

ORIGINAL RESEARCH

A hierarchical target recognition method based on image processing

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Abstract

In order to provide an accurate and rapid target recognition method for some military affairs, public security, finance and other departments, this paper studied firstly a variety of fuzzy signal, analyzed the uncertainties classification and their influence, eliminated fuzziness processing, presents some methods and algorithms for fuzzy signal processing, and compared with other methods on image processing. Where, the fuzzy signal processing is that a blurred signal is dealt with by eliminating fuzziness. Moreover, this paper used the wavelet packet analysis to carry out feature extraction of target for the first time, extracted the coefficient feature and energy feature of wavelet transformation, gave the matching and recognition methods, compared with the existing target recognition methods by experiment, and presented the hierarchical recognition method. In target feature extraction process, the more detailed and rich texture feature of target can be obtained by wavelet packet to image decomposition to compare with the wavelet decomposition. In the process of matching and recognition, the hierarchical recognition method is presented to improve the recognition speed and accuracy. The wavelet packet transformation is used to carry out the image decomposition. Through experiment results, the proposed recognition method has the high precision, fast speed, and its correct recognition rate is improved by an average 6.13% than that of existing recognition methods. These researches development in this paper can provide an important theoretical reference and practical significance to improve the real-time and accuracy on fuzzy target recognition.

Key Words: Fuzzy processing, Denoising, Matching and recognition, Wavelet packet transformation, Energy feature

1 Introduction

In the modern society of higher information age, target recognition and identity validation become more and more important in our life, and have infiltrated every aspect of everyday life. For instance, finance, security, network, digital electric business, etc. Due to the requirement of confidentiality on traffic, communications and military, the rapid development of network technology, as well as the increasingly complex signal environment, the characteristic parameters of the characteristic vector that is constituted have a certain ambiguity. Thus, the difficulty and importance to target recognition or identity validation have become more

and more prominent. Therefore, the signal processing to fuzzy image is an urgent solved problem in many departments now.

For carrying out the target recognition, the literature^[1] studied uncertain power signal processing method. Ref. 2 used the fuzzy lifting wavelet packet transform to solve the noise suppression of magnetic flux leakage signal. On the basis of analyzing fast convolution and fast Fourier transform of digital signal processing, Ref. 3 proposed a kind of asymptotic range of convolution to process uncertain signals. The literature^[4] presented a learning machine which was called clustering instructions possibility associative memory (CIPAM).

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The CIPAM consisted of a clustering equipment and an annotator. The clustering equipment was a feedback neural network of unsupervised processing units (UPUs). The annotator was many supervisory processing units (SPUs) from the clustering equipment to branch. Through using the novel and efficient parallel computing platform of CIPAM to carry out the signal processing, to process temporary and hiberarchy pattern clustering, the detection and recognition of digital signal carried out.

But in order to process the fuzzy, incomplete and uncertain signals, people have developed various mathematical theories and methods, for example, fuzzy mathematics, rough set, fuzzy automata, probability theory and Dempster-Shafer (D-S) evidence-based reasoning. In order to scientifically solve the universal fuzzy phenomena in the objective world, the concept of fuzzy set was introduced,^[5] and the fuzzy theory were widely used in civil, military and many other aspects.^[6-8]

In order to better target identification, this paper will implement the signal processing of fuzzy images by using the rich fuzzy set theory and fuzzy technology. However, that these technologies are only used is difficult to achieve accurate recognition and multi-dimensional parameter extraction of fuzzy signal to image. This will require developing new theories and methods. To solve the accurate recognition of fuzzy signal so as to achieve finally accurate image understanding, this paper studies how to solve a large number of fuzzy and incomplete signal problems exist in the reality, and further studies fuzzy target recognition methods. For reducing signal processing costs, lowering personnel's labor intensity to target recognition, these researches in this paper have a special practical significance and broad practical application prospects.

2 Signal processing method to fuzzy image

Because of image acquisition system, different physical phenomena such as illumination cannot be completely evenly distributed, and many other reasons, the obtained edge intensity of image is different. Moreover, in real-world situations, image data is often contaminated by noise. While the scenery features mixed together so that it makes subsequent interpretation very difficult. To achieve the accurate grasp of the picture intent, it needs to study a target recognition method that can not only detect the non-continuity of intensity, but also can determine their exact position. It needs to develop new uncertainty processing methods and algorithms to solve such problems.

In some cases, the acquired most of images are fuzzy. In addition to objective reasons, there are also some subjective reasons to cause the images are fuzzy, such as images were dissevered, soiled, etc. For the fuzziness in these images, this paper uses the threshold approach to process fuzzy signal on the basis of uncertainty factor classification and influence analysis, and presents fuzzy signal processing method

and algorithm that can improve the image quality, as shown in Figure 1.

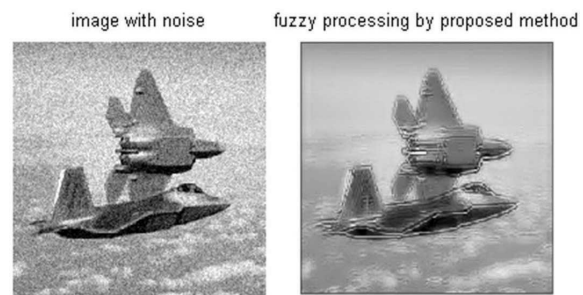


Figure 1: Fuzzy image pre-processing

The threshold value is used to smooth image processing and eliminate the fuzziness of image. The basic algorithm is given as follows.

2.1 Fuzzy processing by using the threshold value

After the wavelet transform is used for the signal with noise, the correlation of wavelet coefficients between adjacent scales is calculated. According to the correlative degree, the type of wavelet coefficient is distinguished, chosen and given up, and then the wavelet coefficient is reconstructed.

The traditional denoising methods were to make the signal by noise interference pass through a filter, so as to filter out the frequency component of noise. However, for pulse signal, white noise, non-stationary signals, and so on, the traditional methods had certain limitations. For these types of signals, after they were filtered in low signal to noise ratio situations, the signal to noise ratio not only could not be greatly improved, but also the position information of signals had been blurred.

The denoising method based on wavelet transform uses variable scale characteristic of wavelet transform so that it has a "concentration" capability for sure signal. If a signal's energy focuses on a small number of wavelet coefficients in wavelet transform domain, so their values must be greater than values of wavelet coefficients of the energy-dispersive many signals and noise in the wavelet transform domain. For this case, this threshold method can be used.

For a given threshold value δ , the wavelet coefficients that all absolute values are less than δ are classified as "noise", and their values are replaced by 0. But the wavelet coefficients that are more than the threshold value δ are got values again after they are reduced, and the symbols of the obtained coefficients are the symbols of the original wavelet coefficients. This approach means that it can remove minor extent noises or undesired signals by using the threshold. The desired signal can be obtained by wavelet inverse transform.

(1) Threshold value

The soft threshold method and the hard threshold method are two main methods to the wavelet coefficient that is more than the threshold value.

The soft threshold method is

$$W_{\delta} = \begin{cases} \text{sgn}(W)(|W| - \delta) & |W| \geq \delta \\ 0 & |W| < \delta \end{cases}$$

The hard threshold method is

$$W_{\delta} = \begin{cases} W & |W| \geq \delta \\ 0 & |W| < \delta \end{cases}$$

Where W_{δ} and W are the wavelet coefficient.

The two threshold methods are different. The former has the continuity, and it is easy to be processed in mathematics. However, the latter is closer to the practical situation. The key of the threshold method are the choice of threshold value. If the threshold value is too small, the noise remains after the image is denoised, but if the threshold value is too big, some important signals and characteristics of image will be filtered out, which it causes the deviation.

(2) Choice of threshold value

Intuitively say, for the obtained wavelet coefficient, the more the noise is, the greater the threshold value should also be. The selection chosen process of the majority threshold value is for a group of wavelet coefficients, according to the statistical properties of this group of wavelet coefficients, a threshold value δ can be obtained by calculating.

Donoho, etc presented a typical threshold selection method which were given and proved in theory, and the threshold value δ was direct proportional to the covariance δ of the noise. The relationship between the two is

$$\delta = \sigma \sqrt{2 \log n}$$

Where n is the number of layers of wavelet decomposition. In fact, for finite length signal, the formula is only the upper bound of optimization of threshold value. The optimization formula of threshold value is gradual change with signal length. When the length of signal is infinite, the threshold value is accord to the above formula. Therefore, when the signal is enough long, the denoising effect is obvious.

(3) De-noising step of wavelet threshold

The step of threshold denoising method based on wavelet transform is outlined as follows:

(i) The appropriate wavelet function is chosen to carry out wavelet decomposition transform to a given signal, and then the wavelet transform coefficient W is obtained.

(ii) The wavelet threshold value δ is calculated, and the appropriate threshold method is chosen, such as soft threshold or hard threshold, to choose and give up for the wavelet coefficients. Thus, the new wavelet coefficients Wb are obtained;

(iii) The obtained wavelet coefficients Wb are carried out the inverse wavelet transform, i.e., the wavelet coefficients are reconstructed, and then the denoised images are acquired.

In denoising, assume the variance of the noise is estimated, and then the problem has been resolved. In practice, how to determine the type of noise and its variance is a very important problem.

2.2 Simulation and analysis

(1) Denoising by threshold

In simulation, we use the original image and the image after adding noise. The added noise is the Gauss white noise with the covariance $\sigma=0.1$, as shown in Figure 2.

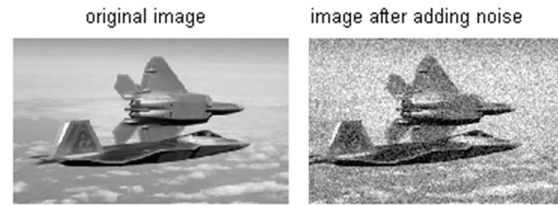


Figure 2: Original image and image after adding noise

Based on the above given denoising method, the image after adding noise is denoised by using the soft and hard threshold. The results are shown in Table 1 and Figure 3.

Table 1: Comparison of image denoising effect by wavelet in $n=2$ to image after adding noise

Denoising method	Noise and denoising Image of adding noise	Mean-square variance	Signal to noise ratio
		0.11	20.2235
Haar filter	Denoising by soft threshold	0.0556	25.5648
	Denoising by hard threshold	0.0758	25.136
db4 filter	Denoising by soft threshold	0.0539	25.3606
	Denoising by hard threshold	0.0651	25.0667

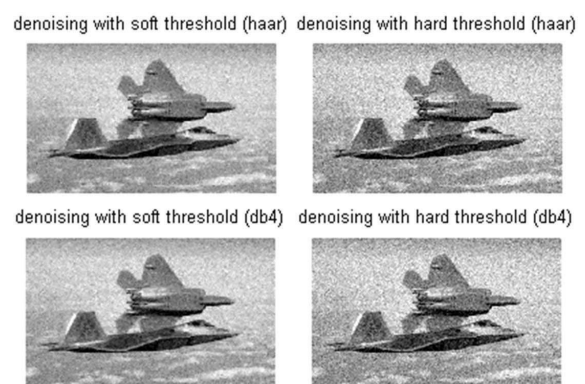


Figure 3: Denoising effect by using soft and hard threshold based on haar and db4

From Table 1 and Figure 3, after the images are denoised via the haar and the db4 filters, the mean-square variances of the noise in the image all decrease, while the signal to noise ratios all increase. Moreover, for the same filter, the denoising effect of soft threshold is better than that of hard threshold, i.e., the image denoised by soft threshold is clearer and smoother. The effect by using db4 is better than that using Haar.

Then, the images with noise are carried out by different layers decomposition for denoising. The comparison of denoising effect by different levels is shown in Table 2 and Figure 4.

Table 2: Comparison of different decomposition layers for image denoising

Layers for denoising	Noise and denoising	Mean-square variance	Signal to noise ratio
	Image of adding noise		
n=2	Denoising by soft threshold	0.0508	26.0069
	Denoising by hard threshold	0.0714	22.9239
n=3	Denoising by soft threshold	0.0588	24.6059
	Denoising by hard threshold	0.0711	22.9654
n=4	Denoising by soft threshold	0.0482	26.3345
	Denoising by hard threshold	0.0586	24.6401
n=6	Denoising by soft threshold	0.0457	26.8088
	Denoising by hard threshold	0.0485	26.2789

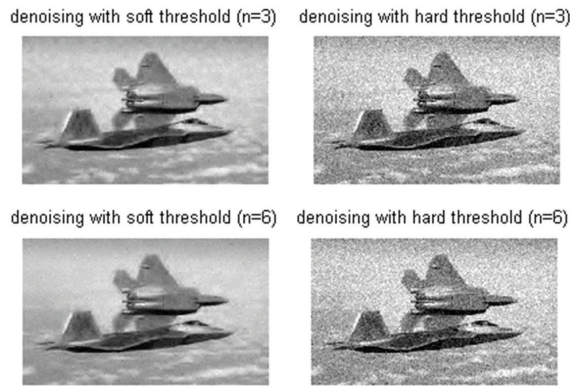


Figure 4: Image denoising in different decomposition levels for $n=3, n=6$

From Table 2 and Figure 4, at different decomposition level, the mean-square variances of the noise in the image all are reduced, all SNR are also improved. But for image polluted seriously by noise, as shown in Figure 4, the more the number of decomposition layers is, the better the denoising effect is. However, the mean-square variance of denoising based on soft threshold at $n=2$ is less than that at $n=3$, and the signal to noise ratio of denoising based on soft threshold at $n=2$ is higher than that at $n=3$. These results show that the denoising effect is best when the number of decomposition layer reaches a certain fixed value. The number of decomposition layers is too small or too large, thus the effects all are not good.

(2) Fuzzy processing by weight adjustment

No matter the soft threshold or the hard threshold are used for image denoising, if a public threshold value is shared in all directions, then the denoising method is called a public threshold denoising. If the different threshold value is used in different direction, the denoising method is called an alone threshold denoising.

The weighting function $\omega=[1, 0.9, 1; 0.8, -7.1, 1; 0.85, 0.9, 1.1]$ is used to adjust a given image I , and the image is adjusted as follows:

$$G = \omega \otimes I$$

Then, the image smoothing is carried out by the 3 layers coefficient decomposition of the wavelet haar, and then the fuzziness of image is eliminated by using the threshold so as to sharpen it. By this signal processing method for image processing, the quality of fuzzy image is improved, and its clarity degree is also improved.

To compare the proposed fuzzy image processing method with the existing image processing methods, the proposed fuzzy processing method has the faster processing speed and the better effect than other processing methods for image, as is shown in Figure 5.

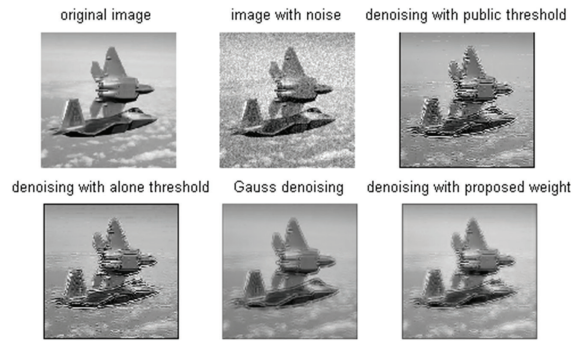


Figure 5: Comparison of the proposed fuzzy image processing method and existing image processing methods

In order to evaluate the image quality, the literature^[11] gave an objective perceptual quality assessment method in wireless imaging. The literature^[11] mainly discussed the design of reduced-reference objective Normalized Hybrid Image Quality Metric and a perceptual relevance weighted L_p -norm, which evaluated and predicted the performance of images by measuring related image features, but not involved in the denoising or eliminating fuzziness processing algorithm to image. The overall image quality measure in literature^[11] was computed as a weighting sum of the features with the respective perceptual relevance weight obtained from subjective experiments. However, this paper gives the denoising algorithm in order to improve image quality and target recognition. After denoising processing proposed in this paper, the fuzzy image can be evaluated to be better by the quality assessment method given in literature.^[11]

3 Image processing

3.1 Image processing by wavelet packet

Choose a function $\psi(\vec{t})$ to construct $\psi_{\vec{j},\vec{k}}(\vec{t}) = 2^{\vec{j}/2} \psi(2^{\vec{j}}\vec{t} - \vec{k})$, and make it do inner product with image $p(x, y)$, i.e. $\langle \psi_{\vec{j},\vec{k}}(\vec{t}), p(x, y) \rangle$ which can carry out some processing for an image such as smoothing, denoising, enhancing, compressing and so on. Where, $\vec{t} = (x, y)$, $\vec{j} = (j_1, j_2)$, $\vec{k} = (k_1, k_2)$.

To implement the processing to the image $p(x, y)$, the concrete algorithm is $W_{\vec{j},\vec{k}} = \langle \psi_{\vec{j},\vec{k}}(\vec{t}), p(x, y) \rangle$, which can

carry out a decomposition and feature extraction to energy coefficient of image $p(x, y)$. From the decomposition calculation of wavelet, the i th level energy feature of ripple is calculated by the i th level decomposition coefficient of wavelet, which shows the energy feature of an image in the 2^{-i} scale, in different directions and different positions.

In order to further carry out the subdivision to the decomposed frequency band, that is, to further carry out the localization of time-frequency, the definition of wavelet packet is introduced.

To wavelet packet, here we give a one-dimensional wavelet packet transform. Assume the $\phi(t)$ is the orthogonal scaling function of wavelet decomposition, and the $\psi(t)$ is the wavelet basis generated by scaling functions. Again, assume $\psi_0(t) = \phi(t)$ and $\psi_1(t) = \psi(t)$, if the two satisfy the following progression, respectively

$$\begin{cases} \psi_0(t) = \sum_k p_k \psi_0(2t - k) \\ \psi_1(t) = \sum_k q_k \psi_0(2t - k) \end{cases} \quad (1)$$

Then, a wavelet packet can be defined. Because the wavelet $\psi(t)$ is an orthogonal, there is $q_n = (-1)^{n-1} \bar{p}_{-n+1}$, Where \bar{p}_{-n+1} is the conjugation of p_{-n+1} . The wavelet packet can be defined as follows:

Definition 3.1: A function sequence $\psi_n(t)$ is defined by $\begin{cases} \psi_{2l}(t) = \sum_k p_k \psi_l(2t - k) \\ \psi_{2l+1}(t) = \sum_k q_k \psi_l(2t - k) \end{cases}$ which is called a wavelet packet about orthogonal scaling function $\phi(t)$ Where $n = 2l$ or $2l + 1, l = 0, 1, \dots$

The $\{2^{j/2} \psi(2^j t - l) : l \in Z\}$ is the normal orthogonal basis of wavelet subspace W_j . The wavelet packet can further subdivide each wavelet subspace W_j .

Use the $\{\psi_n\}$ to generate a family of subspaces $U_j^n := \text{clos}_{L^2(R)} \langle 2^{j/2} \psi_n(2^j t - k) : k \in Z \rangle, j \in Z, n \in Z^+$. For each $j = 1, 2, \dots$, the wavelet subspace W_j can be further subdivided into

$$\begin{cases} W_j = U_{j-1}^2 \oplus U_{j-1}^3 \\ W_j = U_{j-2}^4 \oplus U_{j-2}^5 \oplus U_{j-2}^6 \oplus U_{j-2}^7 \\ \dots \\ W_j = U_{j-k}^{2^k} \oplus U_{j-k}^{2^k+1} \oplus \dots \oplus U_{j-k}^{2^{k+1}-1} \\ \dots \\ W_j = U_0^{2^j} \oplus U_0^{2^j+1} \oplus \dots \oplus U_0^{2^{j+1}-1} \end{cases} \quad (2)$$

Then, for each $m = 0, 1, \dots, 2^k - 1, k = 1, 2, \dots$ and the family of functions $\{2^{\frac{j-k}{2}} \psi_{2^k+m}(2^{j-k} t - l) : l \in Z\}$ is an orthogonal basis of $U_{j-k}^{2^k+m}$.

The multiresolution analysis of image decomposes the original image into low-frequency approximate detail images in three directions, i.e., horizontal, vertical, diagonal directions, further decomposes each low frequency approximate image into four images step by step. In addition to

the decomposition of low frequency approximate image, the wavelet packet analysis of image decomposes also the high frequency detail image, which the decomposition process is represented as a full quad-tree. Figure 6 and Figure 7 give the quad-tree representation method of wavelet packet and the instance of 2-level image decomposition, respectively. The first parameter of brackets in Figure 6 denotes the scale, and the second parameter is the decomposition parameter of wavelet packet.

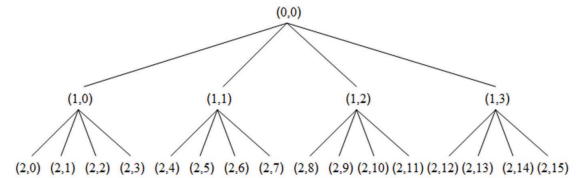


Figure 6: Quad-tree of wavelet packet to image decomposition



Figure 7: 2-level image decomposition by using wavelet packet

3.2 Feature extraction of target

3.2.1 Feature extraction of decomposition coefficient to image

Assume $g_j^n(t) \in U_j^n$, it can be expressed as $g_j^n(t) = \sum_l d_l^{j,n} \psi_n(2^j t - l)$. According to the calculation of wavelet packet decomposition, the decomposition coefficient is

$$\begin{cases} d_l^{j,2n} = \sum_k a_{k-2l} d_k^{j+1,n} \\ d_l^{j,2n+1} = \sum_k b_{k-2l} d_k^{j+1,n} \end{cases} \quad (3)$$

Where $a_n = \frac{1}{2} \bar{p}_n$ and $b_n = \frac{1}{2} \bar{q}_n$, \bar{p}_n and \bar{q}_n are the conjugation of p_n and q_n , respectively.

By the calculation of wavelet package reconstruction, the reconstruction coefficient is

$$d_l^{j+1,n} = \sum_k [p_{l-2k} d_k^{j,2n} + q_{l-2k} d_k^{j,2n+1}] \quad (4)$$

Firstly, the 2-level image decomposition to preprocessed images is carried out by using wavelet packet function $\psi(t)$. The decomposition results based on Haar wavelet basis are shown in Figure 8. The function $\psi_n(t)$ returns the tree structure of wavelet packet decomposition. It is an image user interface. The detailed images of the corresponding node are obtained by clicking at each node. Secondly, the wavelet

packet coefficients of each node can be calculated by using the reconstruction coefficient function $d_l^{j+1,n}(t)$ at each decomposition layer, and the result is shown in Figure 9. Finally, all the coefficients are normalized to compose the characteristic vectors. Assume the characteristic vector of wavelet packet decomposition coefficient at the i th layer is V_i , then there is

$$V_i = (c_{i0}, c_{i1}, c_{i2}, \dots, c_{i,2^{2^i}-1}) \quad (5)$$

Where i denotes the number of layers of wavelet packet decomposition, c_j denotes the normalization coefficient values of wavelet packet at each layer.

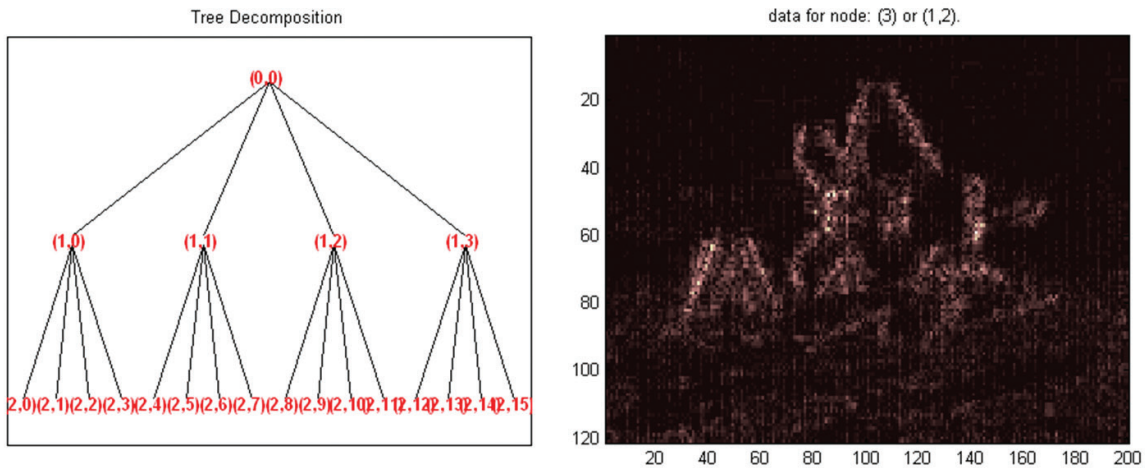


Figure 8: Nodes of wavelet packet and the detailed image at node (1,2)

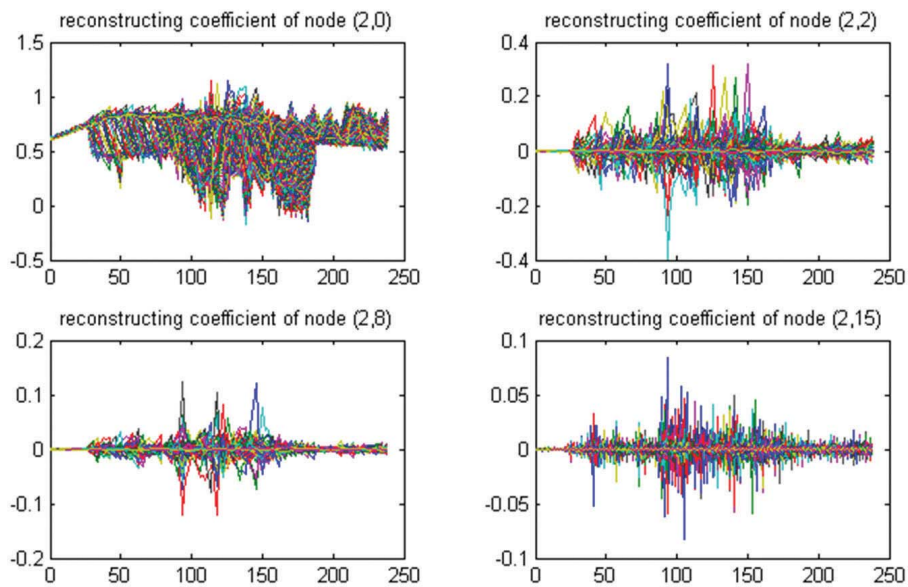


Figure 9: Reconstruction coefficients at different nodes

3.2.2 Feature extraction of energy to image decomposition

The energy feature can be calculated by using the decomposition results of wavelet packet to image. According to the algorithm described in this paper, the energy of image decomposed by wavelet packet is defined as follows:

$$E_{(i,j)} = \sum_{x=1}^{n \times 2^{-i}} \sum_{y=1}^{m \times 2^{-i}} [H_{(i,j)}(x,y)]^2 \quad (6)$$

Where, $E_{(i,j)}$ is the energy of image at each node, and (i,j) denotes different nodes in a quad-tree of wavelet packet decomposition. Under the 2-level wavelet packet decomposition, there are $i \in \{0, 1, 2\}$ and $j \in \{0, 1, 2, \dots, 15\}$. $H_{(i,j)}(x,y)$ is the energy of detailed image on each node. m and n are the height and width of the image, respectively. To extract the energy of detailed image on each layer, the energy feature of the image decomposed by the wavelet packet can be established as follows:

$$E_i = (E_{i,0}, E_{i,1}, E_{i,2}, \dots, E_{i,2^{2i}-1}) \quad (7)$$

Therefore, the E_i is called the energy feature of image decomposition at the i th layer. It is normalized as follows:

$$E_{i,j} = \frac{E_{(i,j)}}{\sum_{x=1}^n \sum_{y=1}^m [H_{(i,j)}(x,y)]^2} \quad (8)$$

Where i denotes the decomposition level, $j \in \{0, 1, 2, \dots, 2^{2i} - 1\}$. The further simplification can be obtained:

$$E_i = (E_{i0}, E_{i1}, E_{i2}, \dots, E_{i,2^{2i}-1}) \quad (9)$$

4 Matching and recognition method

4.1 Matching and recognition

The feature matching is to carry out the judgment of the similarity between the two characteristic vectors. The two targets are judged whether they are from the same target by calculating the similarity of two characteristic vectors. The similarity is expressed by the similar degree of the distance between characteristics.

We compare the characteristic vectors of unknown target image with the characteristic vectors of known classificatory target image that has been trained and stored in the retrieval system. If and only if the similarity between the characteristic vector of unknown target image and the characteristic vector of given i_0 th target image is maximum, we judge that the unknown target belongs to the i_0 th category based on the maximum membership principle. The matching algorithm is given as follows:

If W_l is the known characteristic vector in the retrieval system, V is the characteristic vector to be identified. Where $l = 1, 2, \dots, Q$ and Q is the number of known characteristic vectors. The similarity between the characteristic vectors V and W_l of two targets is defined as follows:

$$d_l = e^{-\|V-W_l\|} = e^{-\sum_{i=1}^n |V_i - W_{li}|} \quad (10)$$

Where, $|V_i - W_{li}| = \frac{1}{2^{2i}} \sum_{j=0}^{2^{2i}-1} |c_{ij}^{V_i} - c_{ij}^{W_{li}}|$ represents the similarity between the characteristic vectors of coefficient for image, or $|V_i - W_{li}| = \frac{1}{2^{2i}} \sum_{j=0}^{2^{2i}-1} |E_{ij}^{V_i} - E_{ij}^{W_{li}}|$ is the similarity between the characteristic vectors of energy of the image decomposed by wavelet packet. $c_{ij}^{V_i} \in V_i$, $c_{ij}^{W_{li}} \in W_{li}$, $E_{ij}^{V_i} \in E_i^{V_i}$, $E_{ij}^{W_{li}} \in E_i^{W_{li}}$, i is the number of layers of the wavelet packet to the image decomposition. The similarity d_l represents the degree of similarity between the characteristic vector V and the characteristic vector W_l of the l th category. The recognition principle is as follows: If $\exists l_0 \in 1, 2, \dots, Q$, subject to

$$l_0 = \arg \max_{l \in \{1, 2, \dots, Q\}} \{d_l\} \quad (11)$$

Then based on the maximum membership principle, we judge that the target to be identified belongs to the l_0 th category.

4.2 Hierarchical recognition method

In the recognition process, it needs to search for all the samples in the database, so as to find the sample which it and the identified target image are from the same target, and then the target recognition is achieved. In order to improve the accuracy and efficiency of recognition, the hierarchical recognition method is introduced for searching. After preprocessing and feature extraction to each target image, the target image is determined by two kinds of characteristics. Firstly, the database is searched by the feature of image decomposition coefficient for the first time, and then the candidate set that consists of the target images of similar features of coefficient is obtained. Then, in the candidate set, the second search is carried out by using the energy feature of image decomposition achieved by wavelet packet, and then the final recognition results are obtained. In the recognition process, we use the feature of image decomposition coefficient to search for the first time is because of its computational complexity is relatively small, which increases the speed of recognition. To implement the search for the second time to the candidate set, because the number of samples in candidate set is less than that of in the database, similarly, the overall recognition efficiency is also improved. Figure 10 shows the flow chart of hierarchical recognition.

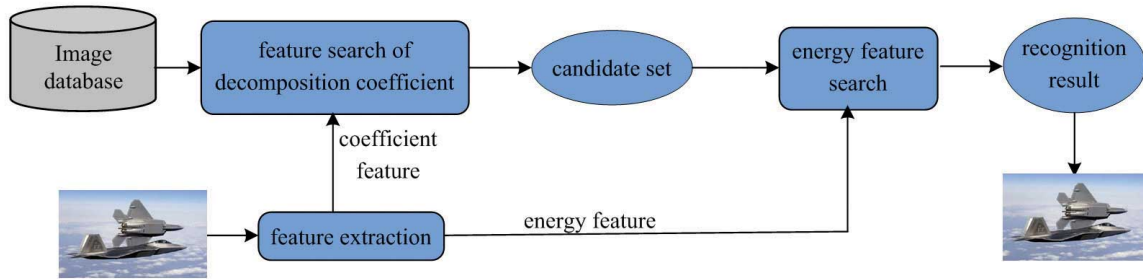


Figure 10: Flow chart of hierarchical recognition

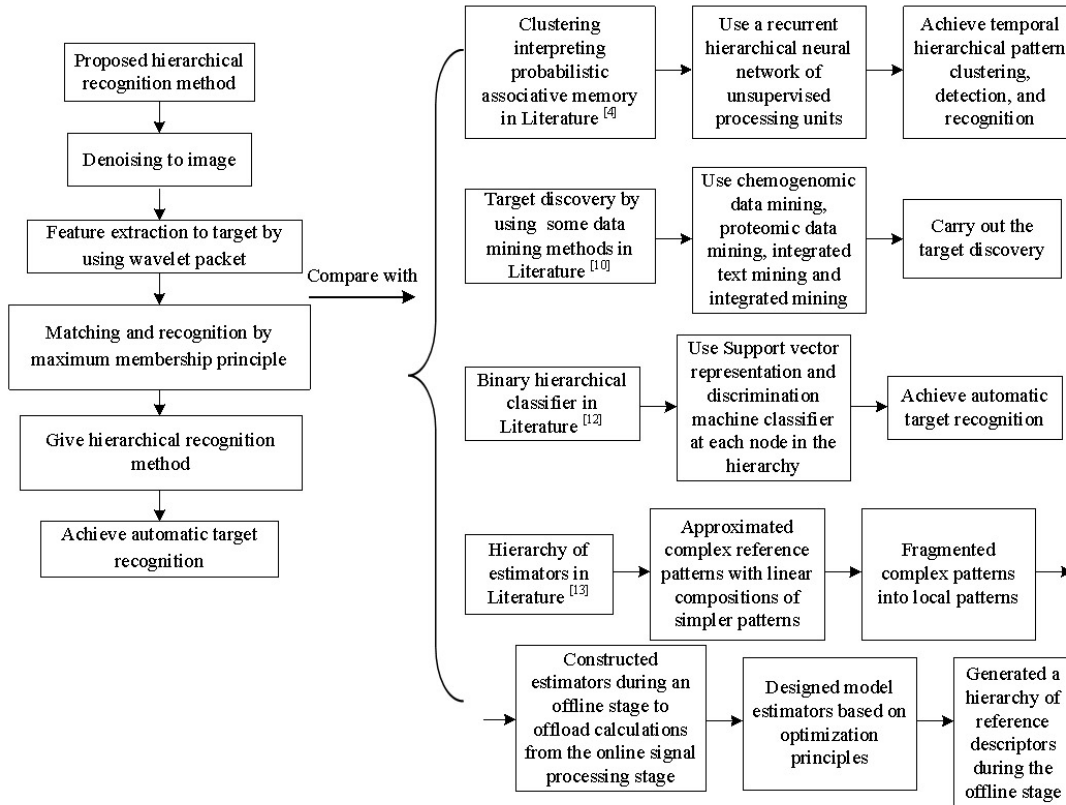


Figure 11: Comparative flowchart for several target recognition methods

In the last years, there were several literatures^[4,10,12,13] on the similar topic to also discuss hierarchical target recognition. However, the target recognition methods discussed in these literatures were different from the hierarchical method discussed in this paper. This paper proposes the denoising method to carry out fuzzy image preprocessing, discusses feature extraction of target by using wavelet packet, gives the hierarchical target recognition method, to carry out better target recognition. However, the literature^[4] gave a learning machine, called a clustering interpreting probabilistic associative memory (CIPAM), to achieve temporal hierarchical pattern clustering, detection, and recognition. CIPAM consisted of a clusterer and an interpreter. The clusterer was a recurrent hierarchical neural network of unsupervised processing units. The clusterer of CIPAM

clustered temporal and spatial data. The interpreter interpreted the resultant clusters, effecting detection and recognition of temporal and hierarchical causes. The literature^[10] used some data mining, such as chemogenomic data mining, proteomic data mining, integrated text mining and integrated mining, to carry out the target discovery. The literature^[12] proposed a binary hierarchical classifier that was called support vector representation and discrimination machine classifier (SVRDM) to achieve automatic target recognition. The SVRDM classifier was used at each node in the hierarchy. The literature^[13] constructed a hierarchy of estimators to simplify and enhance the recognition of the models of interest; approximated complex reference patterns with linear compositions of simpler patterns; fragmented complex patterns into local patterns so that interference be-

tween the local patterns was sufficiently small for linearization methods to be applicable; constructed estimators during an offline stage to offload calculations from the online signal processing stage; designed model estimators based on optimization principles to enhance performance and to provide performance metrics for the estimated model instances; generated a hierarchy of reference descriptors during the offline stage, which were used for the design and construction of the model estimators. A comparative flowchart is shown in Figure 11.

4.3 Experiment and results analysis

(1) Establish a standard template database

The target image database used in experimental test and the sample database are established as follows:

- 100 different samples are chosen randomly from image database, and 3 images are chosen randomly from 10 images of each target. Thus, a total of 300 target images are obtained.
- An image is chosen randomly from 3 images of each target, which the total is 100 images to compose experimental database of target image. The remaining 200 target images compose the test samples database.
- The established 100 target images are carried out a preprocessing and feature extraction by 5-level Daubechies-4 wavelet packet decomposition. The 100 characteristic vector sets P of decomposition coefficient and 100 characteristic vector sets Q of energy of image decomposition are acquired, respectively. Each characteristic set contains 100 characteristic vectors.

(2) Matching The basic step of the target matching recognition is as follows:

P1. The target images in test database are carried out a preprocessing by 5-level Daubechies-4 wavelet packet and the feature extraction of 2-level decomposition. The coefficient features V and the energy features E based on 2-level image decomposition by using wavelet packet are obtained. Where $V = (V_0, V_1, V_2)$, $V_0 = (c_{00})$, $V_1 = (c_{10}, c_{11}, c_{12}, c_{13})$, $V_2 = (c_{20}, c_{21}, c_{22}, \dots, c_{2,15})$, $c_{ij} = d_l^{j,2n}$ or $c_{ij} = d_l^{j,2n+1}$ is computed by the formula (3). $E = (E_0, E_1, E_2)$, $E_0 = (E_{00})$, $E_1 = (E_{10}, E_{11}, E_{12}, E_{13})$, $E_2 = (E_{20}, E_{21}, E_{22}, \dots, E_{2,15})$. E_{ij} can be obtained by the formula (6) and formula (8), $i = 0, 1, 2, j = 0, 1, 2, \dots, 15$ and $m = 239, n=398$.

P2. According to the hierarchical recognition process as shown in Figure 10, the test coefficient feature V is carried out the first matching with all characteristic vectors of decomposition coefficient feature sets P in the standard database. The candidate set is composed by the corresponding energy features which correspond to the matched similarity coefficient features. The test energy feature E is carried out the second matching with the characteristic vectors in the candidate set. The corresponding target image which corresponds to the maximum similarity of energy features is

the recognition result after the matching is finished.

P3. For each image in the test sample database, after 300 times recognition are done according to the steps P1~ P2, the times of the correct recognition and the error recognition are recorded respectively, and the correct recognition rates are obtained by calculating.

(3) Results analysis

As a result of an evaluation for recognition effect, here we consider the correct recognition probability R_c , which it is obtained by recognizing correctly from the same feature of two local nodes in wavelet transformation. We really want to obtain the analytical expression of R_c , it is usually very difficult, so we use its relative frequency instead of its probability in simulation. Assume $N_l = \max(n_{1l}, n_{2l})$, where n_{1l} and n_{2l} are the number of features that two local nodes 1 and 2 participate in matching testing at time l respectively. N_c is the number of features for the correct recognition, and then there is

$$R_c = \frac{N_c}{N_l} \quad (12)$$

Obviously, for different values l , the above result is different, but R_c will converge to a certain value with the increase l . The conclusion may be confirmed by the following simulation.

For each target image, 12 times repeating experiments are carried out by the step P1 to step P3 based on Daubechies-4 wavelet basis function in simulation. The number of samples is different in each experiment. The proposed hierarchical recognition method compares with those currently usually used recognition methods such as Gabor,^[9] statistical method.^[10] The experimental results show that the average correct recognition rates of these methods are 96.82%, 89.93%, 85.98% in simulation of 300 times, respectively. The simulation results are shown in Figure 12.

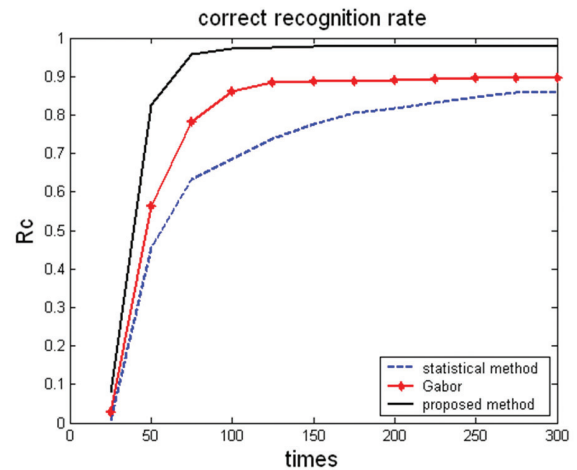


Figure 12: Comparison of correct recognition rate of the proposed and existing recognition methods

From Figure 12, the average correct recognition rate based on the hierarchical recognition method is the maximum

among all referred methods. In experiment, the average correct recognition rate increases constantly with the increasing number of samples, and the curve of average correct recognition rate gradually levels off as the samples increase when the number of samples reaches a certain value.

The proposed hierarchical recognition method and the usual used recognition methods^[9,10] are compared from two aspects that are the computing speed and the correct recognition rate. Table 3 gives the results of a comprehensive comparison. From the comparison, the proposed hierarchical recognition method has better recognition effect than other methods.

Table 3: Comparison of different target recognition methods

Recognition methods	Statistical method	Gabor	Proposed method
Average correct recognition rate	0.8598	0.8993	0.9682
Computing speed	0.141 s	0.171 s	0.167 s

In Table 3, the computing speed is the mean time obtained by the mean computing time of 12 times repeating test of these methods at each step in simulation environment, which the computing time is only the computing time of algorithm itself. In simulation, the computer used is the Pentium 4 and 2G memory, and the programming language is MATLAB. The average correct recognition rates are the average of two stages which are an average of 300 times simulations and then taking an average of 12 time steps for every method under the given simulation environment. In fact, they are the average of the correct recognition rates in space and time, so they are an overall average of the correct recog-

niton rates. Moreover, through programming procedure to the proposed method with C or C++, the proposed method can be implemented onto the embedded systems like the FPGA, ARM etc.

From the simulation results, the hierarchical recognition method not only has the faster processing speed, but also has better recognition effect.

5 Conclusion

This paper uses the wavelet packet analysis to carry out feature extraction of target for the first time, and presents the hierarchical recognition method. In target feature extraction process, the more detailed and rich texture feature of target can be obtained by wavelet packet to image decomposition to compare with the wavelet decomposition. In the process of matching and recognition, the hierarchical recognition method is used to improve the recognition speed and accuracy. Therefore, this method provides a new way of thinking for target recognition.

How to choose or construct a proper wavelet basis function, and how many levels of decomposition can be carried out to obtain the best recognition effect, are some questions which need further study in the future.

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