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Fuzzy automata system with application to target recognition based on image processing

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ABSTRACT

In order to get better image processing and target recognition, this paper presents a fuzzy automata system to target recognition. The system first performs image processing, and then accomplishes the target recognition. The system consists of four parts: image preprocessing, feature extraction, target matching and experiment. Compared with existing approaches, this paper uses both global features and local features of the target image, and carries out target recognition by using a fuzzy automata system. Simulation results show that the correct recognition rate based on the fuzzy automata system for target recognition is higher at 94.59%, an improvement on an average of 29.24%, compared to other existing approaches. Finally, some directions for future research are described.

1. Introduction

In the modern society of higher information age, target recognition and identity validation become more and more important in our life, for instance, finance, security, network, digital electric business, etc. The traditional methods are unsafe by using passwords or certificates because it is possible to forget passwords, and it is easy to forge certificates, which has fallen short of the requirements of a modern digital society. However, recognition technologies based on target features show wide applied prospects.

As an important aspect in target recognition, image recognition has many virtues, such as the uniqueness and the feature of data collected, etc. In addition, there are some target images, for example, recognizing a person using a human face or iris, that has the virtue of uniqueness, stability and nonaggression [1]. At present, there are many image processing algorithms [2–5]. The Canny operator [3] and Susan operator [2] were relatively perfect operators for edge detection and corner detection of images. 2D-wavelet transforms could be used in filter smoothening, eliminating noise, enhancement and compression of image, etc. [4,5]. The Gabor filter [2,3] performed well in texture segmentation.

Because of the gradually complicated signal environment and some requirements of the secrecy in communication and military affairs, etc., the feature information of targets has a certain extent fuzzy character. However, the fuzzy functions [6] and fuzzy approaches [7–10] were an effective tool in the process of fuzzy feature information processing. Image processing algorithms and characteristics of fuzzy functions provide a powerful base on target recognition. We improve the Susan operator to image processing in this paper, and make use of the fuzzy operators other than the usual

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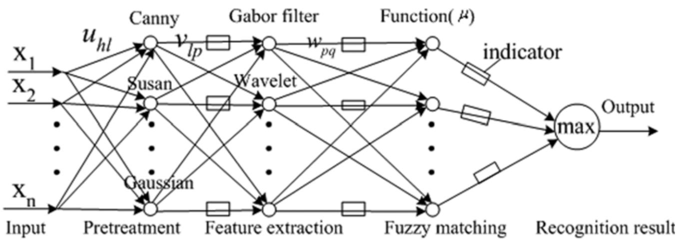

Fig. 1. Fuzzy automata system to target recognition.

recognition operator [11,8,12]. In order to get better image processing and target recognition, this paper presents a system for target recognition based on fuzzy automata (FA). The Fig. 1 shows the FA model for image processing. The system consists of four parts: image preprocessing, feature extraction, target matching and recognition. The simulation results indicate that the correct recognition rate of this system is high at 94.59%. These researches on the system not only develop fuzzy automata theories, but also enhance and promote the combination of FA and image processing in broad applications. Finally, we give a view for future research.

2. Image preprocessing

In the preprocessing layer of FA, there exist M neurons that are the operators to image processing, such as the Canny operator [3] and the Susan operator [2], etc. Based on these operators to image processing and by adjusting the weights u_{hl} of the input layer, the image processing can be better performed, where u_{hl} is the membership degree of transitions between the sub-states of FA, and $0 \leqslant u_{hl} \leqslant 1$. At the same time, it needs to adjust the membership degree u_{hl} between the input layer and the preprocessing layer. The adjustment for u_{hl} is: From the display of data obtained in neurons of this layer, if the local characteristic information of the image is more, we increase the value of weight u_{hl}, otherwise, we decrease its value, where $h = 1, 2, \dots, N$ is the number of input value, $l = 1, 2, \dots, M$ is the number of neurons in the preprocessing layer. At time t, the input S_l^t in the preprocessing layer is $S_l^t = b_l + \sum_h u_{hl} I_h^t$, where b_l is a regulating constant, I_h^t is the information data of an input image.

The purpose of image preprocessing is to do better work for locating features of image and feature extraction. The images we get by the gathering equipment not only contain the target to be recognized, but also contain other non-target parts and some noise. Because of illumination and other reasons, the images are probably fuzzy. These conditions will bring some difficulties to feature extraction and exact matching for the target image in next step, so it is necessary to do preprocessing to eliminate some influences of side effects that are brought by the above factors to the image. The image preprocessing includes smoothness, eliminating noise, enhancement, edge detection in an image and its localization. Because the 2D-wavelet transform can be used for filter smoothness, elimination of noise, enhancement and compression of the image, etc. [4,5], this paper mainly uses the Wavelet Transform for carrying out image preprocessing.

The wavelet is gaining more and more attention for its favorable time–frequency characteristics. The two-dimensional continual wavelet can be defined as

$$\Psi(a; b_1, b_2) = \frac{1}{a}\Psi\left(\frac{x_1 - b_1}{a}, \frac{x_2 - b_2}{a}\right) \tag{1}$$

where $\Psi(x_1, x_2)$ denotes a two-dimensional mother wavelet.

The fundamental model for image processing is the two-dimensional continual wavelet transform, i.e.,

$$WT_f(a; b_1, b_2) = \frac{1}{a}\iint f(x_1, x_2)\Psi\left(\frac{x_1 - b_1}{a}, \frac{x_2 - b_2}{a}\right) \mathrm{d}x_1 \mathrm{d}x_2 \tag{2}$$

where $f(x_1, x_2) \in L^2(R^2)$ is a two-dimensional signal.

The type of mother wavelet that is determined by the type of the filter determines the result of wavelet transform. Here we adopt the Daubechies-4 Wavelet [4] that is widely used.

2.1. Denoising the image

If the image was damaged on many sides, for example, the image was dirtied, or the texture was dissevered, we need to perform image filtering to reduce or eliminate the noise so that the outline of the image is distinct. For better extracting the target features, denoising processing of the image is necessary.

The common denoising methods for an image are the wavelet threshold value denoising method, which it is a simple and effective denoising method. The threshold value denoising method deals with the each layer coefficient of decomposed wavelet, respectively, where these coefficients are greater than or smaller than some threshold value, and then makes use of the processed wavelet coefficient to reconfigure the denoised image. In training sets, for a given image with bigger white noise, we make use of two-dimensional wavelet analysis to carry out the denoising processing for a signal. Here, the wavelet is decomposed to be 5-layered for denoising of the image. The original image is Fig. 2(a), and the image with noise is Fig. 2(b). The denoised image is shown in Fig. 2(c) and (d).

2.2. Smoothening the image

In order to improve the edge detection of the image, smoothening the image is necessary. For images with a higher SNR (signal noise rate), we use the convolution of the Gaussian function and the image signal to filter images. For a lower SNR, we use the wavelet transform for smoothness processing.

The main purpose of smoothening an image is to reduce the noise. In training sets, for a given image with noise, we use a two-dimensional wavelet analysis and median filter to perform the image smoothening. First, we enhance the image in frequency space, and then add the bigger white noise in airspace. By smoothening an image with noise, this gives the image with noise a better smoothening effect. When training, we add a bigger white noise to the image, then use the median filter to process the image with noise. The transition of the edge contour of the smoothened image is more natural. The smoothened image is shown in Fig. 2(e).

2.3. Image enhancement

Because of other many-sided causes, the illumination on an image cannot scatter completely uniformly homogeneously, which will affect the analysis effect of texture. For much better improvement in the recognition results, we amplify the local structural contrast ratio on the unfolded image. Accordingly, we realize the image enhancement and decrease the effect of non-homogeneous illumination.

The image enhancement is not able to increase the information that the image data itself contains, but it may bulge to show the specific characteristics, so that the processed image may be favorably recognized. Here, the purpose of image enhancement is mainly to enlarge the interest structure contrast ratio in the image, and strengthening intelligibility, at the same time, decreasing or restraining the noise in image, and then improving the vision quality.

The wavelet transform decomposes an image into different components that have different size, position and direction. We can alter the size of some coefficients in the wavelet transform region before doing an inverse transform, accordingly some interest components can be enlarged but the unnecessary components can be diminished.

The wavelet to image enhancement processing is as follows: for a given image signal, the enhancement processing is performed by using a two-dimensional wavelet. After the images are decomposed by the two-dimensional wavelet, the contours of the image mainly represent the low frequency part of image, but the details mainly represent the high frequency part, so, in order to perform image enhancement, we can increase the low frequency coefficients of decomposition and decrease the high frequency coefficients of decomposition in order to perform the image enhancement. Here we use the 2-layer wavelet decomposition. The enhanced image is shown in Fig. 2(f).

2.4. Edge detection and localization

After the comparatively clear image is obtained by the above-mentioned three steps, the outline of the image will be detected. Edge extraction is an effective means to fix the position of the target image. Though a part of the image edge information comes into being by the physical border of an object in the imaging process, the two-dimensional image is understood as it consists of different closing areas. The boundary among closing areas embodies the important scenery structure, and these boundaries also show non-continuity of intensity in the image. But, the non-continuity of intensity in the image originates from different physical phenomenon, such as surface reflection, texture diversity, illumination, surface tropism, depth, and so on, these characteristic properties of the scenery mixed together may make a succedent explanation about the image very difficult. And, in actual situations, the image data is contaminated usually by noise. To solve the above-mentioned problems, the used edge detection methods can not only detect the non-continuity of the intensity of the image, but also can ascertain their accurate location at the same time.

Another kind of method that can reserve edge detail and restrain the noise is the least squares fitting of a local curved surface, its fundamental thought is: According to the least squares method, the image local area is approximately expressed as the linear combination of a group of primary functions in order to eliminate noise. Haralick [3] used the least squares fitting of local curved surface to study the edge extraction, he denoted the zero cross location of a second-order directional derivative as an edge point, and used the interpolation method to compute the differential coefficient. The experiments showed this method to edge location is comparatively accurate. Canny [3] applied the variation principle to deduce an optimal operator that was approached by using Gauss form board derivative.

All the methods mentioned above have ignored the fact that some real images have a lot of interference edges that sometimes affect the correct detection and allocation of edges. However, the Susan operator [2] could much better detect out effective edges of an image, as well as corner and interference edges at the same time. Here we adopt the Susan edge detection operator, the Canny edge detection operator and the wavelet transform to perform the edge detection and corner

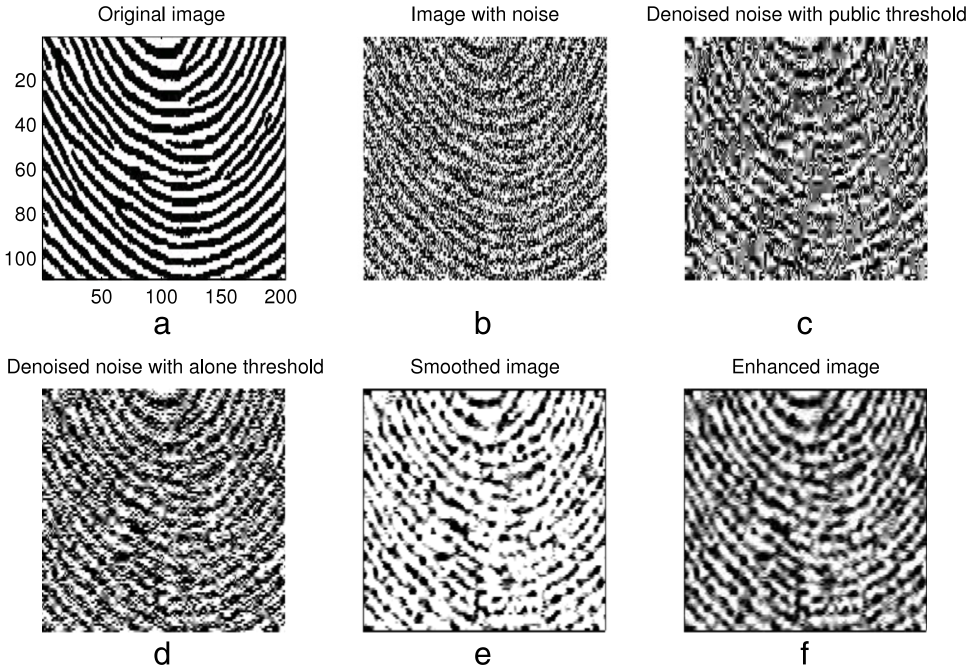

Fig. 2. Image preprocessing.

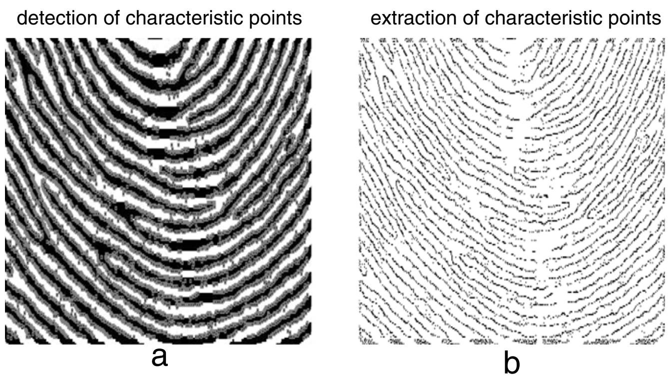

Fig. 3. Detection of characteristic points.

detection. Here we take the fingerprint as an example to perform the feature extraction. The detection results for the fingerprint are shown in Fig. 3.

3. Feature extraction of target image

In the feature extraction layer of FA, M neurons are the filters, such as, the Susan and the Gabor filter [2,3]. The characteristics of the image are extracted by using these filters. Here, the mean value and variance of the extracted characteristics are regarded as the reference index. However, for much better extraction of the characteristics of the target image, we also need to adjust the weights $0 \leqslant v_{lp} \leqslant 1$ between the preprocessing layer and the feature extraction layer. The adjustment for v_{lp} is: From the display of data obtained in neurons of this layer, if the variance of the characteristic is smaller than the given threshold value, we increase the value of weight v_{lp}, otherwise, we decrease its value, where $l, p = 1, 2, \ldots, M$ is the number of neurons in the preprocessing layer and the feature extraction layer, respectively. At time t, the input C_p^t in the feature extraction layer is $C_p^t = \sum_l v_{lp} P_l^t$, where P_l^t is the output data in the preprocessing layer.

After preprocessing, if we take an image by preprocessing as a texture image, then many methods of texture analysis can be used to extract the target features [6,13]. We generally choose textures which are in the center of textures when we extract the features of textures, it is because the area includes a lot of detailed information of textures, i.e., these are the rotation direction of the texture, length, breadth, height, width, depth, area coverage, distance between textures, etc. The method for their extraction is introduced in [14]. Additionally, the texture features also have end-points and intersections.

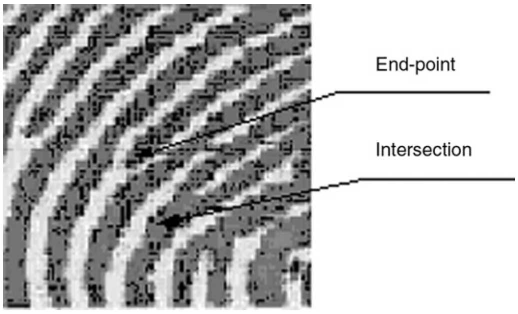

Fig. 4. Detail features of fingerprint.

In order to recognize them, we again distinguish them further after we perform the corner detection by using the Susan operator. The global features are extracted by using the Gabor filter and two-dimensional Wavelet Transform. All the above features are used as the fuzzy geometrical features attribute of the texture images. For performing the feature extraction of any images, we also use laser measure apparatus, expert systems and other assistant equipments, and treat them as modules of FA installed in the neural network of the FA. We take these attribute sets of fuzzy geometrical features that are obtained as input, and train the network of FA.

3.1. Extractions of end-points and intersections based on the Susan operator

To take the fingerprint image as an example, the sketch map of end-points and intersections are given in Fig. 4. From their known geometrical features attributes, they are the points that have high curvature, so the Susan operator can perform well to extract them, but the Susan operator cannot distinguish whether a point is an end-point or an intersection on earth. We perform further work on the basis of the Susan corner operator, i.e., give an improved Susan corner operator as follows:

Based on the fact that Susan algorithm has detected the corner points but is unable to distinguish the edge points, we take these points as the centre of a circle O to do a group of concentric circle rings. We inspect a circle along the clockwise direction on the circle rings in order to know the times of change of gray. If the times of change of gray are more than twice, then the above corner points or edge points are called intersections. We carry out the algorithm in detail as follows:

If the gray value of the pixels is the same or similar as that of the center of a circle O in neighborhood of the point O, then we label the pixels as '1', and mark the other pixels as '0'. We inspect the pixel distribution things for any circle along the clockwise direction or anti-clockwise direction from a certain point on the circle ring. We count the change times of gray of pixels from '1' to '0' or from '0' to '1'. If the times of change of gray are just right twice, the point O is called an end-point, however, if the times of change of gray are more than twice, then the point O is called an intersection.

3.2. Extraction of other (global) features

We could extract the other (global) features by using texture segmentation. The Gabor filter [2,3] is an ideal operator for the texture segmentation. The two-dimensional Gabor function is expressed as follows:

$$g(x, y) = \frac{1}{2\pi\delta_x\delta_y}.\mathrm{e}^{-\frac{1}{2}\left[\left(\frac{x}{\delta_x}\right)^2+\left(\frac{y}{\delta_y}\right)^2\right]+j(ux+vy)}. \tag{3}$$

And its Fourier transform is

$$\widehat{g}(\omega_x, \omega_y) = \mathrm{e}^{-2\pi^2\left[\delta_x^2(\omega_x-\frac{u}{2\pi})^2+\delta_y^2(\omega_y-\frac{v}{2\pi})^2\right]}. \tag{4}$$

The two-dimensional Gabor function is the result of translation of a two-dimensional Gaussian function at the two frequency axes, and it is shown in Fig. 5. The two-dimensional Gaussian function is a two-dimensional smoothness function, while the two-dimensional Gabor function is a two-dimensional band-pass filter.

We make the convolution of the Gabor function $g(x, y)$ and a two-dimensional texture image $p(x, y)$, that is

$$f(x, y) = g(x, y) \otimes p(x, y). \tag{5}$$

Quite a good result of image edges can be obtained. Usually, we design the Gabor function as

$$g(x, y) = \mathrm{e}^{-\frac{1}{2}\left[(\frac{x}{16})^2+(\frac{y}{16})^2\right]+j(\frac{\pi}{8}x+\frac{\pi}{8}y)}. \tag{6}$$

The convolution result of the original image and the Gabor function is shown in Fig. 6(b), and the Fig. 6(a) is the original image. The experiment results indicate that this segmentation algorithm also performs reliably on the textures segmentation

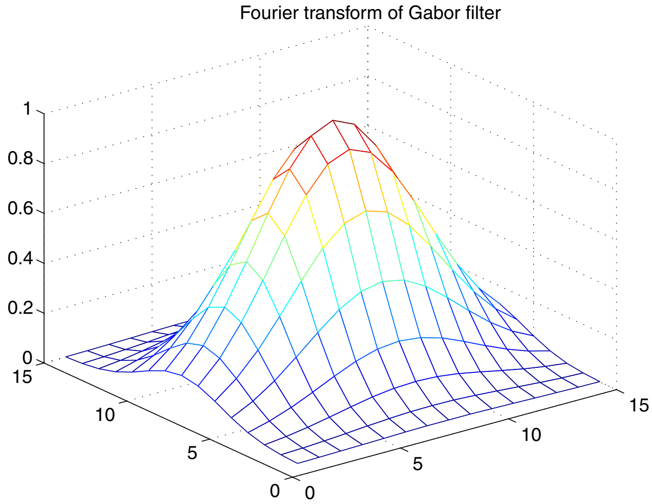

Fig. 5. Fourier transform of 2-D Gabor function.

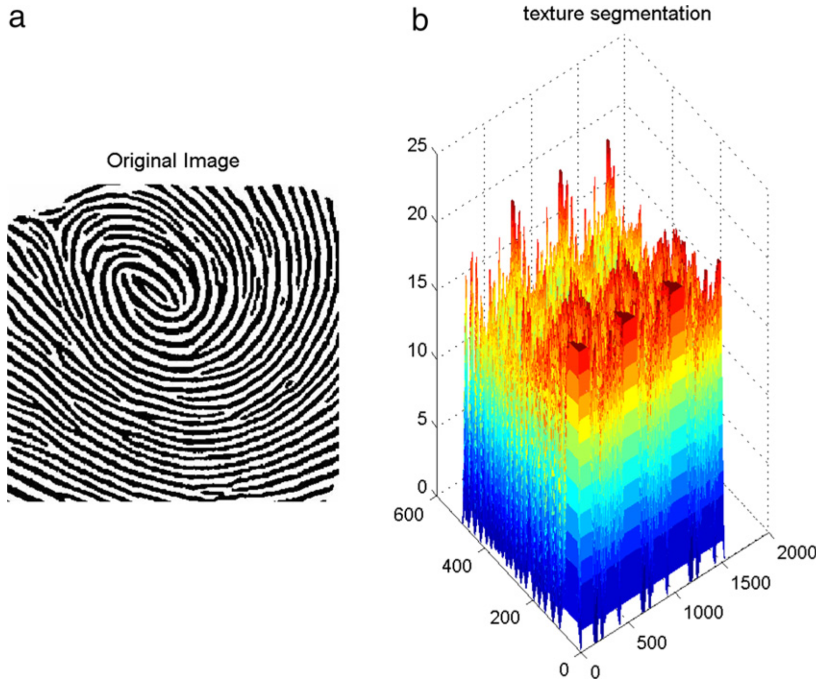

Fig. 6. Original image (a) and convolution result of it and Gabor function (b).

for deterministic textures with heavy noises. We use the multicenter Gabor filter to perform texture analysis. Assume the mathematical model for every channel is

$$\begin{cases} q(x,y) = \sqrt{q_e^2(x,y) + q_o^2(x,y)} \\ q_e(x,y) = h_e(x,y) \otimes p(x,y) \\ q_o(x,y) = h_o(x,y) \otimes p(x,y) \end{cases} \tag{7}$$

where $p(x, y)$ is the input image of the channels, $h_e(x, y)$ and $h_o(x, y)$ are the even symmetry Gabor filter and odd symmetry Gabor filter respectively. In order to simplify the discussion, under no loss of universality, we use the isotropy Gabor filter [15]

$$\begin{cases} h_e(x,y,f,\theta,\sigma) = g(x,y,\sigma).\cos\left[2\pi f\,(x\cos\theta + y\sin\theta)\right] \\ h_o(x,y,f,\theta,\sigma) = g(x,y,\sigma).\sin\left[2\pi f\,(x\cos\theta + y\sin\theta)\right] \end{cases} \tag{8}$$

where $g(x, y, \sigma)$ is the Gaussian function, i.e.,

$$g(x, y, \sigma) = \frac{1}{2\pi\sigma^2} . \mathrm{e}^{-\frac{x^2+y^2}{2\sigma^2}} \tag{9}$$

where f, θ and σ in equality (8) and (9) are three important parameters of the Gabor filter respectively, i.e., they are the spatial frequency, phase and spatial constant. The Fourier Transforms of even Gabor filter and odd Gabor filter in equality (8), i.e., the frequency-domain forms are respectively

$$\begin{cases} H_e(\omega_x, \omega_y, f, \theta, \sigma) = \left[H_1(\omega_x, \omega_y, f, \theta, \sigma) + H_2(\omega_x, \omega_y, f, \theta, \sigma)\right]/2 \\ H_o(\omega_x, \omega_y, f, \theta, \sigma) = \left[H_1(\omega_x, \omega_y, f, \theta, \sigma) - H_2(\omega_x, \omega_y, f, \theta, \sigma)\right]/2j \end{cases} \tag{10}$$

and

$$\begin{cases} H_1(\omega_x, \omega_y, f, \theta, \sigma) = \mathrm{e}^{-2\pi^2\sigma^2\left[(\omega_x - f\cos\theta)^2 + (\omega_y - f\sin\theta)^2\right]} \\ H_2(\omega_x, \omega_y, f, \theta, \sigma) = \mathrm{e}^{-2\pi^2\sigma^2\left[(\omega_x + f\cos\theta)^2 + (\omega_y + f\sin\theta)^2\right]}. \end{cases} \tag{11}$$

In practice, we usually perform the convolution by using a Fourier Transform, i.e.,

$$\begin{cases} q_e(x, y) = h_e(x, y) \otimes p(x, y) = FFT^{-1}\left[P(\omega_x, \omega_y)H_e(\omega_x, \omega_y, f, \theta, \sigma)\right] \\ q_o(x, y) = h_o(x, y) \otimes p(x, y) = FFT^{-1}\left[P(\omega_x, \omega_y)H_o(\omega_x, \omega_y, f, \theta, \sigma)\right] \end{cases} \tag{12}$$

where $P(\omega_x, \omega_y) = FFT\,[p(x, y)]$.

In the algorithm, every pair of Gabor filters $h_e(x, y)$ and $h_o(x, y)$ corresponds to the given spatial frequency and direction. We extract the frequency information and direction information for feature extraction of an image at the same time. Tan once pointed out, for the purpose of texture recognition, it is unnecessary to choose the filter parameter space that covers the whole frequency-domain [15]. The smaller the central frequency of the filter is, the larger is the scale of texture features extracted. We usually choose the central frequency that is an exponent of 2. In the fingerprints recognition algorithm, we choose the central frequency as 2, 4, 8, 16, 32, 64 respectively. For every central frequency, four phase angles are selected, and they are $\theta = 0, \pi/4, \pi/2, 3\pi/4$. Thus, there are 24 channels of the Gabor filter. For the filter result of every channel, we extract its mean and variance as the features of the Gabor filter. Thus, for every input image, the multicenter Gabor filters extract 48 features in total. The simulation results show, when we use all 48 features or use the central frequency $f = 2, 4, 8, 16, 32$, we get a higher correct recognition rate of 93.8%.

4. Matching and recognition

The neurons in the fuzzy matching layer of FA are some fuzzy matching filters, such as, fuzzy operators, fuzzy rules, etc. By making use of these fuzzy matching filters, the degree of similarity in a certain parameter between the identified target and the known target is computed. For better identifying the target, it requires adjustment to the weights $0 \leqslant w_{pq} \leqslant 1$ in the fuzzy matching layer. The adjustment for w_{pq} is: From the display of data obtained in the neurons of this layer, if the degree of similarity is greater than the threshold value, we increase the value of weight w_{pq}, otherwise, we decrease its value, where $p, q = 1, 2, \ldots, M$. The input F_q^t in the fuzzy matching layer is $F_q^t = \sum_p w_{pq}E_p^t$ at time t, where E_p^t is the output data in the feature extraction layer.

Based on the extracted characteristic vector of the image, we perform target recognition, as it is a typical problem of pattern recognition. Since some images are complicated or fuzzy, the characteristic parameters that the characteristic vectors consist of fuzzy images have fuzzy characteristics to some extent. Thus, we can think of the known characteristic parameters are all fuzzy numbers, and then both the known characteristic vectors and the extracted characteristic vectors all are fuzzy number vectors. So, we perform the target recognition well by using fuzzy automata technology. We compare the characteristic vectors of the unknown target image with the characteristic vectors of the known classificatory target image that has been trained in a matching layer. Based on the maximum membership principle in fuzzy mathematics, if and only if the degree of similarity between the characteristic vector of unknown target image and the characteristic vector of given i_0th target image is maximal, we judge that the unknown target belongs to the i_0th category. The recognition algorithm based on the FA is given in the following.

4.1. Calculation of degree of similarity

Assume there are n categories of the target image. For simplifying the discussion, the 'target image' is called the 'target' for short in the following. The characteristic vector of every target consists of k characteristic parameters, for example, the characteristic vector of the fingerprint consists of the length, width, height, etc. We assume the ith category target has n_{ij} values on the jth characteristic parameter, X_{ij}^m denotes the mth fuzzy number of the ith category target on the jth characteristic parameter, and θ_{ij}^m is its mean; $\widetilde{X}_j$ is the fuzzy observation of the unknown target on the jth characteristic parameter, and x_j is its mean, where $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, k$, $m = 1, 2, \ldots, n_{ij}$.

According to the above descriptions, we then assume the set of target numbers, the set of corresponding parameter numbers, and the set of fuzzy numbers of the ith category target on the jth characteristic parameter are as follows, respectively:

$$\begin{aligned} &U = \{1, 2, \ldots, n\}, \qquad K = \{1, 2, \ldots, k\}, \\ &M_{ij} = \{1, 2, \ldots, n_{ij}\}, \quad i \in U,\ j \in K \end{aligned} \tag{13}$$

Here, the target recognition denotes the fuzzy observation vector which consists of the observed fuzzy number $\widetilde{X}_j$ of an unknown target merged sorts a characteristic vector of a known target category, and the known characteristic vector that consists of the known fuzzy number are the most similar to the fuzzy observation vector of an unknown target.

Assume that $\mu_{X_{ij}^m}(u)$ and $\mu_{\widetilde{X}_j}(u)$ are the membership functions of X_{ij}^m and $\widetilde{X}_j$ respectively. We can choose the normal membership function or the Cauchy membership function based on experience.

When we choose the normal membership function, there is

$$\mu_{X_{ij}^m}(u) = \mathrm{e}^{-\frac{(u-\theta_{ij}^m)^2}{2\sigma_{ij}^2}} \tag{14}$$

and

$$\mu_{\widetilde{X}_j}(u) = \mathrm{e}^{-\frac{(u-x_j)^2}{2\sigma_j^2}} \tag{15}$$

where u is a fuzzy factor to corresponding to X_{ij}^m or $\widetilde{X}_j$, σ_{ij} and σ_j are the ductility degree of $\mu_{X_{ij}^m}(u)$ and $\mu_{\widetilde{X}_j}(u)$, respectively.

When we choose the Cauchy membership function, there is

$$\mu_{X_{ij}^m}(u) = \frac{\sigma_{ij}^2}{\sigma_{ij}^2 + (u - \theta_{ij}^m)^2} \tag{16}$$

and

$$\mu_{\widetilde{X}_j}(u) = \frac{\sigma_j^2}{\sigma_j^2 + (u - x_j)^2}. \tag{17}$$

In order to make sure the type of the unknown target, we need to make certain the degree of similarity d_{ij}^m of $\widetilde{X}_j$ and X_{ij}^m, i.e.,

$$d_{ij}^m = \left(\left(\widetilde{X}_j \cdot X_{ij}^m\right) \bigwedge \left(1 - \widetilde{X}_j \oplus X_{ij}^m\right)\right) \tag{18}$$

where

$$\widetilde{X}_j \cdot X_{ij}^m \triangleq \bigvee_{u \in R^1} \left(\mu_{\widetilde{X}_j}(u) \bigwedge \mu_{X_{ij}^m}(u)\right) \tag{19}$$

$$\widetilde{X}_j \oplus X_{ij}^m \triangleq \bigwedge_{u \in R^1} \left(\mu_{\widetilde{X}_j}(u) \bigvee \mu_{X_{ij}^m}(u)\right). \tag{20}$$

The formula (19) and the formula (20) denote the inner product and cross product of $\widetilde{X}_j$ and X_{ij}^m, respectively.

When $\mu_{\widetilde{X}_j}(u)$ and $\mu_{X_{ij}^m}(u)$ are both normal membership functions, the $\widetilde{X}_j \cdot X_{ij}^m$ is the supremum of the intersection of $\mu_{\widetilde{X}_j}(u)$ and $\mu_{X_{ij}^m}(u)$, that is, it is the height of the intersection of two fuzzy distribution curves between $\widetilde{X}_j$ and X_{ij}^m, therefore, there is

$$\frac{(u - \theta_{ij}^m)^2}{2\sigma_{ij}^2} = \frac{(u - x_j)^2}{2\sigma_j^2}. \tag{21}$$

Then

$$u = \frac{\sigma_{ij} x_j + \sigma_j \theta_{ij}^m}{\sigma_j + \sigma_{ij}}. \tag{22}$$

Thus, there is

$$\widetilde{X}_j \cdot X_{ij}^m = \mathrm{e}^{-\frac{(u-\theta_{ij}^m)^2}{2\sigma_{ij}^2}}\Bigg|_{u=\frac{\sigma_{ij}x_j+\sigma_j\theta_{ij}^m}{\sigma_j+\sigma_{ij}}} = \mathrm{e}^{-\frac{(x_j-\theta_{ij}^m)^2}{2(\sigma_j+\sigma_{ij})^2}}. \tag{23}$$

Obviously, there exists $\widetilde{X}_j \oplus X_{ij}^m = 0$, and then we obtain the degree of similarity of the unknown target and the mth fuzzy number of the known ith category target on the j characteristic parameters, the degree of similarity is

$$d_{ij}^m = \mathrm{e}^{-\frac{(x_j-\theta_{ij}^m)^2}{2(\sigma_j+\sigma_{ij})^2}}. \tag{24}$$

Similarly, when $\mu_{\widetilde{X}_j}(u)$ and $\mu_{X_{ij}^m}(u)$ are both the Cauchy membership functions, there is

$$d_{ij}^m = \frac{(\sigma_j + \sigma_{ij})^2}{(\sigma_j + \sigma_{ij})^2 + (x_j - \theta_{ij}^m)^2}. \tag{25}$$

Since the ith category target has n_{ij} values on the jth characteristic parameter, the ith category target has $\prod_{j=1}^k n_{ij}$ characteristic vectors. Thus, we get $N = \sum_{i=1}^n \left[\prod_{j=1}^k n_{ij}\right]$ characteristic vectors in total for n target categories. We can directly construct N similarity vectors by using d_{ij}^m, where $\forall i \in U,\ j \in K,\ m \in M_{ij}$, and determine the category of the unknown target based on the maximum norm principle of similarity vectors, but when the number of target categories or the number of characteristic vectors for every target category is more, it takes time to adopt the direct comparative method. Therefore, after getting the degree of similarity of two fuzzy sets, we can perform the fusion of attributes to determine the category of the unknown target by using the reasoning model in the following.

Since the fuzzy observation values press close to some characteristic fuzzy values of some target categories with different degrees of similarity, we can adopt the idea of "soft classification", which we assume the d_{ij}^m which is smaller than a certain threshold value is zero, that is, we only perform the judgement of classification of observation patterns in the near neighborhood where the d_{ij}^m is bigger than a certain threshold value. Assume

$$B_j = \left\{i | \exists j, \forall i, m,\ \text{make } |x_j - \theta_{ij}^m| < \varepsilon\left(\sigma_j + \sigma_{ij}\right)\right\} \tag{26}$$

$$B_{ij} = \left\{m | \exists i, j, \forall m,\ \text{make } |x_j - \theta_{ij}^m| < \varepsilon\left(\sigma_j + \sigma_{ij}\right)\right\} \tag{27}$$

$$B = \bigcap_{j=1}^k B_j. \tag{28}$$

Here we assume: P_{ij}^m and P_{ij} express the proposition '$\widetilde{X}_j$ presses close to X_{ij}^m' and the proposition '$\widetilde{X}_j$ presses close to the jth category characteristic parameter of the ith target' respectively, and true value of P_{ij}^m is d_{ij}^m. Again assume the true value of P_{ij} is d_{ij}. Because m denotes the serial number of value of a certain parameter, if only $\widetilde{X}_j$ presses close to any fuzzy value of the jth category characteristic parameter of the ith category target, then there are all $\widetilde{X}_j$ presses close to the jth category characteristic parameter of the ith category target. That is, $\forall m_1, m_2, \ldots, m_q \in B_{ij}$, if $P_{ij}^{m_1}, \ldots,$ or $P_{ij}^{m_q}$, then P_{ij} can be inferred. Obviously, this is a compound statement, which can be deduced by a fuzzy disjunctive proposition. Then

$$\bigvee_{m \in B_{ij}} d_{ij}^m \left(P_{ij}^m\right) \Longrightarrow d_{ij}\left(P_{ij}\right), \quad i \in B. \tag{29}$$

Since the fuzzy value which is extracted by the disjunctive proposition is the maximum of fuzzy values in the compound statement, there is

$$d_{ij} = \bigvee_{m \in B_{ij}} d_{ij}^m, \quad \forall i \in B. \tag{30}$$

So, we obtain the similarity vector between the unknown fuzzy vector and the fuzzy vector of the ith category target as

$$D_i = [d_{i1}, d_{i2}, \ldots, d_{ik}]', \quad \forall i \in B. \tag{31}$$

4.2. Recognition principle

Here, we use the method of vector norm in the recognition layer of FA, i.e., if $\exists i_0 \in B$ such that

$$i_0 = \arg\max_{i \in B} \{\|D_i\|\}. \tag{32}$$

Based on the maximum membership principle, then, we judge that the unknown target belongs to the i_0th category target. Here $\|\cdot\|$ is the vector norm.

4.3. Computer simulation and analysis

In simulation, we assume there are 40 known target categories that have been trained, and select three characteristic parameters to construct the characteristic vector of the target. We choose randomly 120 characteristic parameters according to the uniformity distribution, normal distribution and logarithmic normal distribution respectively, and distribute them randomly and equiprobably to 40 target categories. Assume the measurement error of the unknown target obeys the

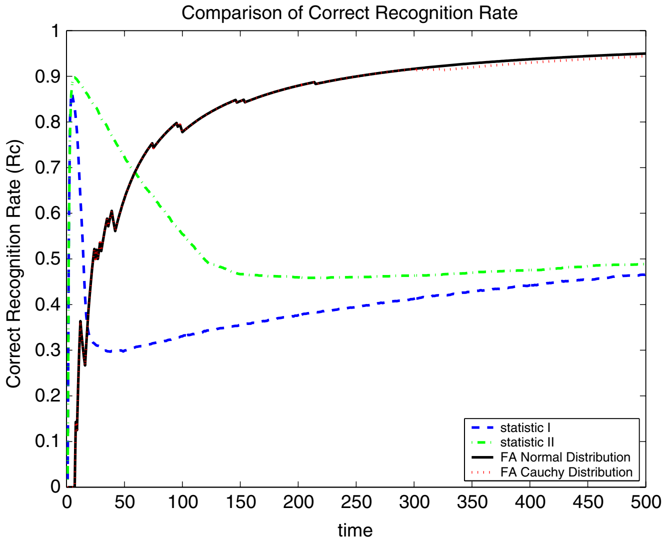

Fig. 7. Comparison of correct recognition rates of algorithms based on FA system and statistical algorithms.

Table 1
Comparison of recognition algorithm based on FA and statistic.

Recognition algorithm	Computing speed (s)	Memory capacity	Commun. traffic	Correct recog. rate	Acclimation	Parameters setup
Statistical recog. I	97	Middle	Middle	0.4755	Sparse target	No
Statistical recog. II	570	Middle	Middle	0.4935	Dense target	No
FA recognition	336	Low	Low	0.9459	Dense target	Yes

Gaussian distribution, and the standard variance of measurement error is 2% of the corresponding known characteristic parameter. We choose the 1-norm of vector as the discriminant function for target recognition in the simulation, and then after the simulation is carried out 500 times, we obtain the correct recognition rates are 94.59% and 93.39% by using the normal membership function and the Cauchy membership function based on FA respectively. We carry out the comparison of the proposed recognition algorithm based on FA and existing statistical recognition algorithm [11], and the comparison results are shown in Fig. 7 and Table 1 after 500 simulations. Fig. 7 shows some curves of the correct recognition rate. At the same time, Table 1 gives the results of a comprehensive comparison.

By the simulation results, to compare the fuzzy algorithm based on FA by fuzzy membership functions and the statistical algorithms for target recognition, the correct recognition rates of the former are larger than that of statistical algorithm I and statistical algorithm II. The performance of the fuzzy algorithm based on FA is better than that of statistical algorithm I and statistical algorithm II for target recognition. We refer to [11] for the statistical algorithms.

On the basis of Fig. 7 and Table 1, the fuzzy recognition algorithm based on FA not only has the faster processing speed, lower memory capacity and communications traffic, but also has better recognition effect.

From the simulation results also known, the results that are obtained by using the normal membership function and the Cauchy membership function are very adjacent, therefore, we use the Cauchy membership function to reduce the calculation in practice applications.

The greatest advantage of the fuzzy recognition algorithm compared with the statistical recognition algorithms is that it not only has good real time, but is also appropriate to dense target environments. However, its biggest disadvantage is that the system parameters setup is complicated. For example, some parameters in weights adjustment need a great deal simulations to determine them, and these parameters are related with the choice of the threshold value. The greatest advantage of statistical recognition algorithms is that they are able to integrate new data and old knowledge, but their biggest disadvantage is that we must know the exact probability or priori probability of condition items and statistic distribution.

5. Conclusions

This paper presents a target recognition algorithm based on the fuzzy automata (FA) system. We discuss image preprocessing, feature extraction of target, matching and recognition respectively. The simulation results show that the correct recognition rate of this system can attain more than 94.59%.

In the future research, there is a wide applicable prospect to combine the more complex fuzzy image of satellite and fuzzy signals with FA. In the image processing and feature extraction, if the combination method of the global texture features and the local texture features is performed, we will further improve the accuracy for target recognition. On the design of classifiers, we will also try to test other classifiers for the future, such as K-NN, MK-NN and fuzzy synthetic function classifier, etc.

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