if } R_m \geq T_m \\
\text{Failed} & \text{if } R_m < T_m
\end{cases}
\]

Where the thresholds: \( T_m \) varies according to the quality of the fingerprint images. For different fingerprint collecting sensor, the quality of the fingerprint images would be different, thus the threshold should be adjust accordingly. According to the experiment, the better the fingerprint image is, the larger \( T_m \) should be. In our experiment, the \( T_m \) is 12.

3. Experimental result and analysis

Figure 5 shows the distribution of the \( V_d \) calculated from two images of the same fingerprint. And Figure 6 shows the distribution of the \( V_d \) of two images from different fingerprints. The average value of the \( V_d \) from the same fingerprint is 0.069, and almost all the finger codes stay below 0.1463. While the average value of the \( V_d \) from two different fingerprints is 0.278, and almost all the finger codes stay above 0.1336. It can be inferred that our algorithm has a good ability in discriminating different fingerprints.

Figure 5. The \( V_d \) of the same fingerprint

Figure 6. The \( V_d \) of two different fingerprints

115 images from 23 fingerprints are tested in the experiment. Since the fingerprints are matched against each other, 6555 times matches are carried out. The FRR is 26.09% for a FAR of 1.5%. This performance needs to be improved significantly. The average time to calculate the template (feature vector) is 0.5s, and the average matching time is 4.53us (Tested on Intel Pentium4 3.0GHz, 512 memory), which is extremely low comparing with the traditional ways.

4. Conclusions

In this paper, the minutia and the ridge information are fused to generate the discriminating feature of the fingerprint. The experimental result shows that the feature vector \( V_d \) is good enough to discriminate different fingerprints.

Since it needn’t revision in the matching step, the matching speed of our algorithm is much faster than traditional ways. As a result, this algorithm is quite appropriate for the identification, which needs a lot of
matching computing when comparing the inputted fingerprint with the templates in Databases.

The accuracy of our algorithm is still unsatisfactory, which is because the fingerprint images collected by the sensors are always incomplete, different part of the same fingerprint will generate a much different $V_d$, which can cause a false reject. If the fingerprints are collected completely, the accept rate would be much higher. The future work of us will be focused on the improvement of the sensor to make it more suitable for our algorithm. We will also exert ourselves on the frequency transformation algorithm to make it work better on fingerprint images.

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5. References


