A DIMENSIONALITY REDUCTION ALGORITHM OF HYPER SPECTRAL IMAGE BASED ON FRACT ANALYSIS

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Commission VII, WG VII/3

KEY WORDS: Hyper spectral, dimensionality reduction, spectral domain, fractal analysis, feature image

ABSTRACT:

A dimensionality reduction algorithm based on feature extraction of the spectral curve using fractal analysis which considering both the spatial characteristic and spectral characteristic of hyper spectral remote sensing image is proposed A spectral domain feature analysis based on fractal measurement technique is designed for hyper spectral images. Fractal characteristic of spectral curve is discussed. A brief description is given to explain the nonlinear mechanism resulting in fractal of spectral curve. And the spectral curves of same objects are presented to show the self similar. And some computational results are given to show exponential relation between the total length of spectral curves and the different measurement unit. A fractal dimension calculation algorithm of hyper spectral curve is designed. A noise remove algorithm based on wavelet transformation is done before the fractal analysis of spectral curve. Then a feature analysis procedure in spectral domain based on fractal measurement is also proposed to reduce dimensionality of hyper spectral images. The fractal dimension value is taken as the feature of spectral curve and the fractal dimension feature image is proposed to represent the dimensionality reduction result of hyper spectral image. Experiments of fractal dimension value of different objects spectral curve show fractal can be used to represent the spectral feature to reduce dimensionality of hyper spectral image. Finally, the application of fractal measurement of spectral domain feature analysis is briefly discussed.

1. INTRODUCTION

The characteristics of hyper spectral remote sensing data are numerous channels, high spectral resolution and large amounts of data, which makes it easy to discriminate objects in the scene, however, the vast amounts of data not only makes it difficult for transmission and storage, but also feature extraction and classification. Therefore, it is very important to reduce the dimension in the hyper spectral image analysis (C. Lee,1993; A. Jain,1997). As hyper spectral sensors acquire images in very close spectral bands, the resulting high-dimensional feature sets contain redundant information. Consequently, the number of features given as input to a classifier can be reduced without a considerable loss of information. Dimensionality reduction can general fall into feature extraction and band selection. Feature selection techniques generally involve both a search algorithm and a criterion function while feature selection is usually done in the image spatial space and feature transformation and feature extraction is used to reduce the image dimension such as the principal component analysis, absorption features extraction and spectral statistical analysis. Band selection is usually based on the spectral curve of hyper spectral image which can convert hyper spectral vector into low dimensions or one dimension. Due to their combinatorial complexity, band selection algorithms cannot be used when the number of features is larger than a few tens (L. Bruzzone, 1995; L. Bruzzone, 2000; C. Lee,1993; C.I Chang,2006; A. Plaza,2005). And dimensionality reduction algorithms based on feature extraction and band selection can not combined spectral and spatial characteristic. All these dimensionality reduction algorithms have the disadvantages of less considering the spectral information and low efficiency. Fractal theory is used in many applications for the advantage to solve the non-linear system of the complex phenomenon. Thus Fractal is usually used to solve the complex non-linear system analysis. Fractal theory has been used in the remote sensing research while it does not obtain the full application (Qiu H L; Weng Q, 2003). Commonly, fractal dimension of hyper spectral remote sensing image is calculated by the spatial characteristic and then the fractal dimension is used for the band selection. And the fractal dimension value is calculated with spectral curve to unify the spectral information to the spatial distribution feature image thus it can be used to reduce the dimensionality of hyper spectral remote sensing image.

In this paper, a dimensionality reduction algorithm based on feature extraction of the spectral curve using fractal analysis which considering both the spatial characteristic and spectral characteristic of hyper spectral remote sensing image is proposed A spectral domain feature analysis based on fractal measurement technique is designed for hyper spectral images. Fractal characteristic of spectral curve is discussed. A brief description is given to explain the nonlinear mechanism resulting in fractal of spectral curve. And the spectral curves of same objects are presented to show the self similar. And some computational results are given to show exponential relation between the total length of spectral curves and the different measurement unit. A fractal dimension calculation algorithm of hyper spectral curve is designed. A noise remove algorithm based on wavelet transformation is done before the fractal analysis of spectral curve. Then a feature analysis procedure in spectral domain based on fractal measurement is also proposed to reduce dimensionality of hyper spectral images. The fractal dimension value is taken as the feature of spectral curve and the fractal dimension feature image is proposed to represent the dimensionality reduction result of hyper spectral image. Experiments of fractal dimension value of different objects

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spectral curve show fractal can be used to represent the spectral feature to reduce dimensionality of hyper spectral image. Finally, the application of fractal measurement of spectral domain feature analysis is briefly discussed.

2. DATA ANALYSIS

2.1 Spectral feature of hyper spectral image

Spectral feature is the main difference of the hyper spectral image and the common remote sensing image (Peter F, 2001; Shu N,2001). Pixel value in each band which constructs the spectral curve can represent the object information for image classification. With the high resolution of spectral band, the spectral curve can be used for feature extraction, band selection and classification. Spectral matching method is used to identify the object with the spectral library supporting while it is time consuming with the vast mount of spectral data. In order to full use the spectral information of each pixel in hyper spectral image, the feature analysis can be done to each spectral curve to obtain feature and form the feature image of hyper spectral data. Thus the classification can be done with the spectral curve feature image. Dimensionalities reduce and feature analysis is done at the same time which can increase the processing efficiency. The key problem of spectral feature analysis is to extract the feature from the spectral curve.

2.2 Fractal characteristic of spectral curve

Fractal is a tool to analysis the spatial structure and spatial complex and it obtains fast progress in the remote sensing application. Fractal dimension is used to present the spatial structure thus the fractal research focus on the image spatial fractal analysis (Qiu H L; Weng Q, 2003). For the hyper spectral image, both the spatial domain and spectral domain has fractal characteristic. The fractal characteristic in spectral domain is from the spectral curve as the following items:

1) Hyper spectral curve represent the object spectral imaging course is non-linear

Hyper spectral curve represent the object spectral imaging course. And the object spectral imaging course is a non-linear. As the remote sensing physical principle, spectral imaging model is:

$$L_\lambda = K_\lambda \left\lfloor \tau_\lambda \left(\int N_\lambda \sin\theta \rho_\lambda d\Omega + W'_{e\lambda} \cdot \varepsilon_\lambda \right) + b_\lambda \right\rfloor \quad (1)$$

Where K_λ is the spectral response coefficient of the sensor. τ_λ is the atmosphere spectral transmittance. N_λ is the solar incident spectral energy. θ is the solar altitude angle. ρ_λ is the object spectral reflectivity. Ω is the solar azimuth. $W'_{e\lambda}$ is the black body spectrum radiation flux density. ε_λ is the object spectrum emissive. b_λ is the energy of atmospheric scattering and radiation. As the equation (1), object spectral imaging course is a complex non-linear system. Non-linear is the main characteristic of fractal phenomenon. Thus we can conclude that the spectral curve has the characteristic of fractal as the spectral imaging model.

2) Spectral curve has some statistical self-similar property

As the fractal definition of Mandelbrot in 1986, fractal is a model which the partial is similar to the total object. Thus the fractal has the important property that the local part of fractal model is similar to the whole model in some sides such as the structure, correlation. The spectral curve has the self-similar in statistics which indicate it has the fractal characteristic. The self-similar property of spectral curve can be represented in the SPOT image and TM multiple image as figure 1 shown:

Figure 1 Self-similar property in spectral image

Figure 1 is one of the SPOT image and TM image in Wuhan city. The two images are similar. SPOT image has the total information of the visible spectral bands and it can be taken as the total model. TM image is just one band of the total 7 bands and it can be taken as a local partial model while it is quite similar to the SPOT image. Thus we can conclude that the local partial spectral is similar to the whole spectral and it is one of important characteristic of fractal. As the spectral self-similar property, the spectral curve has the characteristic of fractal model.

3) The length of spectral curve under different measurement unit shows exponential relation

Different objects of 30 bands MAIS images are selected to measure the length of spectral curve under different band width. The result is shown as table 1:

Road		Tree		Water	
Band width	length	Band width	length	Band width	length
0.0152	1919.891	0.0152	1919.788	0.0151	1919.927
0.0303	959.8975	0.0303	959.8264	0.0303	959.9269
0.0455	639.9032	0.0455	639.841	0.0454	639.9231
0.0606	479.9182	0.0606	479.8622	0.0605	479.9199
0.0758	383.9039	0.0758	383.8579	0.0757	383.9047
0.091	319.8651	0.091	319.855	0.0908	319.9119
0.1061	274.1918	0.1061	274.1394	0.1059	274.1956
0.1213	239.9018	0.1213	239.8822	0.1211	239.9165
0.1365	213.2343	0.1365	213.2071	0.1362	213.2365
0.1516	191.9162	0.1516	191.8814	0.1513	191.9256
0.1668	174.4568	0.1668	174.4649	0.1665	174.4974
0.1819	159.8929	0.1819	159.8763	0.1816	159.9186
0.1971	147.6093	0.1971	147.6089	0.1967	147.6362
0.2123	137.0428	0.2123	137.0259	0.2119	137.0728
0.2274	127.9135	0.2274	127.8472	0.227	127.9143
0.2426	119.9109	0.2426	119.8937	0.2422	119.9301
0.2578	112.8496	0.2577	112.8472	0.2573	112.8621
0.2729	106.5528	0.2729	106.5297	0.2724	106.5741
0.2881	100.9874	0.2881	100.8711	0.2876	100.9878
0.3032	95.9225	0.3032	95.8372	0.3027	95.9008
0.3184	91.3273	0.3184	91.2451	0.3178	91.3375
0.3336	87.2123	0.3336	87.2308	0.333	87.2487
0.3487	83.3676	0.3487	83.2667	0.3481	83.3575
0.3639	79.901	0.3639	79.8703	0.3632	79.9195
0.3791	76.7229	0.379	76.6772	0.3784	76.7366
0.3942	73.7573	0.3942	73.7568	0.3935	73.7788
0.4094	71.0025	0.4094	70.9662	0.4086	71.0291
0.4245	68.4847	0.4245	68.3921	0.4238	68.5072
0.4397	66.1024	0.4397	66.0308	0.4389	66.0975
0.4549	63.9291	0.4548	63.871	0.454	63.9264
0.4700	61.8521	0.4700	61.8318	0.4692	61.8694
0.4852	59.8985	0.4852	59.8314	0.4843	59.9113

Table 1 Spectral Curve length under different spectral width

As table 1 shown, the measurement length of spectral curve decrease with the increase of spectral band width and the trend of the decrease is smaller and smaller. And this relationship shows the measurement length of spectral curve has the exponential relation to the measurement band width. Thus the spectral curve can be described with the fractal dimension. Take different measurement spectral width as ε , the length of spectral curve as N , the statistics curve between $\log(\varepsilon)$ and $\log(N)$ as figure 2:

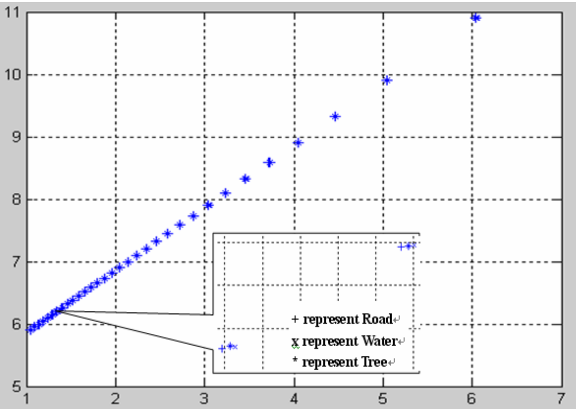

Figure 2 Log relation between spectral curve length and width

As figure 2 shown, the $\log(\varepsilon)$ - $\log(N)$ has obvious linear relation. The result of line fitting, it can realize the level of $\alpha < 0.02$, thus the spectral curve has the characteristic of fractal and the fractal dimension value can be used to present the spectral feature of spectral curve to each pixel.

3. METHODLOGY

The dimensionality reduction algorithm can be explained into the following three steps.

Firstly, noise removal processing is done to the hyper spectral curve for the dimensionality reduction. Wavelet transformation is used to filter the noise of spectral curve of the hyper spectral image. With the multiple resolution analysis of wavelet transformation, the spectral curve which can be constructed by the pixel vector in spectral dimension is decomposed into smooth component and noise component. The high frequency noise component is removed before the inverse wavelet transformation to obtain the noise removal spectral curve. Secondly, fractal dimension value is calculated to the noise filtering spectral curve. The fractal dimension calculation algorithm is designed to the spectral curve. Finally, the dimensionality reduction is done with the fractal dimension feature of the spectral curve. Spatial spectral data cube of hyper spectral remote sensing image is formed by the fractal dimension value of spectral value, which can obtain spectral distribution image in spatial space. The spatial spectral data cube image can combine spectral and spatial texture characteristic together. Figure 3 gives the dimensionality reduction procedure of hyper spectral image.

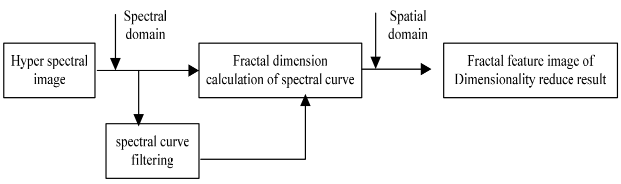

Figure 3 Dimensionality reduction with fractal analysis

3.1 Spectral curve filtering

Spectral curve noise will affect the result of spectral feature analysis. A non-linear strength wavelet filtering algorithm (nLWF) is proposed to spectral curve filtering. First the 2 level wavelet decomposition is done to the spectral curve with Morlet filter. The deviation of low frequency is selected as the noise threshold. High frequency coefficient under noise threshold is set zero and the coefficient above the noise threshold is non-linear strength. With the wavelet reconstruction, we can obtain the spectral curve after noise removal. Following is the detail procedure of spectral curve filtering.

Step 1: Determine Morlet filter and filter window size

Morlet wavelet filter with the window size of 13 is selected as the wavelet filter as equation (2) and (3):

$$h[] = \{-0.00332761, 0.00569794, 0.0196637, -0.0482603, -0.0485391, 0.292562, 0.564406, 0.292562, -0.0485391, -0.0482602, -0.0196637, 0.00569794, -0.0033276\} \quad (2)$$

$$g[] = \{0.00332761, 0.00569794, -0.0196637, .0196637, -0.0482603, 0.0485391, 0.292562, -0.564406, 0.292562, 0.0485391, -0.0482602, 0.0196637, 0.00569794, 0.0033276\} \quad (3)$$

Where $h[]$ is the low pass filter of Morlet wavelet and $g[]$ is the high pass filter of Morlet wavelet.

Step 2: Cycle expand of spectral curve as the filter window size as equation (4).

$$\begin{aligned} l_{-i,} &= l_{i,} \\ l_{N-1+i} &= l_{N-1-i} \\ i &= 1,2,3,4,5,6 \end{aligned} \quad (4)$$

Where $l_{i,}$ is the spectral curve and N is the feature point number or band number.

Step 3: Two level wavelet decomposition of spectral curve as equation (5).

$$\{LL_{l_i}, HL_{l_i}, LH_{l_i}, HH_{l_i}, 1 \le i \le N\} \quad (5)$$

Step 4: Non-linear strength of noise removal

Noise is central at the high frequency coefficient after wavelet transformation. The common noise removal methods is to select noise threshold and set the coefficient under threshold with zero to remove noise from the original signal (Pan Quan,2007,1998; Jansen M,2001; Wu C. Q,2004). The noise threshold can be determined from the original spectral curve noise level. And the noise level of original spectral curve can be calculated from the low frequency coefficient thus the deviation of low frequency coefficient can be taken as the noise level as equation (6).

$$\sigma_0 = \sigma\{LL_{l_i}, 1 \le i \le N\} \quad (6)$$

Thus the noise level of each decomposition coefficient can be calculated as the noise expands theory.

$$\sigma_m = \sigma_0 \left\| \left(\prod_{i=0}^{m-2} * H_i\right) * G_{m-1} \right\|_F \quad (7)$$

Where H is the Fourier transformation of low pass filter of $h[]$. G is the Fourier transformation of high pass filter of $g[]$. $*$ represents convolution, H_i is the 2^{m-1} scale expansion of H , G_{m-1} is the 2^{m-1} scale expansion of G , $\|\bullet\|_F$ is the norm. If the scale is $m = 2$, the noise level of each decomposition coefficient is,

$$\sigma_m = \sigma_0 \|H * G\|_F \quad (8)$$

Considering $\|H * G\|_F$ is tend to 1, the noise level of low frequency can approximately present noise level of high frequency coefficient thus it can be taken as the noise threshold. If the coefficient of high frequency is under $3\sigma_m^2$, it can be done as equation (9).

$$\{HL_{l_i}, LH_{l_i}, HH_{l_i}\} = 0 \qquad \left\|\{HL_{l_i}, LH_{l_i}, HH_{l_i}\}\right\|^2 \le 3\sigma_m^2 \qquad (9)$$

If the coefficient of high frequency is above $3\sigma_m^2$, it should be non-linear strength as equation (10) and (11).

$$f(y) = \frac{sigm(c*(y/y_{\max} - b)) - sigm(-c*(y/y_{\max} + b))}{sigm(c*(1-b)) - sigm(-c*(1+b))} * y_{\max} \qquad (10)$$

$$f(y) = \frac{sigm(c*(y/y_{\max} - b)) - sigm(-c*(y/y_{\max} + b))}{sigm(c*(1-b)) - sigm(-c*(1+b))} * y_{\max} * \exp^{(y/y_{\max}-1)*d} \qquad (11)$$

Where

$$sigm(t) = \frac{1}{1+\exp^{-t}} \qquad (12)$$

y is the high frequency coefficient of wavelet decomposition. c, d is to adjust the strength coefficient. b is to adjust the initial value of the strength detail and it is the threshold of the strength processing. In this paper, b is taken as the threshold of filtering that means $b = 3\sigma_m^2$. c is taken as the characteristic of image between 20 and 40. In this paper, c is 30. d is ranged among 1 and 0.05.

Step 5: Wavelet reconstruction

Mallat reconstruction is done to wavelet coefficient after filtering and strength to obtain the filtered spectral curve with noise removal.

A spectral curve filtering processing experiment is done with mean filter smoothing, least squares smoothing and the non-linear strength wavelet filtering algorithm (nLWF). Figure 4 gives the different curve filtering result.

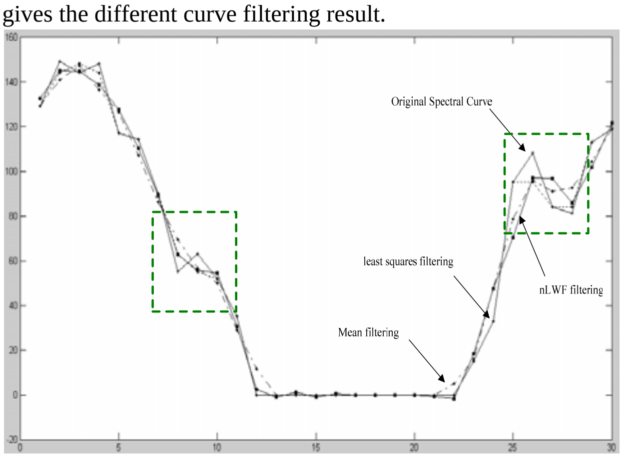

Figure 4 Different filtering result of spectral curve

As figure 4 shown, nLWF filtering algorithm of spectral curve can obtain reasonable result in two typical noise cases (as the rectangle in figure 4) compared with mean filter filtering, least squares filtering. Mean filtering is over smoothing and some detail is lost while the least square filtering is coordinate to the original spectral curve.

Signal noise ratio and noise level of spectral curve are selected to further assess different spectral curve filtering algorithms. Table 2 gives the different spectral curve filtering algorithms to different objects of the 30 bands MAIS images and 128 bands OMIS images.

Sensor	Object	Noise parameter	Original Spectral Curve	Mean filtering	Least square filtering	nLWF
MAIS	Water	Noise level	0.996	1.011	1.006	1.05
		SNR	10.129	7.432	8.192	3.829
	Tree	Noise level	1.312	1.332	1.324	1.338
		SNR	9.061	6.341	8.929	3.513
	Resident Area	Noise level	2.306	2.438	2.387	2.445
		SNR	13.072	6.713	5.22	3.798
	Spare Area	Noise level	9.418	9.939	9.756	9.953
		SNR	5.428	2.344	2.202	1.656
OMIS	Road	Noise level	3.576	3.948	3.867	3.955
		SNR	18.962	7.274	4.948	4.673
	Tree	Noise level	0.585	0.783	0.691	0.794
		SNR	28.386	8.179	9.66	6.03
	Resident Area	Noise level	1.778	1.786	1.845	1.873
		SNR	24.049	11.365	7.536	6.887
	Field	Noise level	3.054	3.48	3.674	3.674
		SNR	27.43	7.899	11.309	7.316

Table 2 Different spectral curve filtering results

As table 2 shown, different object in different sensor hyper spectral image has different noise level and signal noise ratio. nLWF algorithm obtains higher SNR and lower noise level than original spectral curve. And its result is better than the mean filtering and least square filtering algorithm.

3.2 Fractal dimension calculation algorithm

In this paper, a step measurement method of fractal dimension calculation algorithm considering the spectral curve characteristic is proposed. Curve length $L(r)$ under different step measurement units is determined by the step length $N(r)$ and steps r as equation (13).

$$L(r) = N(r) \cdot r \qquad (13)$$

And the curve length $L(r)$ can be represented as equation (14) under the definition of fractal.

$$L(r) = q \cdot r^{\mu} \qquad (14)$$

Where r is the step number under different step measurement unit. $\mu = 1 - D$ is the reminder dimension, D is the fractal dimension value of the spectral curve, q is the coefficient to determine. Thus we can obtain,

$$\log(L(r)) = (1-D)\log r + C \qquad (15)$$

Where C is the coefficient to determine. With the different step measurement unit, we can obtain point array of $(\log(L(r)), \log r)$. Thus we can calculate the slope of the line K(or μ) which is the fractal dimension value of spectral curve.

$$D = 1 - K \qquad (16)$$

The detail procedure of step measurement fractal dimension calculation can be described as following steps: ① Take d_1 as the initial step unit, calculate the distance d_{12} between the first point P_1 and the second point P_2 of spectral curve. ② if $d_{12} > d_1$, interpolate one point p between P_1 and P_2 to make the distance from p to P_1 as d_1. ③ if $d_{12} < d_1$, to calculate the distance d_{13} between P_1 and P_3, if $d_{13} > d_1$, to interpolate one point p between P_2 and P_3 to make the distance from p to P_1 as d_1 from the curve. if $d_{13} < d_1$,considering P_4 as step ③ until the last point of the spectral curve. ④ summarize the step number n_1 under the step measurement unit d_1 . Then the length of spectral curve under d_1 is,

$$L(d_1) = n_1 d_1 \tag{17}$$

⑤ Change step measurement unit to obtain spectral curve length as equation (18).

$$L(d_2) = n_2 d_2 ,......, L(d_m) = n_m d_m \tag{18}$$

Thus we can calculate the fractal dimension value of spectral curve as equation (15).

3.3 Dimensionality reduction with fractal feature image

With the fractal dimension calculation of spectral curve for each pixel, it can be taken as the feature of spectral curve. This feature value is the result of dimensionality reductions of spectral curve. The fractal feature of spectral curve cab be used for hyper spectral image segment and classification for it can transform the hyper spectral information into one dimension fractal feature image. Thus the fractal feature image analysis can realize dimensionality reduction and increase the efficiency of data processing for it can full use the image analysis algorithm in spatial domain.
The fractal dimension value is taken as the feature of spectral curve and the fractal dimension feature image is proposed to represent the dimensionality reduction result of hyper spectral image. The dimensionality reduction procedure based on the fractal analysis has been described as figure 3. Figure 5 gives the dimensionality reduction feature image of MAIS image. Figure 5(a) is one of band images. Figure 5(b) is the fractal feature image.

Figure 5(a) Original band image of MAIS

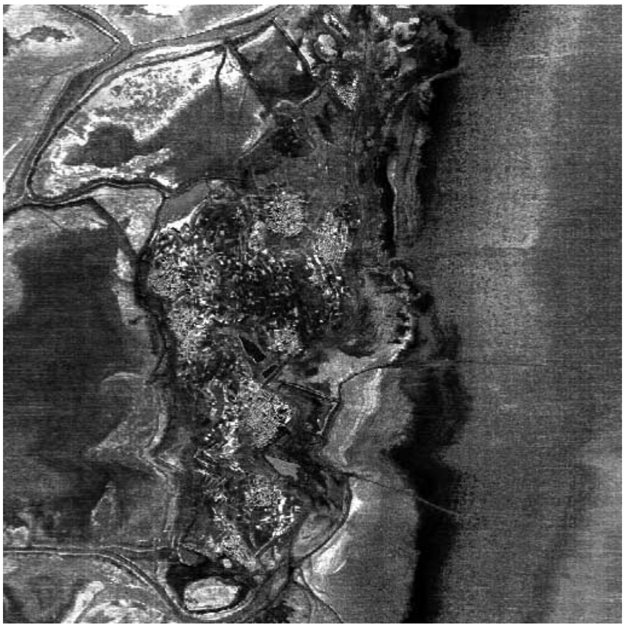

Figure5 (b) Spectral fractal dimension feature image of MAIS

Figure 5 Dimensionality reduction result based on spectral fractal analysis

As figure 5, the fractal feature can combine the spectral information and spatial information together and realize the dimensionality reduction through the spectral feature transformation. The fractal feature image can represent the spectral information of hyper spectral image and obtain better detail representation and it is a new method of spectral feature analysis of hyper spectral image.

4. EXPERIMENTS AND CONCLUSIONS

Hyper spectral texture code is taken as the important hyper spectral image analysis technique[12]. In order to verify the dimensionality reduction algorithm based on fractal analysis, the author select different object texture unit to calculate the fractal dimension value of spectral curve of each pixel together with the correlation of the centre pixel. The texture unit is 3×3. The result is shown as table 3.

	resident area		tree		water	
	Fractal dimension	correlation	Fractal dimension	correlatio n	Fractal dimension	correlatio n
1	1.0237	0.8869	1.0210	0.9786	1.0128	0.9652
2	1.0271	0.8771	1.0169	0.9919	1.0152	0.9851
3	1.0262	0.8204	1.0197	0.9951	1.0146	0.9891
4	1.0243	0.9835	1.0152	0.9929	1.0105	0.9830
5	1.0239	1.0000	1.0200	1.0000	1.0145	1.0000
6	1.0202	0.8325	1.0161	0.9967	1.0176	0.9974
7	1.0244	0.9621	1.0179	0.9886	1.0111	0.9623
8	1.0237	0.9644	1.0198	0.9942	1.0138	0.9806
9	1.0199	0.8377	1.0175	0.9924	1.0153	0.9743
max	***1.0271***	1.0000	***1.0210***	1.0000	***1.0176***	1.0000
min	***1.0199***	0.8204	***1.0152***	0.9786	***1.0105***	0.9623
deviation	0.0024	0.0707	0.0020	0.0060	0.0022	0.0130
range	0.0072	0.1796	0.0058	0.0214	0.0071	0.0377

Table 3 Fractal dimension and correlation of spectral curve in texture unit

As table 3 shown, the correlation of spectral curve among the centre pixel and each pixel in texture unit has obvious difference especially for the resident texture unit. And different object has very similar correlation which will lead the pixel confuse for the pixel classification. The fractal dimension value can obtain better result for the classification. The different object has different fractal dimension value of spectral curve in texture unit. The resident object has the fractal dimension value ranged with 1.0199～1.0271, the tree ranged with 1.0152～1.0210 and water ranged with 1.0105～1.076. Thus the dimensionality reduction result using the fractal feature of spectral curve can realize better texture code matching which is very useful for image classification.

For the Huges phenomenon, there are still some of different object fractal dimension feature while the fractal dimension of the centre pixel is quite difference. The dimensionality reduction based on spectral curve fractal analysis can combine the spectral information and spatial texture information together to realize the feature analysis and it can obtain better processing efficiency of hyper spectral data. The dimensionality reduction based on spectral curve fractal analysis provide a new method to differ the confuse pixel such as the feature analysis combined the spatial fractal analysis and spectral fractal.

ACKNOWLEDGEMENTS

The research work is supported by the Nation Science Founder of China. (NSFC: 40371079) and 973 Project of China (2006CB701303).

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