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Texture Feature Extraction Method for Ground Nephogram Based on Contourlet and the Power Spectrum Analysis Algorithm

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Abstract: It is important to extract texture feature from the ground-base cloud image for cloud type automatic detection. In this paper, a new method is presented to capture the contour edge, texture and geometric structure of cloud images by using Contourlet and the power spectrum analysis algorithm. More abundant texture information is extracted. Cloud images can be obtained a multiscale and multidirection decomposition. The coefficient matrix from Contourlet transform of ground nephogram is calculated. The energy, mean and variance characteristics calculated from coefficient matrix are composed of the feature information. The frequency information of the data series from the feature vector values is obtained by the power spectrum analysis. Then Support Vector Machines (SVM) classifier is used to classify according to the frequency information of the trend graph of data series. It is shown that altocumulus and stratus with different texture frequencies can be effectively recognized and further subdivided the types of clouds.

Keywords: Ground nephogram, super-wavelet, Contourlet, the power spectrum.

1 Introduction

Automated ground nephogram recognition using computers has been attempted but remains a challenging issue, because of the ever-changing shape of clouds [Chen, Song, Li et al. (2014); Hu, Yan, Xia et al. (2017)]. Image recognition is a hot research topic in the scientific community and industry [Wei, Zhang, Victor et al. (2018)]. The performance relies on features extraction of image. Cloud texture information is exceedingly rich and relatively stable. However, the frequency information of most different clouds varies greatly, such as stratus and cirrocumulus. It is an effective image recognition method to analyze texture in spatial frequency domain by imitating human visual system. Similar to the human visual perception system, this method can automatically decompose an observing image into separate frequency and direction components [Shan, Hu and Li (2007)].

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In this paper, a method is presented to more effectively capture the edge contour and the geometric structure of nephogram. More abundant texture information can be extracted. The classification algorithm based on Contourlet and power spectrum is represented to classify cloud types from the ground nephogram. In addition, a test run of random images is presented, which outperforms existing algorithms by yielding a higher success rate.

2 Wavelet analysis

Wavelet analysis [Mallat (1989)] has been used in a wide variety of applications in signal and image processing, such as image compression, edge detection, image filtering, feature extraction, solving fractal index, etc.

The progenitor of wavelet analysis is Fourier analysis. Wavelet analysis is local analysis in the time domain and frequency domain, which represents the signal property using combination of the time domain and frequency domain. It is more superior to Fourier transform and Gabor transform.

Wavelet analysis is the approximation of a square integrable function, $\psi(t) \in L^2(R)$. It can be expressed as follows:

$$C_\psi = \int_{-\infty}^{+\infty} \frac{|\psi(w)|^2}{w} dw < \infty \tag{1}$$

where $\psi(t)$ is basic wavelet or mother wavelet.

Then $\psi_{a,b}(t)$ can be obtained for $\psi(t)$ by the expansion and translation operations:

$$\psi_{a,b}(t)=\frac{1}{\sqrt{a}}\psi(\frac{t-b}{a}), a>0, b\in R \tag{2}$$

The function $\psi_{a,b}(t)$ is the wavelet basis function which is generated by the basic wavelet $\psi(t)$, a is expansion coefficients, b is translation coefficients.

Wavelet Transform [Chen (2002)] is a convolution operation of the original signal and the wavelet function of scale expansion. In $L^2(R)$ space, the wavelet transform of base wavelet $\psi(t)$ under the condition of any square integrable function $f(t)$ is constructed using

$$W_{\psi,f}(a,b)=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} f(t)\overline{\psi(\frac{t-b}{a})}dt \qquad (a,b\in R, a>0) \tag{3}$$

where, a is expansion coefficients, b is translation coefficients.

Therefore, the wavelet transform of $f(t)$ can reflect the overall information of $f(t)$ from the whole to the details by calculating expansion coefficients a. It can also move the wavelet function on the time axis by translation coefficients b, so that the wavelet basis function can be moved to any position.

Further, the inversion formula can be obtained using

$$f(t)=\frac{1}{C_{\psi}}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}W_{\psi,f}(a,b)\psi_{a,b}(t)\frac{da}{a^{2}}=db \tag{4}$$

where $C_{\psi}=\int_{-\infty}^{+\infty}\frac{\left|\psi(w)\right|^{2}}{w}dw$.

3 Super-wavelets analysis based on Contourlet

Super-wavelets [Yan (2008)] refers to the oversize space of wavelet. It is a new signal analysis and sparse signal expression method based on wavelet analysis. This method has preferable advantages over wavelet in signal multiplicity cases [Li and Wang (2007)] and is widely applied in data compression, signal de-noising, image analysis, speech signal processing, video processing [Shukla and Maury (2018)].

The wavelet can provide excellent representation for one-dimensional piecewise smooth signals. However, when dealing with multi-dimensional signal with “line singularity” [Lu (2011)], the separable wavelet bases of wavelet transform have only several limited directions for image texture with the strong direction transformation. Some researchers try to find better method which takes advantages of the sparse representation tool of structured data than wavelet analysis. A series of methods for super-wavelets analysis is proposed. It is also called the multiscale geometric analysis which include Curvelet, Ridgelet, Contourlet, Bandelet, Wedgelet, Beamlet, and Surfacelet transform. The generation of the super-wavelets meets the requirements of the human visual cortex for image locality, directionality and multi-scale. In 2000, super-wavelets complete definition was presented [Han and Larson (2000)]. In 2002, Do and Vetterli proposed Contourlet Transform (Tower Direction Filter Group), which is a two-dimensional representation of image [Do and Vetterli (2002)]. This method not only inherits the anisotropic scale of Curvelet Transform, but also grasps well the geometric structure of image with flexible, changeable, multi resolution, local and directional.

Contourlet transform [Gao (2011)] is used to approximate the image using a basic structure similar to contour segments. The support interval of Contourlet transformation is a “long strip” structure. It can vary with the aspect ratio of scale and can be transformed by direction analysis and multiscale analysis respectively. Therefore, it has both directivity and anisotropy. Ordinary two-dimensional wavelet is constructed by tensor product of one-dimensional wavelet. Its basis is neither direction nor anisotropic. The effect of direction information such as edge and texture can be more realistically represented by Contourlet Transform than that of two-dimensional wavelet transform. It is more effective in capturing the smooth contours and geometric structure [Xiao (2012)].

Firstly, Contourlet Transform is a multi-scale analysis based on Laplacian Pyramid decomposition (LP) to deal with the singular points of different scale. Then, directional filter banks (DFB) are used to connect singular points of the same scale into lines. Thus, the multiscale and multi-direction image decomposition is completed.

3.1 Laplasse Pyramid transformation

The image is firstly decomposed into different frequency subband using Laplasse Pyramid [Do and Vetterli (2001)], that is, frequency division processing may be used. Laplasse Pyramid is comprised of low-pass filtering and down sampling. Laplacian pyramid decomposition of each layer obtains a low-frequency approximate signal by low-pass filtering and down-sampling decomposition. Then the difference, filtering and smoothing of the signal is utilized to make the difference between the result and the original image signal, and the high frequency signal is obtained. The multi-scale decomposition is achieved by cyclic iteration. The reconstructed structure of LP is an optimal linear reconstructed structure with time-doubled frame operators [Xiao (2012)].

3.2 Directional filter transformation

In Contourlet Transform, diamond filter [Bamberger and Smith (1992)] and sector filter [Do (2001)] are used to realize directional filtering. Bamberger and Smith proposed a method to construct two-dimensional filter banks using diamond type non-separable filters banks [Bamberger and Smith (1992)]. It has good directionality and reconfiguration. However, diamond filter is gradually replaced by sector filter because of its complexity and difficulty in implementation. Modulation of the input signal can be avoided by using sector filter for multi-scale. Do and Vetterli proposed an improved DFB structure, including the two-channel quincunx filter bank and the shearing operation two building blocks [Do and Vetterli (2005)].

DFB combines shearing operators together with two-direction partition of quincunx filter at each node in a binary tree-structured filter bank to obtain the desired 2-D spectrum division. The two-dimensional frequency plane is divided into wedge-shaped structures with directivity [Wang (2011)].

3.3 Contourlet decomposition

Coutourlet Transform combines Laplacian pyramid (LP) and the directional filter bank (DFB). The frequency division processing ability and the capability of capturing the high frequency of the input image are synthesized. It can efficiently represent the characteristics of multiresolution, multidirection and localization of images.

Contourlet Transform can select appropriate parameters according to the texture characteristics of the image contrast with wavelet transform. Directional subbands that can be flexibly decomposed at each chosen scale. By contrast, the wavelet transform can only decompose four directional subbands at each scale. Both transformations are just an iterative process and the Contourlet transformation program can be implemented recursively. Contourlet Transform coefficients are one-dimensional vector. The values of the elements in the vector represent the decomposition parameters of a pyramid filter bank. The number of elements in the vector is the scale parameter decomposition. If the value of an element in the vector is i, it means that in this Laplacian pyramid decomposition, the number of decomposition layers is 2^i. The subband is divided into 2^i direction. If the directional subband number of pyramid filter bank decomposition is 0 on a certain scale, the program uses the Wavelet Transform to obtain high-frequency information and low-frequency part information in vertical, horizontal and diagonal directions. In MATLAB program, such as preferences nlevels=[3,3,3], indicating that a three Laplacian pyramid decomposition. The image is divided into three scales and processed. The low-frequency information and high-frequency information of each scale are obtained. Each scale has exploded eight directions.

Contourlet wavelet is superior to the traditional two-dimensional wavelet transform. In this paper, this method is used to the feature extraction of ground-based cloud images.

4 Texture feature extraction Algorithm of ground nephogram based on Contourlet and power spectrum

4.1 Texture feature extraction

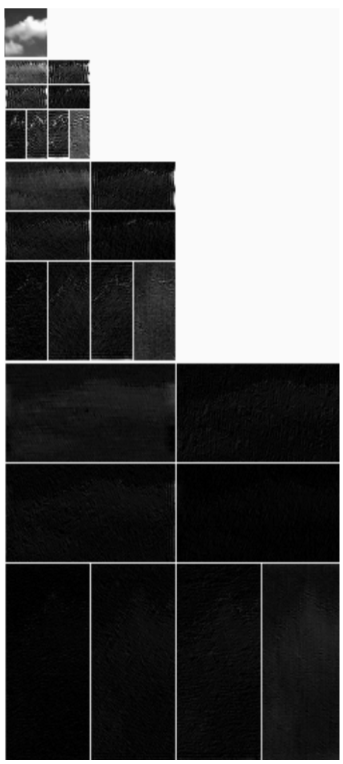
In this paper, the image can be decomposed flexible multi-scale and multi-directional by the Contourlet Transform. The transform coefficients contain a lot of texture information. The feature vector is extracted from the coefficients of nephogram samples by the Contourlet Transform. The feature information in the coefficient is preserved to distinguish from other kinds of nephogram. The coefficients transformed by Contourlet are represented as eigenvectors.

Specific steps to realize this algorithm are as follows:

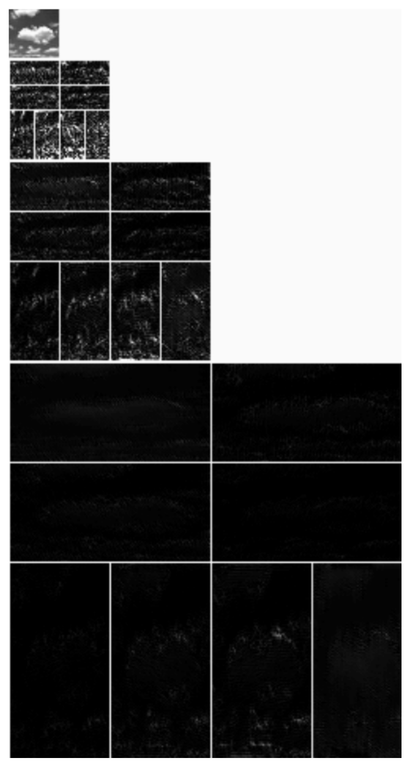
Contourlet decomposition. First, the cloud images were intercepted into 256×256 pixels of nephogram samples, then Contourlet Transform is performed. According to the transformation rules, the coefficients contain several subbands. Contourlet transform of several nephogram with nlevels=[3,3,3] is shown in Fig. 1 .

(a0) (b0)

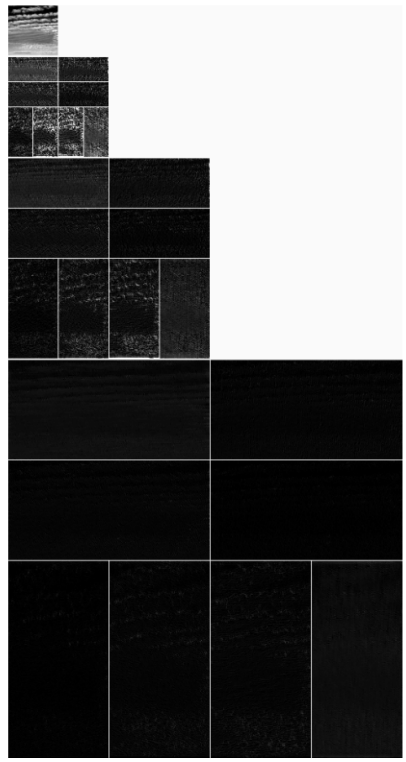
(c0)



(a1)



(b1)



(c1)

Figure 1: (a0), (b0), (c0) for the sample cumulus humilis 1, cumulus humilis 3, altocumulus 7; (a1), (b1), (c1) is corresponding Contourlet decomposition image with nlevels=[3,3,3]

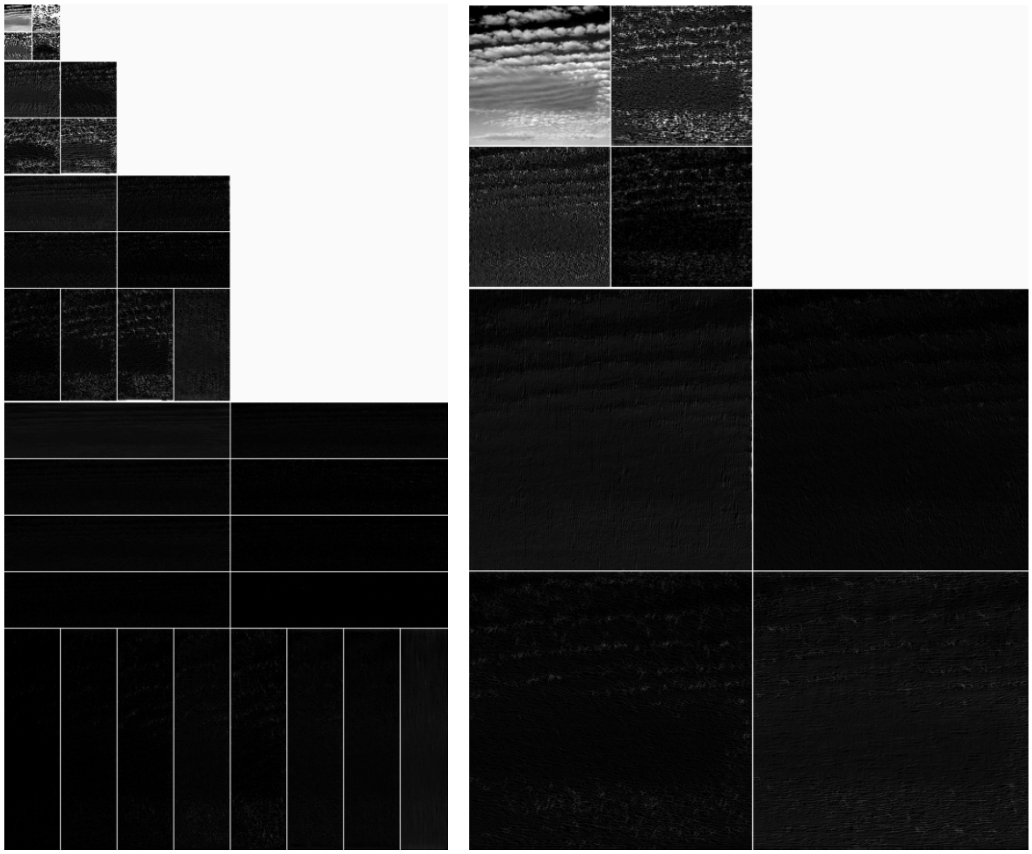
The Contourlet transform image of sample altocumulus 7 under different parameter settings is shown in Fig. 2. As can be seen from the figure, when the parameter of a layer is 0, the decomposed image of this layer is the same as that of the parameter of 2, which are all four images.

The meaning with nlevels=[3,3,3] is to adopt three-scale Contourlet transform and each scale is decomposed into eight directions. Three scales produce 24 elements reflecting high frequency information and one element reflecting low frequency information. There are 25 elements in total. Contourlet is used to process nephogram samples, and multi-scale and multi-directional analysis of nephogram can more accurately describe the nephogram texture.

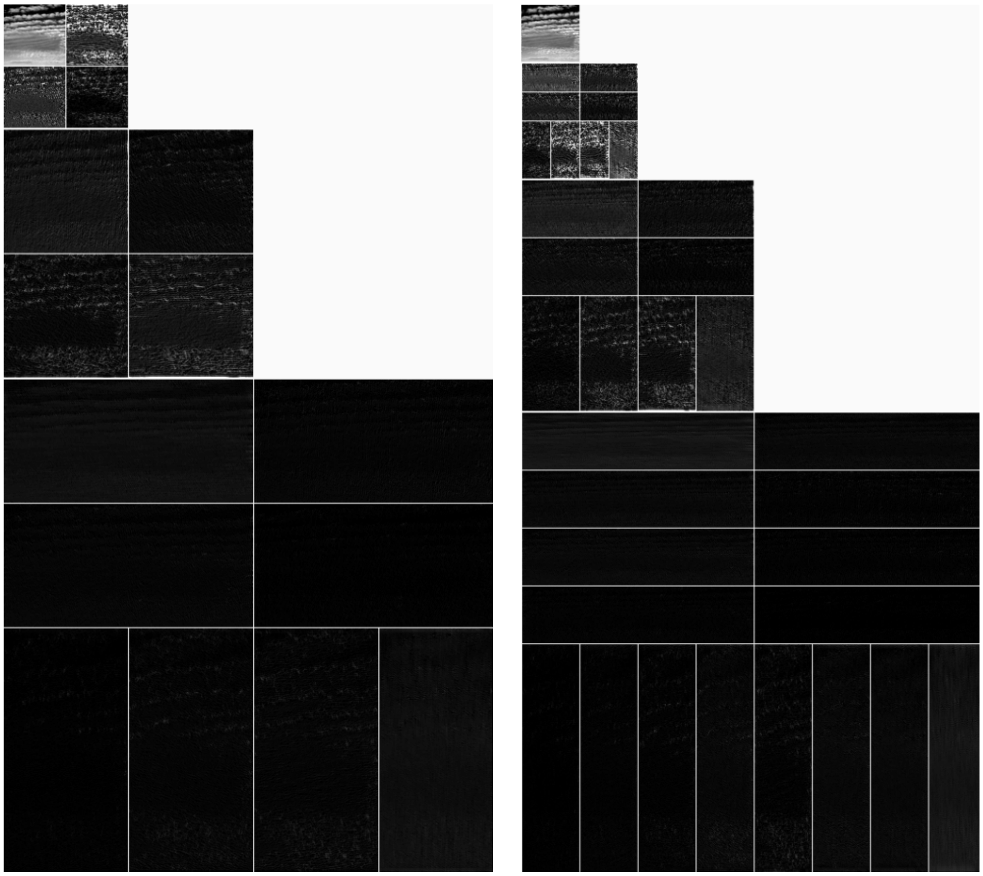
Select the feature vector [Yang (2011)] The energy, mean and variance of each sub-band after Contourlet decomposition are taken as the eigenvalues, that is

energy: $$E_k(i,j)=\sum_{x\in M,y\in N} C_k(x,y,i,j)^2 \tag{5}$$

means: $$m_k(i,j)=\frac{1}{M\times N}\sum_{x\in M,y\in N} C_k(x,y,i,j) \tag{6}$$



(a) (b)



(c) (d)

Figure 2: Contourlet decomposition image of altocumulus 7 at nlevels=[0,2,3,4], nlevels=[0,2], nlevels=[0,2,3], nlevels=[3,3,4]

variance: $$Cov(C_k(x,y,i,j)) = \frac{1}{M \times N} \sum_{x \in M, y \in N} (C_k(x,y,i,j) - m_k)^2 \tag{7}$$

where $C_k(x,y,i,j)$ is the decomposition coefficients of subband coefficient matrix in the j^{th} direction, i is the number of layers of Contourlet transform decomposition, and j is the number of directions. The original image is $M \times N$ in pixels, with gray value $f(x,y)$, $(x = 1, \cdots, M, y = 1, \cdots, N)$.

4.2 Results

Firstly, the features of ground-based cloud image samples were extracted using Contourlet algorithm in the super -wavelets method. There are 40 nephograms in each category and 400 pictures in 10 categories. The images were captured with 512×512 pixels as learning samples which contained the region of main cloud texture. The Contourlet algorithm was written by using the MATLAB tools. Nephogram features were extracted and classified by support vector machine (SVM).

Nephogram feature extraction process is defined as follows:

1) First, the observers are asked to artificially judge the type of cloud image. The cloud images are classified manually and the cloud image database is established. Then the clouds divided class will be captured with 512×512 pixels.

2) 20 samples of each category clouds were selected as learning samples. Another 20 samples are used as predicting samples.

3) Contourlet transform is applied to all samples to obtain Contourlet transform coefficients.

4) The characteristics vectors such as energy, mean and variance were calculated by Contourlet Transform coefficients for each sample.

When the nephogram samples were decomposed using Contourlet transform, the DFB parameters were selected as nlevels=[3,3,3]. The image is filtered by a filter bank consisting of a frequency and four directions. Each kind of sample cloud image is a feature sample. After the Contourlet transform of class image, the Contourlet coefficient matrix in 3 layers and eight directions is calculated. The features such as energy, mean and variance of each coefficient matrix were extracted as the attribute value with 72 eigenvalues. These 72 eigenvectors were written as training text and predictive text according to a fixed input format, and then the training and the predicting are performed.

The feature extraction of stratus and altocumulus is taken as an example to illustrate the feature extraction method. Several 256×256 pixels stratus samples and altocumulus samples were selected as learning samples. An eigenvector with 72 eigenvalues for each sample is calculated. And then some additional stratus and altocumulus samples were selected to calculate the feature vectors using the same method. Finally, the classification method of support vector machine is used to classify cloud. It is found that the classification effect is not satisfactory. Therefore, the feature vector for each sample are analyzed to find ways to extract more suitable feature values. The feature vector data with 72-dimensional row vector of a stratus sample is selected. The trend graph of data series from the feature vector values which is calculated based on the coefficient matrix Contourlet Transform are shown in Fig. 3. The position of the data onto the array is used as the abscissa in Fig. 3. The ordinate is the size of each element of the feature vector values.

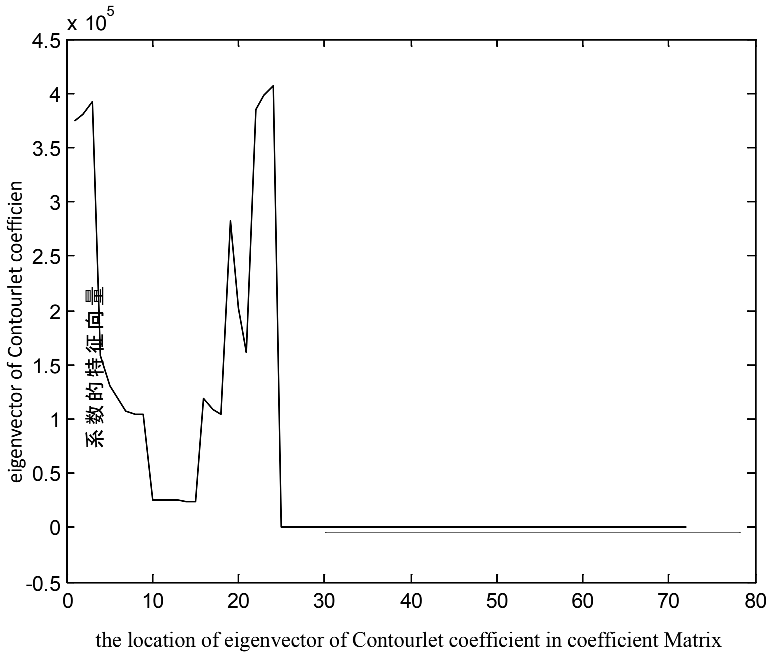


Figure 3: The change of Contourlet coefficient of one of stratus

Then an altocumulus sample is selected. The trend map is also shown in Fig. 4. It is found that the frequency change of stratus samples is small and the trend is relatively gentle. However, the frequency change of altocumulus samples varies greatly and the trend is more intense. In order to find out the general rule, the trend maps of the characteristic vectors of all the learning samples of stratus and altocumulus are shown in Fig. 5. Although the variation of amplitude is quite different in the trend map of characteristic vectors of altocumulus samples, the frequency of variation is relatively close. The location of the frequency extreme is very close. There are many sharp peaks and troughs. In the trend map of the characteristic vectors of stratus samples, the frequency of change is similar and the data change is mainly in a gentle step shape.

To further extract information from these features effectively, the power spectrum distribution of the data sequence is calculated for these features. Fig. 6 shows the power spectrum distribution of the Contourlet coefficient characteristic associated with a sample of stratus. Fig. 7 shows the power spectrum distribution of the Contourlet coefficient characteristic associated with a sample of altocumulus. it can be seen from Fig. 6 and Fig. 7 that there is only one relatively large peak at low frequency stage and no peak at high frequency stage in the power spectrum distribution of stratus samples (Fig. 6). With the increase of frequency, the trend of oscillation become smaller. There is more than one relatively large peak in the low frequency stage and also a large peak in the high frequency stage for the power spectrum distribution of altocumulus samples (Fig. 7).

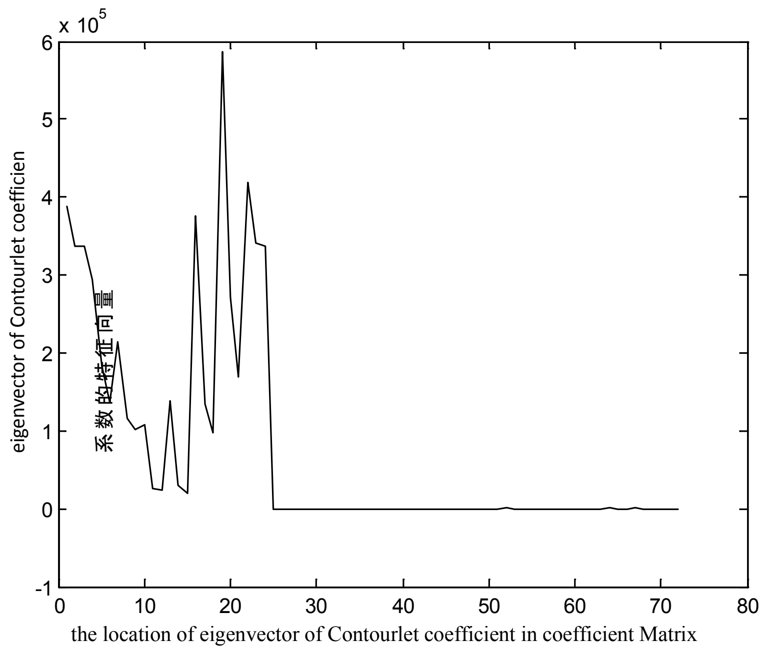


Figure 4: Changes in the Contourlet coefficient of one of the altocumulus clouds

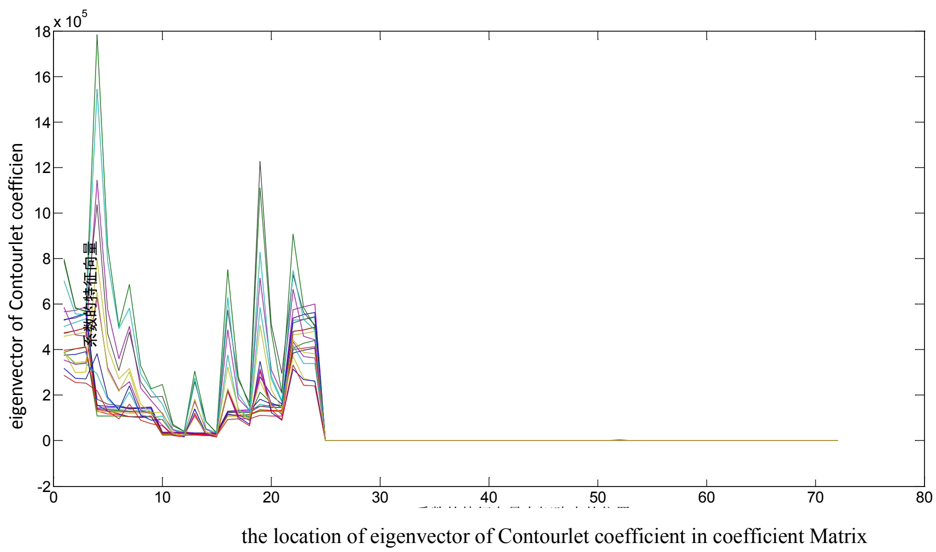


Figure 5: Changes of Contourlet coefficient in ten stratus and ten altocumulus samples

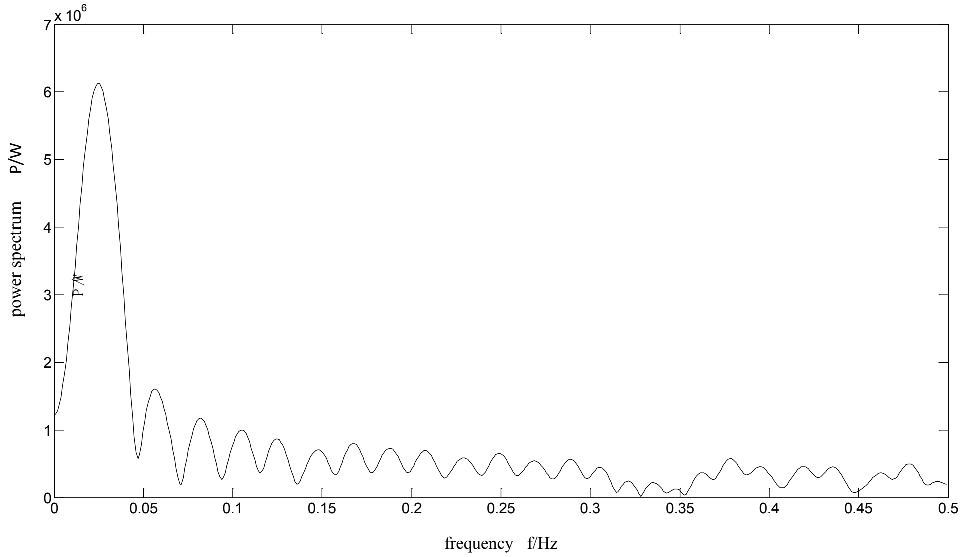


Figure 6: The power variation characteristics of Contourlet coefficient of the sample volume stratus spectrum

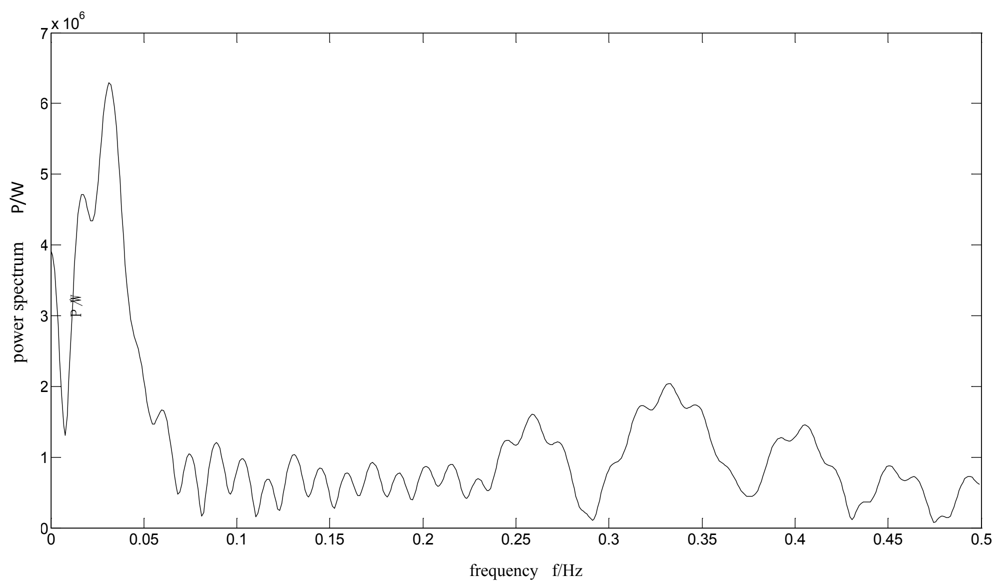


Figure 7: Power spectrum change of Contourlet coefficient eigenvalue of one of the altocumulus samples

These features could be found during analyzing twenty learning samples of cloud image. Therefore, extracting the frequency information of the Contourlet coefficient with each cloud image can be effectively classified altocumulus and stratus with different texture frequencies.

Finally, Support Vector Machine (SVM) classifier is used to train and predict cloud image samples. According to the above analysis, 40 cloud images samples were identified and the experimental results of classification are shown in Tab. 1.

Table 1: Cloud classification confusion matrix

	altocumulus	stratus	total	accuracy (%)
altocumulus	20	0	20	100
stratus	0	20	20	100

Compare with wavelet transform, Contourlet can provide a flexible multiscale and directional decomposition for images and better description of the image edge information. The experimental results show that the extraction algorithm based on Contourlet and power spectrum for cloud image is effective.

5 Conclusions

In this paper, a ground nephogram feature extraction algorithm based on Contourlet and power spectrum is presented. The ground-based cloud images are decomposed by Contourlet transform. The feature information includes in the energy, mean and variance characteristics calculated from coefficient matrix. The frequency information of data series is obtained by the power spectrum analysis. Then Support Vector Machines (SVM) classifier is used to train and predict cloud image samples. The experimental results showed that this method can effectively capture the cloud edge contour and texture geometry features and improve the recognition rate of typical clouds from ground nephograms.

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