PERGAMON

Pattern Recognition 34 (2001) 2245–2248

**PATTERN
RECOGNITION**

THE JOURNAL OF THE PATTERN RECOGNITION SOCIETY

www.elsevier.com/locate/patcog

Rapid and Brief Communication

Fingerprint feature reduction by principal Gabor basis function

Chih-Jen Lee, Sheng-D. Wang*

Department of Electrical Engineering, National Taiwan University, EE Building, Room 441, 1 Roosevelt Road, Sec 4 Taipei 106, Taiwan

Received 15 December 2000; accepted 15 January 2001

1. Introduction

Fingerprint patterns are full of ridges and valleys and these structures provide essential information for matching, recognition, and classification. Conventionally, most researchers use minutiae, a group of ridge endings and bifurcations, as the features of fingerprint patterns [1]. Unfortunately, the minutia-based approach contains many time-consumption steps and relies heavily on the quality of input images. In fingerprint images, however, minutiae are not always clear even though the information of ridge directions and inter-ridge distances is preserved.

To avoid above drawbacks, therefore, we proposed a Gabor-based approach to extract features directly from the raw images without involving preprocessing and convolution [2]. This approach applied a bank of Gabor filters to every region of fingerprint images and used their responses as the feature vectors for recognition. That is, we did not concern the positions of minutiae, but the responses of a bank of Gabor filters. To obtain a satisfactory recognition result, nonetheless, this approach needs a lot of time to find a suitable bank of Gabor filters by global consideration.

In fact, each local fingerprint has its particular ridge direction and spatial-frequency. In order to capture these intrinsic characteristics of ridge structures, we propose a local Gabor-based approach to determine the suitable Gabor filters by using only local information. For further feature reduction, the selected Gabor filter is mapped to an index of the complete Gabor basis functions (GBFs). At last, we also compare GBFs in the spatial-frequency domain to illustrate the similarities of ridge structures

and analyze the feasibility of the proposed method to test a small-scale access control system.

2. Fingerprint images and Gabor basis functions

2.1. Power spectra of fingerprint images

In a local fingerprint image, the ridge directions and inter-ridge distances are similar. To analyze the phenomenon of fingerprint images in the spatial-frequency domain, we transfer these images by Fourier transform and observe their power spectra. Fig. 1(a) shows some various directions with similar inter-ridge distances and Fig. 2(a) shows some various inter-ridge distances with the same orientation. The corresponding 2-D power spectra are shown in Figs. 1(b) and 2(b), respectively. All power spectra have two high peaks, which are symmetric to the origin. According to the ridge direction and inter-ridge distance, each pair of twin peaks has its particular position on the spatial-frequency plane. That is, the intrinsic characteristics of fingerprint images are easily captured in the spatial-frequency domain rather than the spatial domain.

2.2. Gabor expansion, Gabor responses, and principal GBF

Because Gabor filters have the abilities of orientation selectivity and spatial-frequency selectivity, we use these filters to capture the orientation and spatial-frequency of a local ridge structure. The 2-D complete set of GBFs can be expressed as [3]

$$G_{pqrs}(x, y) = \exp\left\{-\frac{[(x-p)^2 + (y-q)^2]}{\sigma^2}\right\} \exp[2\pi j(xr + ys)/N_f], \quad (1)$$

where $j = \sqrt{-1}$, $p, q = 0, 1, \dots, N_s - 1$, and $r, s = -N_f/2 + 1, -N_f/2 + 2, \dots, -1, 0, 1, \dots, N_f/2 - 1, N_f/2$.

* Corresponding author. Tel.: + 886-2-2363-5800; fax: + 886-2-2363-8247.

E-mail addresses: sdwang@hpc.ee.ntu.edu.tw (S.-D. Wang), cjlee@hpc.ee.ntu.edu.tw (C.J. Lee).

Fig. 1. (a) Original images and corresponding (b) power spectra (c) responses and (d) coefficients of GBFs for various ridge directions.

N_s is the number of spatial samples, (p, q) is the spatial window center, and σ decides the extent of spatial windows. N_f is the number of spatial-frequency samples and (r, s) is the location of the frequency center. The angle θ and radial frequency f of GBF are determined by $\tan^{-1}(s/r)$ and $\sqrt{(s/N_f)^2 + (r/N_f)^2}$, respectively. Their relationship on the spatial-frequency plane is demonstrated in Fig. 3. As shown in Ref. [3], the orientation-selective property of the GBF is obvious in the spatial domain.

A raw image $I(x, y)$ can be expressed as a combination of the complete 2-D GBFs. The Gabor expansion equation is

$$I(x, y) = \sum_p \sum_q \sum_r \sum_s c_{pqrs} G_{pqrs}(x, y), \quad (2)$$

where c_{pqrs} is the Gabor coefficients indicating their importance for image reconstruction. Unfortunately, the

computational complexity of Gabor coefficients comes from the non-orthogonality of the GBFs, so we use Gabor responses instead.

The Gabor response g of each GBF corresponding (r, s) is defined as follows:

$$g(r, s) = \left| \sum_p \sum_q I(x, y) G_{pqrs}(x, y) \right|, \quad (3)$$

where I is a $N_s \times N_s$ input image. Figs. 1(c) and 2(c) show the corresponding Gabor responses from Figs. 1(a) and 2(a). The Gabor responses also have twin peaks and the corresponding locations are similar to their Fourier power spectra. This means that the two corresponding GBFs (in fact, they are the same) have the highest responses to the local fingerprint image. The orientation and spatial-frequency of the corresponding GBF can represent mainly the local region because the image

Fig. 2. (a) Original images and corresponding (b) power spectra (c) responses and (d) coefficients of GBFs for various ridge frequencies.

Fig. 3. Parameters of GBF on the spatial-frequency plane.

energy concentrates at its frequency. In other words, a local fingerprint image can easily be captured the main characteristics by using only one GBF. We name it as the principal GBF of the local region. Figs. 1(d) and 2(d) show the corresponding magnitudes of Gabor coeffi-

cients. The corresponding positions of the principal GBFs are also the brightest.

3. Fingerprint recognition

Because the principal GBF can exactly capture the orientation and spatial-frequency of a local ridge structures, the input dimension is reduced from pixels to only one GBF. A GBF, determined by (r, s) , can also be reduced to an index of the complete GBFs for storage. If a local region has 16×16 pixels, for example, then there are 256 GBFs and the index of the principal GBF needs only one byte. That is, the input feature vectors are reduced by a factor of 256.

If two fingerprint patterns are collected from the same fingerprint, the ridge directions and inter-ridge distances of the corresponding local regions in fingerprint images

Fig. 4. Block diagram of the proposed method.

Table 1
Results of recognition rate (%)

k patterns/person	1	2	3
Local	90.9	95.6	97.9
Global	88.6	93.8	96.5

are very similar. In other words, the locations of the corresponding principal GBFs are quite near on the spatial-frequency plane, even though there is a little rotation. That is, we can differentiate their similarities from the distance of the corresponding principal GBFs on the spatial-frequency plane. Moreover, the (r, s) of the principal GBF just reflects its location on the spatial-frequency plane. Although the principal GBF is stored as an index value, it is very easily converted to (r, s) by division. Therefore, we adopt a set of (r, s) values from every local fingerprint image as the input feature vectors for recognition.

The whole procedure, including only three processes, is shown in Fig. 4. To avoid the error from the core point detection algorithm, we point out the core points of all fingerprint patterns manually. Based on the core point, we crop the fingerprint image into 96×112 pixels and divide the cropped image into a set of 16×16 non-overlapping regions. According to the maximum Gabor responses to find the principal GBFs of all regions, 6×7 (r, s) values are obtained for each fingerprint image. In the recognition stage, we select single nearest-neighbor (NN) classifier to avoid gaining benefits from the classifier.

4. Experimental results

To compare with Ref. [2], we use the same fingerprint database, which contains 192 fingerprint patterns from

16 persons. In single NN experiments, k patterns per individual are selected as the training database ($16k$ patterns) and the rest $16 \times (12 - k)$ patterns as the test database. The results of recognition rates with no rejection option are shown in Table 1. From Table 1, we find that the recognition rate of the proposed method with only two patterns per individual is higher than 95% and all situations are superior to the global approach.

Besides the recognition rates are improved, the storage for the features of fingerprint patterns is also reduced. In the global approach, a bank of Gabor responses, which are floating point values, is stored for a local region. Nonetheless, only an unsigned integer index value is stored for the principal GBF in the local approach.

5. Conclusions

We develop a local Gabor-based approach to extract the intrinsic characteristics of a local fingerprint image for recognition. The proposed method illustrates that the principal GBF can capture the main characteristics of ridge orientation and ridge frequency when the raw image is transformed into the Gabor space. Therefore, the feature dimension of a local region can be reduced to an index value. On the spatial-frequency plane, according to the locations of the principal GBFs, we can measure the similarities of two local ridge structures easily. Moreover, the recognition rates are also better than the global approach. In conclusion, the proposed approach is efficient and feasible.

References

- [1] A.K. Jain, L. Hong, R. Bolle, On-line fingerprint verification, *IEEE Trans. Pattern Anal. Mach. Intell.* 19 (4) (1997) 302–314.
- [2] C.J. Lee, S.D. Wang, Fingerprint feature extraction using Gabor filters, *Electron. Lett.* 35 (4) (1999) 288–290.
- [3] R.A. Baxter, SAR image compression with the Gabor transform, *IEEE Trans. Geosci. and Remote Sensing* 37 (1) (1999) 574–588.