A GABOR FILTER-BASED APPROACH TO FINGERPRINT RECOGNITION

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Abstract - We propose a Gabor-filter-based method for fingerprint recognition in this paper. The method makes use of Gabor filtering technologies and need only to do the core point detection before the feature extraction process without any other pre-processing steps such as smoothing, binarization, thinning, and minutiae detection. The proposed Gabor-filter-based features play a central role in the processes of fingerprint recognition, including local ridge orientation, core point detection, and feature extraction. Experimental results show that the recognition rate of the k-nearest neighbor classifier using the proposed features is 97.2% for a small-scale fingerprint database, and thus that the proposed method is an efficient and reliable approach.

INTRODUCTION

Because of unchangeability and uniqueness, fingerprints have been widely applied in several fields of personal identification such as criminal investigation, access control, and Internet authentication. In fingerprints, the ridge structures can provide global and local information. Therefore, most researchers use the local ridge orientation of fingerprints for classification and use the minutiae, a group of ridge endings and bifurcations, for identification. However, the minutiae-based approach is very sensitive to noise and deformation. For instance, false ridge endings and bifurcations may appear due to blurred or overinked problem. Moreover, ridge endings and bifurcations may disappear because the finger is pressed too hard or too light [1]. In other words, the performance of minutiae extraction algorithms relies heavily on the quality of input images. Furthermore, the main steps for a minutiae-based approach are image acquisition, enhancement, ridge extraction, thinning, minutiae detection, and matching [2] [3]. For a small-scale fingerprint recognition system, however, it would not be efficient to process all the steps and the recognition result will be heavily dependent on the accuracy of each step.

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The Gabor-filter-based features, directly extracted from gray-level fingerprint images, have been successfully and widely applied to texture segmentation [4] [5], face recognition [6], and handwriting recognition [7]. In fingerprint applications, the Gabor-filter-based features for enhancement [8], classification [9] and recognition [10] are also proposed. The characteristics of the Gabor filter, especially the frequency and orientation representations, are similar to those of the human visual system [11]. In this paper, we will propose the use of Gabor filter-based features for all steps of fingerprint recognition consisting of local ridge orientation, core point detection, and recognition. At last, we will use a small-scale fingerprint database to test the performance of the proposed method.

GABOR FEATURES AND THE PROPOSED METHOD

In [7], the general form of a 2D Gabor filter is defined by

$$h(x,y,\theta_k,f,\sigma_x,\sigma_y) = exp[-\frac{1}{2}(\frac{{x_{\theta_k}}^2}{{\sigma_x}^2} + \frac{{y_{\theta_k}}^2}{{\sigma_y}^2})] \times exp(i2\pi f x_{\theta_k}), \qquad (1)$$

where $x_{\theta_k} = x\cos\theta_k + y\sin\theta_k$ and $y_{\theta_k} = -x\sin\theta_k + y\cos\theta_k$, f is the frequency of the sinusoidal plane wave, θ_k is the orientation of the Gabor filter, and σ_x and σ_y are the standard deviations of the Gaussian envelope along the x and y axes, respectively. To analyze the Gabor filter in terms of the even-symmetric and the odd-symmetric, we express eqn. 1 in the complex form $h = h_{even} + ih_{odd}$, where

$$h_{even}(x,y,\theta_k,f,\sigma_x,\sigma_y) = exp[-\frac{1}{2}(\frac{{x_{\theta_k}}^2}{{\sigma_x}^2} + \frac{{y_{\theta_k}}^2}{{\sigma_y}^2})] \times \cos(2\pi f x_{\theta_k}) \qquad (2)$$

$$h_{odd}(x,y,\theta_k,f,\sigma_x,\sigma_y) = exp[-\frac{1}{2}(\frac{{x_{\theta_k}}^2}{{\sigma_x}^2} + \frac{{y_{\theta_k}}^2}{{\sigma_y}^2})] \times \sin(2\pi f x_{\theta_k}). \qquad (3)$$

Since most local ridge structures of fingerprints come with well-defined local frequency and orientation, f can be set by the reciprocal of the average inter-ridge distance and m as the number of orientations for calculating $\theta_k = \pi(k-1)/m, k = 1,\dots,m$. Also, the cosine/sine form and the sinusoidal-shape of the Gabor filter is suitable for modeling ridge structures and smoothing out noise, respectively. After deciding the parameters of the Gabor filter, the magnitude Gabor feature, the even one, and the odd one at sampling point (X, Y) can be defined as follows:

$$g_{mag}(X,Y,\theta_k,f,\sigma_x,\sigma_y) = |\sum_{x=-w/2}^{w/2-1}\sum_{y=-w/2}^{w/2-1} I(X+x,Y+y)h(x,y,\theta_k,f,\sigma_x,\sigma_y)|, \qquad (4)$$

$$g_{even}(X,Y,\theta_k,f,\sigma_x,\sigma_y) = \sum_{x=-w/2}^{w/2-1}\sum_{y=-w/2}^{w/2-1} I(X+x,Y+y)h_{even}(x,y,\theta_k,f,\sigma_x,\sigma_y), \qquad (5)$$

$$g_{odd}(X,Y,\theta_k,f,\sigma_x,\sigma_y) = \sum_{x=-w/2}^{w/2-1} \sum_{y=-w/2}^{w/2-1} I(X+x,Y+y) h_{odd}(x,y,\theta_k,f,\sigma_x,\sigma_y), \tag{6}$$

where $I(\cdot,\cdot)$ denotes a $w \times w$ 256 gray-level image. We find that the magnitude Gabor features at the sample point and those of its neighboring points within three pixels are similar, while the others are not. This is because the magnitude Gabor filter consists of both the cosine and sine form, so the magnitude Gabor feature has the shift-invariant property. In [10], we showed that only the magnitude Gabor features could be sufficiently used as fingerprint features. It is insufficient to use either the even Gabor features or the odd features alone. For simplicity, we will call the magnitude Gabor feature as Gabor features in the sequel. If the parameters of the Gabor filter are determined, m $w \times w$ Gabor matrices are obtained. Then, each block is sampled by these matrices and m Gabor features are obtained. A $w \times w$ block is then compressed to m meaningful Gabor features.

Local Ridge Orientation

After obtaining m Gabor features,g_{θ_k}, of the block, its local ridge orientation is computed as follows:

$$\Theta = \frac{\sum_{k=1}^{m} g_{\theta_k} \times \theta_k}{\sum_{k=1}^{m} g_{\theta_k}} \tag{7}$$

where $\theta_k = \pi(k-1)/m, k = 1,\ldots,m$. In [2], [8] and [12], for estimating the local ridge orientation it needs to compute the gradients or direction of each pixel, making the complexity increased and the computation expensive. The local ridge orientation is similar to Gabor features in the block direction, but Gabor features have more information (such as ridge density, ending and bifurcation) than just the local ridge orientation. Besides, Gabor features can be directly obtained from gray-level images, and then the value of local ridge orientation is obtained from Gabor features. It is appropriate to use Gabor features to represent the ridge structures of fingerprints.

Core Point Detection

In the recognition stage, the comparison of two fingerprints must be based on the same reference point. The core point, the topmost point on the innermost upward recurving ridge, is the outstanding feature in fingerprints. We use this point as the reference point. According to the local ridge orientation of a fingerprint image, Poincare index [12] [2] or structure information [13] can be applied to find the singular points including the core and delta points. However, these methods must compute the local ridge orientation and search the whole fingerprint image. To overcome the above problem, we develop a fast method to detect the core point by using Gabor features directly.
The following properties can be found by observing the fingerprint images:

1. The intersections of the radii of curvatures for upper ridges are always near the core point.

2. The Gabor features of the adjacent blocks of the core point block have to satisfy the following criteria:

$$g_{45^\circ}(X-1,Y) + g_{90^\circ}(X-1,Y) \gg g_{135^\circ}(X-1,Y) \tag{8}$$

$$g_{135^\circ}(X+1,Y) + g_{90^\circ}(X+1,Y) \gg g_{45^\circ}(X+1,Y) \tag{9}$$

$$g_{0^\circ}(X,Y-1) \gg g_{0^\circ}(X,Y) \tag{10}$$

The adjacent horizontal and vertical blocks of the core point block, $C(X,Y)$, are shown in eqn. 11,

$$\begin{bmatrix} \times & C(X,Y-1) & \times \\ C(X-1,Y) & C(X,Y) & C(X+1,Y) \\ \times & \times & \times \end{bmatrix} \tag{11}$$

where $\times$ is a "don't care" term. According to above properties, we develop a fast algorithm to detect the core point:

1. Sample some points in the upper part of the fingerprint and find the average of the points at the intersections of the radii of curvatures, obtained from their Gabor features.

2. Search the neighborhood of the intersection and use above rules to find the core point.

The Proposed method

Except the frequency and orientation representations, the Gabor features are easily and directly obtained. Therefore, these features are very suitable for representing the ridge structures of fingerprint for core point detection and recognition. A fast real-time algorithm is proposed as follows:

1. Detect the core point of each fingerprint image using the Gabor features of some sampling points.

2. According to the core point, divide the fingerprint image into a set of 8×8 non-overlapping blocks and sample the set by the Gabor filters; then $12 \times 15m$ Gabor features can be obtained for each image.

3. Use these features as the input vector and recognize it with k-nearest neighbor (k-NN) classifiers.

Fig. 1 shows the schematic block diagram of the proposed method.

EXPERIMENTAL RESULTS

Figure 1: Block diagram of the proposed method

In general, the inked fingerprint recognition is more difficult than the inkless because the noisy fingerprint image is easier obtained and no restriction on the position and orientation for inked method. To develop a robust fingerprint recognition system, we adopt inked fingerprint database to test our algorithm. In our database, we collected 192 inked fingerprint images from 16 persons (12 images per finger) and captured their digital format with a scanner at 200dpi and 256 gray-level resolution. Although the NIST fingerprint databases [14] are sampled at 500dpi, the fingerprint images can be recognized at 200dpi by the human eyes. For a small-scale fingerprint recognition system, the use of low-resolution images is efficient and practicable. Fig. 2 shows some of the fingerprint images in our database with different ink pressures and different positions and orientations.

To design the parameters of the Gabor filters, we set $f = 1/2\sqrt{2}$, the reciprocal of the average inter-ridge distance, which is approximately equal to pixels, and $\sigma_x = \sigma_y = 2.0$ is determined empirically. For the steps of local ridge orientation and core point detection, the Gabor features with $m = 4$ are enough. The Gabor features of two fingerprints belonging to the same person and different persons with $m = 4$ (that is $\theta = 0°, 45°, 90°$, and $135°$) are shown in Fig. 3 and 4, respectively. From Fig. 3 and 4, we find that the same person's Gabor features are similar and those of different persons are not. This reveals that the Gabor features can be used as the fingerprint features. In the following, we use these features as the input vectors to the classifiers and compare their accuracy.

In k-NN experiments, we select k images per individual as the training database ($16k$ images) and the remaining $16 \times (2 - k)$ images as the test database. The results of recognition rates with no rejection option for $m = 4$ and $m = 8$ are shown in Table 1. From Table 1, we find that the accuracy for $m = 8$ is only slightly better than that for $m = 4$. This means that the Gabor features with four orientations are sufficient. Besides, the accuracy for 1-NN classifier with $m = 8$ is higher than 90% and the 3-NN is up to 97.2%. This proves that the use of Gabor features for fingerprint image is not only efficient, but also robust.

Table 1. Results of recognition rates

Classifier	1-NN		2-NN		3-NN	
m	4	8	4	8	4	8
accuracy(%)	88.6	90.0	93.8	94.4	96.5	97.2

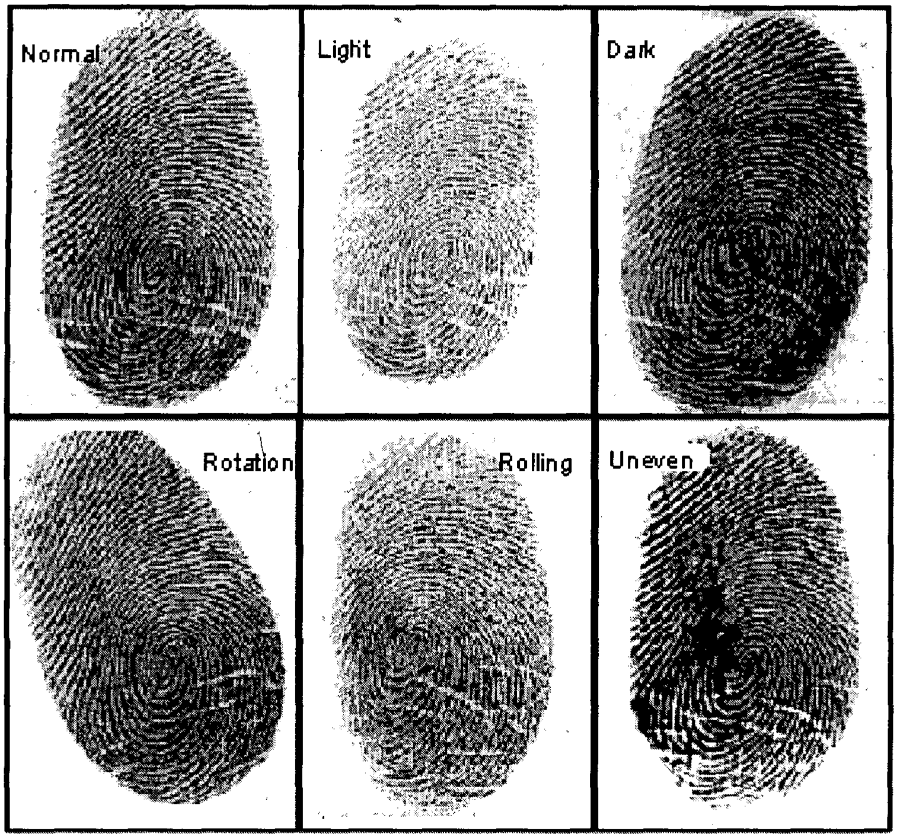

Figure 2: Some examples from our fingerprint database

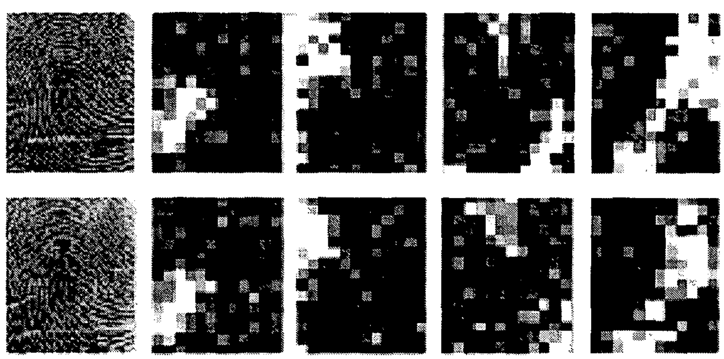

Figure 3: Gabor features of two fingerprints belonging to the same person with $m = 4$

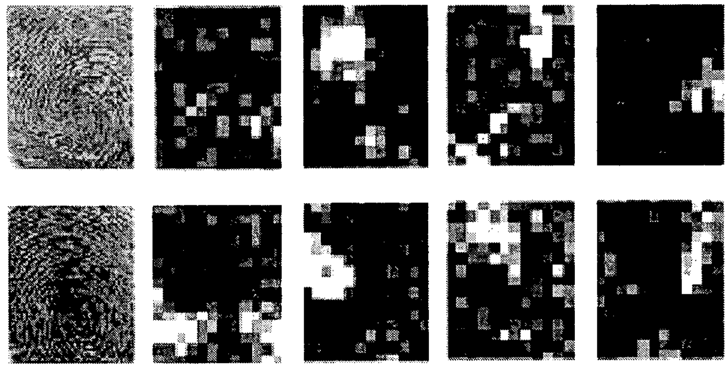

Figure 4: Gabor features of two fingerprints belonging to different persons

CONCLUSIONS AND FURTHER RESEARCH

In this paper, we have developed a fast and robust approach to fingerprint recognition. The proposed approach is simple in the preprocessing process, where only one step, the core point detection, needed before feature extraction. The complexity and computational expensiveness are considerably reduced as compared to the minutia-based approach. Because of the effective representation for both the global and local information in fingerprint, the Gabor features can be successfully applied to local ridge orientation, core point detection, fingerprint classification and recognition .

To further increase the accuracy, our future work is to develop an algorithm to automatically tune the parameters of the Gabor filters and design an efficient classifier to test our algorithm with a large-scale fingerprint database.

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