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New Features Extraction and Application in Fingerprint Segmentation[1)]

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Abstract We present a useful and effective fingerprint image segmentation. We extract two new features with which our algorithm can distinguish the blurred area from foreground, and, therefore, can reduce the number of false minutiae. We use supervised RBF neural network to classify patterns and select typical patterns to train the classifier. Experimental results show a significant improvement in fingerprint segmentation performance.

Key words Biometrics, image processing, fingerprint, segmentation, neural networks, RBF networks

1 Introduction

Fingerprints are the most widely used biometric features for personal identification because of their invariance and uniqueness. A fingerprint is the pattern of ridges and valleys on the surface of a fingertip. The uniqueness of the fingerprint can be identified by the characteristics and relationships of bifurcations and endings in the ridges or valleys (Figure 1). In order to compare two fingerprints, a set of invariant and discriminating features are extracted from the fingerprint images. Most verification systems providing a high security are based on minutiae matching[1,2].

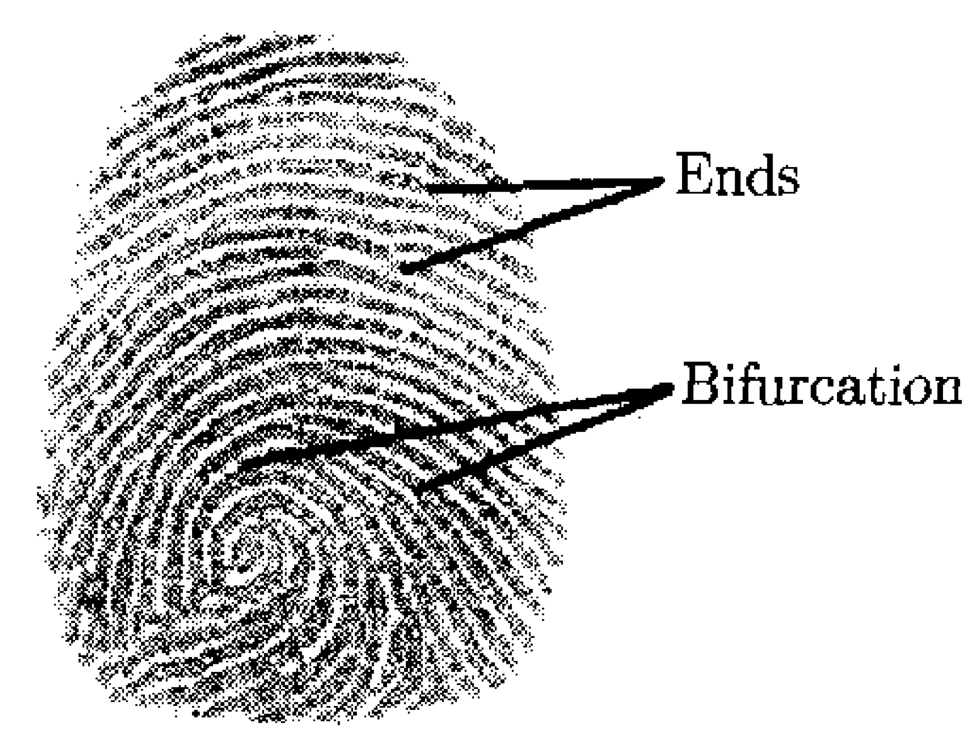

Fig. 1 Examples of minutiae: end and bifurcation

Because more powerful and intelligent image processing techniques are available with the development of computer technology, the automatic fingerprint identification system has become a reality[1]. Unfortunately, noise, image deficiency and deformation may make reliable minutiae detection very difficult. Therefore, one important step in automatic fingerprint identification is the segmentation of fingerprint images. In this paper, the foreground includes good pattern of ridges and valleys. The background includes blurred area and blank area. Because we may extract false minutiae in blurred area, this can heavily influences the performances of the minutiae extraction process and the performance of the overall fingerprint identification system. However, if the segmentation can classify between foregrounds and blurred area, it can reduce the number of false minutiae. In many segmentation algorithms, features they extract can not completely present the feature of pixels, so their algorithm can only identify the blank area but can not classify between foreground and noisy or blurred area[2].

In this paper, we present two new features: contrast and main energy ratio. After that, we use these two new features and other two features and well trained RBF networks to classify foreground and background. Finally, we present some experimental results.

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2 Preprocessing

2.1 Normalization

Because the quality of fingerprint images captured by fingerprint scanner is influenced by many facts, such as dryness and wetness of finger, cleanness of scanner and dryness and wetness of the weather, we firstly use normalization to remove the effects of sensor noise and finger pressure difference[3].

$$N(i,j) = \begin{cases} M_0 + \sqrt{\dfrac{VAR_0 \times (I(i,j)-M)^2}{VAR}}, & \text{if } I(i,j) > M \\ M_0 - \sqrt{\dfrac{VAR_0 \times (I(i,j)-M)^2}{VAR}}, & \text{otherwise} \end{cases} \tag{1}$$

where M_0, VAR_0 are the desired mean and variance values.

2.2 Smooth and histogram equalization

After normalization, we use Gauss-smooth to reduce the influence of noises, and use histogram equalization to make the input fingerprint image look clear.

3 Extraction of new features

3.1 Feature extraction

The first step of segmentation is feature selection. In [4], there are three features which are mean, variance and coherence. However these three features can not completely present the feature of blurred area, so we present the other two new features.

We classify the foreground and background with four features which are contrast, main energy ratio, variance and coherence.

Since fingerprint mainly consists of parallel structures, the coherence in foreground is higher than that in blurred area and blank area. The block is $w \times w$ and the definition of coherence follows[5]:

$$O_x(i,j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} 2G_x(u,v)G_y(u,v); \quad O_y(i,j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} (G_x(u,v)-G_y(u,v))^2 \tag{2),(3}$$

$$O_E(i,j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} (G_x(u,v)+G_y(u,v))^2; \quad \text{coherence} = \sqrt{\frac{O_x^2(i,j)+O_y^2(i.j)}{O_E(i,j) \times w \times w}} \tag{4),(5}$$

where $G_x(i,j)$ $G_y(i,j)$ are the gradients at each pixel.

3.2 Contrast —the first new feature

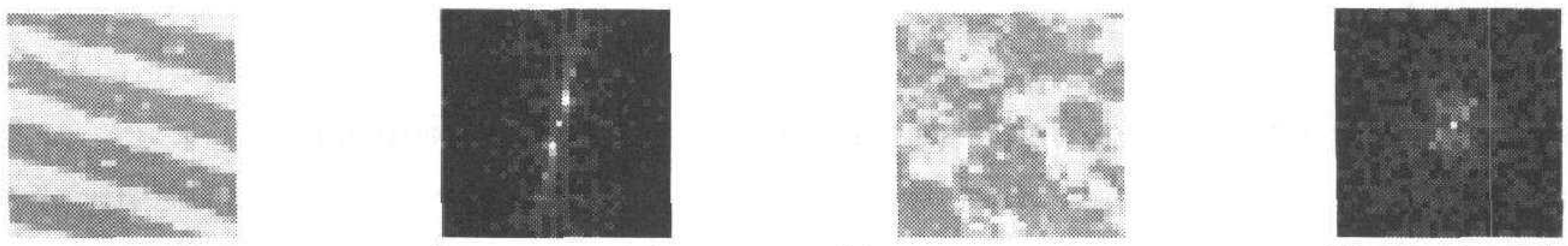
One new feature is the contrast, which is the normalization of variance. The contrast is defined as:

$$m = \frac{\sum_i \sum_j I(i,j)}{w \times w}; \quad v = \sum_w (I(i,j) - m)^2; \quad \text{contrast} = \frac{v}{m} \tag{6), (7), (8}$$

where v is variance in one block, m is mean of one block and $I(i,j)$ is the intensity of the image.

3.3 Main energy ratio—the second new feature

The other new feature is the main energy ratio. A good fingerprint pattern contains narrow ridges separated by narrow valleys and the ridges are almost parallel to each other. The Fourier spectrum of this small area reveals two high peaks except the DC components. However, if the fingerprint pattern is not good enough, the peaks are not distinct[6] (Figure 2).



(a) are original images (b) FFT's of (a) (c) are original images (d) FFT's of (c)

Fig. 2 FFT of fingerprint blocks

So this method can distinguish fingerprint signal area and noise area[7]. This feature extraction algorithm follows:

1) Divide image to blocks of size $w \times w$ (16×16);

2) Transform each block image from spatial domains into frequency domains using FFT;

3) Search for the two peaks except the DC components. The two peaks are symmetrical to the DC components;

4) Because of noise, we define main energy ratio as

$$\text{Main Energy Ratio} = \frac{E_{p1} + E_{p2}}{E - (E_{p1} + E_{p2})} \tag{9}$$

$$E = \sum_{s} F(i,j), \quad \text{if } F(i,j) > E_{p1} \times 30\% \tag{10}$$

where $F(i,j)$ is the value of image in the frequency domain after FFT, s is a circle with radius of r, r is the distance from the peak to the DC component and is round to the nearest integer, E_{p1} is the value of one peak, E_{p2} is the value of the other peak, E_{p1} is approximately equal to E_{p2}.

4 Design the classifier

In [4], a linear classifier was used. Because the pattern may not be linearly classified, there could be an error[8]. We use the RBF network to classify and this can reduce the error which was produced in [4]. The radial basis function is Gauss-kernel function and this PBF network has 4 inputs, one output and three layers[9]. The number of nodes in the hidden layer is determined by the result of training and the target error is 0.0001.

We selected 250 foreground blocks and 250 background blocks and computed the four features in each block. We used these features to train the RBF network and determined every parameter in the RBF network.

We used the well trained RBF network to classify the input fingerprint image. Firstly, we divided the input fingerprint image into $w \times w$ blocks and computed the four features in each block. After that, we put these features into RBF network and classified each block in the input fingerprint image into foreground and background. If a block is foreground then $B(i,j)=1$, else $B(i,j)=0$. After image B is obtained, the classification is completed. We can also compute the percentage of foreground. If the percentage of foreground regions is smaller than a threshold, then the input fingerprint image is rejected.

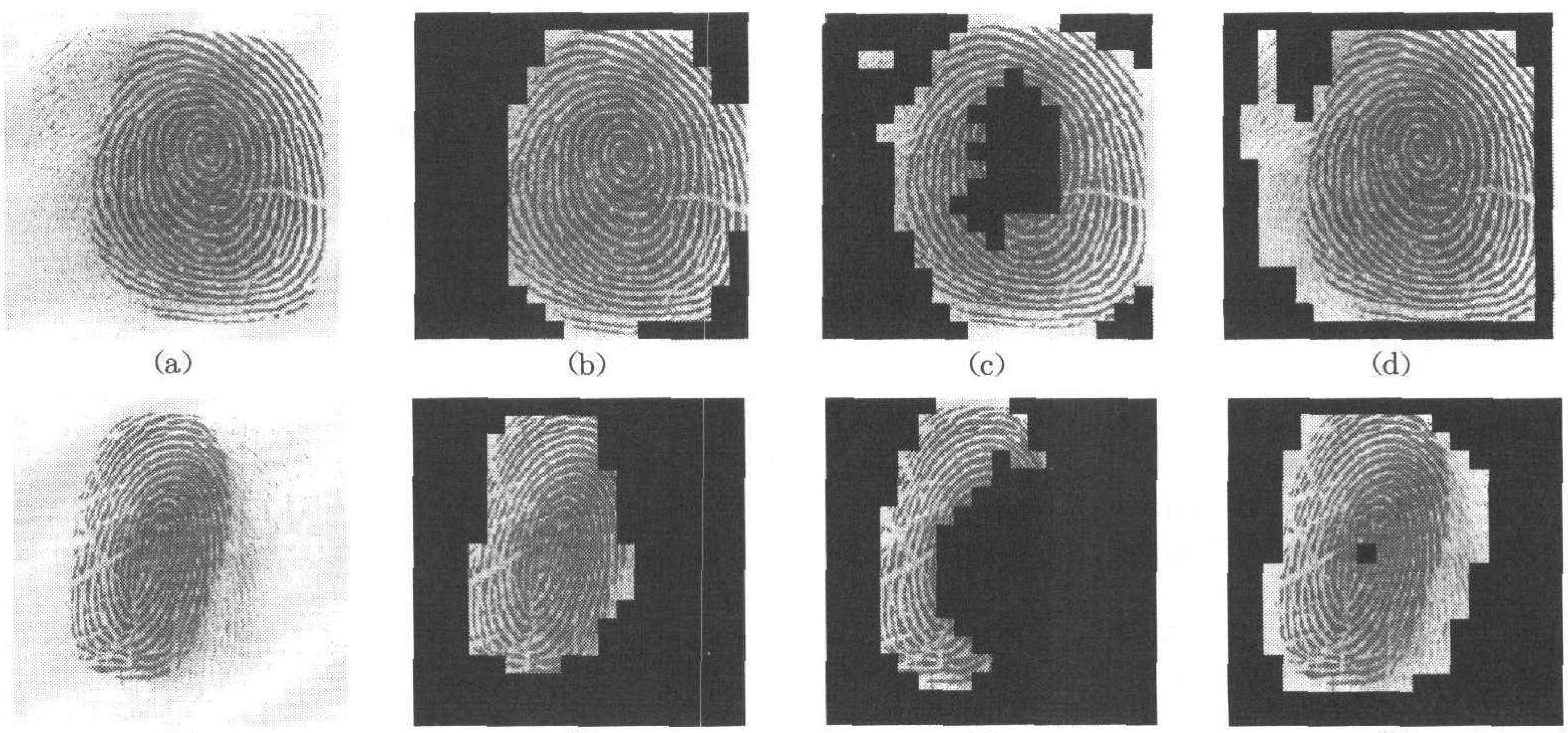
5 Experiment results

In order to validate the performance of our algorithm, this algorithm was tested with the NIST24 standard fingerprint database and the fingerprint database which consists of fingerprint images of size 300×300 captured by a Veridicom™ COMS sensor. We also compared our algorithm with the segmentation algorithm based on direction and the segmentation algorithm based on gray level. We selected randomly 4000 fingerprint images in the NIST24 and the fingerprint database captured by a Veridicom™ COMS sensor, respectively and used three algorithms to classify the foreground and background. The experimental results showed that our algorithm is better than the other two algorithms and is robust in fingerprint image segmentation. Our algorithm is also suitable to the extremely dry fingerprint images and extremely wet fingerprint images.

We select two images in the test database which is captured by a Veridicom^{TM} COMS sensor (the size is 300×300). From the result, we can see that our algorithm has good performance in fingerprint images which have noise, sweat spot and false trace.

In feature 4, the new features we extracted present the pattern of the blurred area well, so the blurred area is identified. However, other algorithms can not identify the blurred area and extract many false features in the blurred area, so the precision of the whole system is reduced.

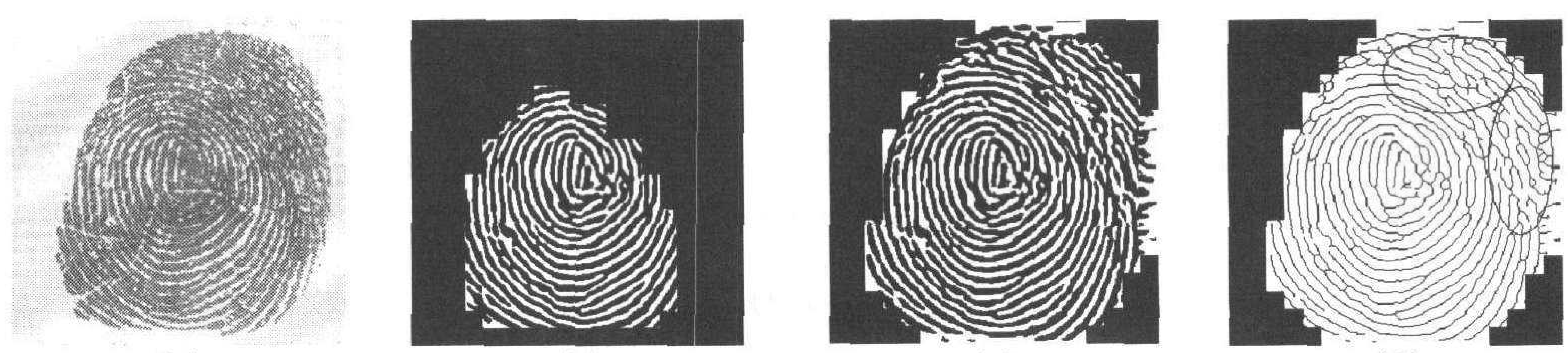
From the experimental results, we can see that our algorithm can identify the blurred area, reduce false minutiae and improve the performance of the fingerprint identification system.



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig. 3 (a) The original fingerprint image with sweat spot; (e) The original fingerprint image with false trace; (b), (f) The results of our algorithm; (c), (g) The results of algorithm based on direction; (d), (h) The results of algorithm based on gray level. The black blocks are the background



(a) (b) (c) (d)

Fig. 4 (a) The original fingerprint image with blurred area; (b) The result of our algorithm after Enhancement and Binarization; (c) The result of algorithms based on direction and gray level after Enhancement and Binarization; (d) The result of other algorithms after thinning and many false minutiae in blurred area (indicated by circles)

Our algorithm of segmentation is efficient and effective, but the result of our algorithm is not very accurate in the edge of fingerprint images and there may have an error because the new features our presented are efficient only when the block is big enough (the size of block is 16×16). However, the minutiae usually do not appear in the edge and when they appear in the edge, the result of minutiae extraction in the edge area is influenced by the enhancement, binarization and thinning.

6 Conclusion

In this paper, we present a segmentation algorithm based on multi-features. In many other papers, they almost can not accurately identify the blurred area and may extract many false minutiae in this area. Because we use the two new features which can present the pattern of blurred area very well, the result of segmentation is highly improved.

We also use RBF network as a classifier and this reduces the deficiency created by the linear classifier. The RBF network is affected by only small parameters and has high training speed compared with global approaching network. So the use of RBF network can improve the accuracy and efficiency of fingerprint image segmentation. The experimental results show that our algorithm not only has a good effect of segmentation but reduces the influence of noise.

References

1 Jain A, Hong L, Bolle R. On-line fingerprint verification. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 1997, **19**(4): 302～314

2 Tico M, Lungu S. Fingerprint segmentation based on directional information. *Acta Technical Napocensis - Electronics and Telecommunications*, 1998, **38**(1): 1～5

3 Hong L, Wan Y, Jain A. Fingerprint image enhancement: Algorithm and performance evaluation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 1998, **20**(8): 777～789

4 Bazen A M, Gerez S H. Segmentation of fingerprint images. In: Proceedings of ProRISC 2001 Workshop on Circuits, Systems and Signal Processing, Veldhoven, 2001

5 Wang S, Zhang W, Wang Y S. Fingerprint classification by directional fields. In: Proceedings of the IEEE 4th International Conference on Multimodal Interface 2002, Pittsburgh, 2002. 395～398

6 Kovacs Z M, Rovatti R, Frazzoni M. Fingerprint ridge distance computation methodologies. *Pattern Recognition*, 2000, **33**:69～80

7 Sherlock B G, Monro D M, Millard K. Fingerprint enhancement by directional Fourier filtering. *IEEE Proceedings Vision, Image Signal Process*, 1994, **141**(2): 87～94

8 Bian Zhao-Qi, Zhang Xue-Gong. Pattern Recognition. Beijing: Tsinghua University Publishing House, 2000(in Chinese)

9 Huang De-Shuang. Neural Network Pattern Recognition System Theory. Beijing: Electronics Industry Publishing House, 1996 (in Chinese)

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指纹图像分割中新特征的提出及其应用

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摘　要　指纹身份鉴定是最可靠的身份鉴定方法之一.指纹图像的分割是自动指纹识别系统中的重要一步.在本论文中,我们提出了一种高效实用的指纹图像分割方法.我们提取出了能使分割算法更加精确的两个新特征.在其它的很多分割算法中,由于应用的特征不能很好的反映出模糊区的特征,因此不能够很好的区分前景和模糊区.由于可能在模糊区提取出虚假的细节,这将很大的程度上影响指纹识别系统的整体性能.然而,由于我们提出的两个新特征,我们的算法可以和很好的区分出前景与模糊区,因此该分割算法可以降低虚假细节的数目.我们选用监督的RBF神经网络来进行分类并选取典型的样本用来训练.实验结果说明我们的分割算法在性能上有一个很大的提高.

关键词　生物识别,图像处理,指纹识别,分割,神经网络,RBF网络

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