Identification and Extraction of Nutrient Content in Hyperspectral Black Soil in Frequency Domain

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Abstract Hyperspectral remote sensing technology, with its high spectral resolution and high spatial resolution, plays a more and more important role in the quantitative remote sensing monitoring of black soil. In order to extract the information from the current spectrum and the object-oriented method, it is impossible to integrate the spectral domain and the space domain to explore the feasibility of the frequency domain processing method to improve the recognition accuracy. The CASI/SASI aero hyperspectral data are obtained from the Jiansanjiang area of Northeast China, and 60 samples are collected on the ground, and the content of organic matter is tested. The characteristics of the amplitude spectrum and phase spectrum of the typical black land are studied, and an adaptive classifier based on Gauss filter is designed for the hyper spectral space spectrum analysis algorithm, and an air spectrum classification framework based on the optimization of the ground laboratory data is constructed. Compared with the traditional hyperspectral classification algorithm, the frequency domain recognition and extraction algorithm proposed in this paper have described and characterized the hyperspectral data from a new viewpoint, which solve the uncertainty of hyperspectral data. In the future, this method may be a new thought to improve the traditional data processing method.

Keywords Black soil nutrient · Frequency domain characteristics · Adaptive gauss low-pass filter · Aero hyperspectral · Hyperspectral remote sensing

1 Introduction

The spectral data of ground objects are understood as electromagnetic radiation characteristics energy distribution maps in the recognition of nutrient content in black soil based on hyperspectral data. This treatment only describes the spectral distribution characteristics of the energy. It is a single pixel analysis method of black soil, which can extract limited information. Especially, in the extraction of

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black soil information of high-resolution remote sensing data, the same pixel area of land structure, shape, texture, and so on is greatly increased. The efficiency and accuracy of information recognition based on spectral energy are difficult to meet the practical application requirements. In essence, it is a method of mathematical statistics. The result satisfies the optimal value of numerical simulation, but disjoins with the expert experience and background knowledge, and it is difficult to further improve the precision to a certain extent.

The Parseval energy conservation theorem proves that the total energy of the remote sensing objects in the spatial domain E_s and the frequency domain E_f is equal [1]. Under the support of this theory, the research direction at home and abroad is concentrated in two aspects; one is to improve the quality of remote sensing image by exploring the response relationship between the airspace and the frequency domain. In order to improve the resolution of remote sensing images, a super-resolution reconstruction method is established by studying the response relationship between resolution and frequency domain information. It shows that the resolution of 2M and 3M remote sensing images is increased by 1.75 and 1.90 times by the frequency domain aliasing [2]. In order to master the information transmission law of remote sensing optical system, from the frequency domain channel matrix derivation of remote sensing optical system, the frequency domain information transmission parameters of the imaging system are calculated from the frequency domain, and the research results have played a reference role to the design of remote sensing optical system [3]. In view of the problem of image degradation in the detector imaging system, an improved multi-frame image super-resolution enhancement method is proposed in the frame of frequency domain, the joint Gauss distribution model is established, and the interpolation reconstruction results are restored with Bayesian method [4].

The second research field, combined with the characteristics of the identified objects, improves the recognition accuracy through the transformation of airspace and frequency domain. According to the characteristics of the direction and frequency of the linear objects, a Fourier transform method is designed to extract roads from high-resolution images [5]. The image of urban river channel is transformed by Fourier transform, and the spectrum is divided into two parts of edge feature and low-frequency information. The log Butterworth filter and low-pass Butterworth filter are designed to extract the edge features and low-frequency information of the urban river, and the information extraction of the urban river is effectively realized [6]. Based on the characteristics of frequency domain, the principle of high vegetation coverage is extracted. After obtaining the maximum energy direction of the road through the frequency curve analysis, the road center line is extracted by Gabor filter. The method has high calculation efficiency [7]. A study on comprehensive utilization of classical spectral features and texture features of the city land use extraction method, combined with the city spectral changes in frequency domain information on different geographical conditions caused by the sensitive characteristic, in a few large city in the USA carried out tests show that the frequency domain extraction methods with spatial domain, and the accuracy has been greatly improved [8].

With the deepening of hyperspectral remote sensing in digital mapping in black land, the introduction of frequency domain recognition technology can effectively combine the energy expression of the pixel spectrum with the representation of frequency spectrum energy in the frequency domain [9]. The significance is not only to redistribute the original spectral data to another space but also be beneficial to the processing and extraction of information [10]. The variation of energy in the spatial image is reflected, and the spatial features such as color, texture, direction, and boundary of the black soil are involved in the soil quality assessment, and a more comprehensive set of black soil features is obtained to improve the precision of nutrient information extraction [11].

In this paper, an adaptive Gauss low-pass filtering algorithm is designed based on the analysis of the characteristics of the black soil spectrum. By eliminating the data of different energy levels gradually, the purpose of land classification is achieved. The cut-off frequency optimal model is established, and it balances image smoothing with detail preservation. The improved Gauss low-pass filter in this paper not only has a smooth function but also imports black soil nutrient information into the frequency domain. CASI hyperspectral imaging experiments are tested in Jiansanjiang area, Heilongjiang Province, which verified the good performance of the proposed frequency domain recognition and extraction classification method.

2 Black Soil Spectrum Characteristics Analysis

2.1 Black Soil Texture Features Description

There are three main features of the black land texture: one is the close correlation between the texture features and the resolution [12]. Under a certain resolution, the field of view is consistent when it moves in the texture region [13]. The two is the basic graph element, not random arrangement, and the three is that all kinds of textures are homogeneous and uniform in the research area. The place has roughly the same structure size. Therefore, statistical parameters can be used to characterize the distribution characteristics of black soil texture. Three typical black soil texture features are analyzed by selecting five eigenvalues of information entropy, two moments, contrast, synergy, and correlation (Table 1).

The results show that (1) the information entropy of the lattices character black soil is the highest, reflecting the high uncertainty of hyperspectral data under this kind of black soil texture, and the amount of nutrient information contained in black

Table 1 Typical black land texture feature statistics results

Texture name	Information entropy	Two-order moment	Contrast	Synergistic	Correlation
Strip	1.819	0.196	18.689	0.307	0.107
Bright spot	1.994	0.121	66.602	0.206	0.010
Lattices	2.003	0.123	65.564	0.190	0.072

soil is also larger. (2) The two-order moment refers to the discrete degree of the spectral value relative to the mean value. The higher the discrete degree is the more characteristic of the spectral data is, and the stripe texture has the highest degree of dispersion in the three kinds of black land texture. (3) The contrast degree affects the change level of the image and the dark, the higher the contrast, the less number of color order from ash to pure black and pure white, the greater the reflectance contrast. The bright spot black soil is significantly higher than that of the other two types of black soil texture. (4) The synergistic calculation can be used to evaluate the enhancement and coherence of different bands of hyperspectral bands, and the highest mutual gain between bands is strip textures. (5) The correlation reflects the redundancy degree of spectral data in different bands, and the correlation of black soil band in strip is the highest, and there is a lot of redundant information in the data.

2.2 Black Soil Phase Spectrum Characteristic Analysis

The amplitude spectrum of the black land expresses the number of each frequency component in the hyperspectral image, and the phase spectrum determines the position of each frequency component in the image, which is an angle between $-\pi$–π [14]. Although the phase spectrum contains the main structure of the original black soil spectrum, the information of black soil content cannot be obtained directly.

By calculating the phase spectrum and histogram of three typical black land, it is found that there is no close relation with the black land texture, especially the information related to the characteristics of the black land direction is not significant. This phenomenon is consistent with the conclusions of previous studies [15]. Although the information on black land cannot be obtained directly from the phase spectrum, the phase spectrum contains the main structure of the hyperspectral image, and it can play a role in the image segmentation in the detection of the black soil edge based on phase consistency. Therefore, the algorithm design based on frequency domain filtering is mainly based on amplitude spectrum.

3 An Adaptive Gauss Low-Pass Filtering Algorithm

3.1 Basic Principle

In order to make the spatial and spectral information as the reference data of the hyperspectral image classification at the same time, an adaptive Gauss low-pass filtering algorithm is designed to add the information of the nutrient content of the black soil in the frequency domain classifier.

The core idea of the algorithm is that a Gauss low-pass filter model can be extracted (or excluded) to transform the energy of hyperspectral images, and the data of different energy levels are eliminated gradually to achieve the purpose of the black land classification [16]. When smoothing the image with Gauss model, the Gauss function determines the filtering result by calculating variance σ. Combining the interpolated data of the known nutrient data in the geospace of the black soil, the adaptive Gauss filter is designed to select different σ on the basis of preserving the local features of the black soil image to realize the original image classification.

In the frequency domain, the basic filter model is:

$$G(u, v) = H(u, v) \times F(u, v) \tag{1}$$

where $F(u, v)$ is a filtered Fourier transform image; $H(u, v)$ is a filter transform function; $G(u, v)$ is the smoothed image generated after the attenuation of high-frequency information [17].

The Gauss low-pass filter which can transform the spatial domain into the frequency domain is:

$$H(u, v) = \mathrm{e}^{-D^2(u,v)/2d^2} \tag{2}$$

where $D(u, v)$ is the distance from the origin of transformation. d is the expansion degree of the Gauss curve, that is, the cut-off frequency. An adaptive Gauss filter is designed to automatically select different d according to the black soil content characteristic of the smooth image so that the corresponding content of nutrient data is obtained in the processed image.

Therefore, suppose the Gauss smoothing of black soil images is expressed in the following function:

$$I_0(x, y) = I_d(x, y) + e_d(x, y) \tag{3}$$

where for pixel point at (x, y), $I_0(x, y)$ is the gray value of the original hyperspectral data, $I_\mathrm{d}(x, y)$ is the low-pass gray value under the cut-off frequency d, $e_\mathrm{d}(x, y)$ is the residual value under the cut-off frequency d.

A method based on energy function is designed:

$$d_{\text{best}} = \arg\min\left\{c/\sigma^3 + e^3\right\} \tag{4}$$

where, c is a constant term and is determined according to the nutrient test data of the sampling points; σ is the variance; e is the residual value.

It is concluded that under the known constant terms of c, the optimal cut-off frequency d needs variance σ as large as possible, and transforms hyperspectral data to more smooth data. The residual error e must be as small as possible, that is, the smaller the change of reflectivity of the original pixel (x, y) after Gauss filtering, the smaller the better. In this way, a comprehensive Gauss filtering method for nutrient content is established, which achieves the balance between smoothing classification and maintaining details.

3.2 Algorithm Steps

The adaptive Gauss low-pass filtering algorithm is as follows:

(1) The original hyperspectral data of black land are transformed in frequency domain to generate frequency domain data.
(2) The initial Gauss low-pass filter is used for the frequency domain data, and the initial cut-off frequency of nutrient content of the first kind is set d_1. The initial variance σ_1 and residual value e_1 are obtained.
(3) The filtering results are compared with the ground test data. If the extracted information is in accordance with a certain level of nutrient content, it is recorded as c_1, otherwise, d_1 is set up to continue filtering until the filtered information is distributed in this nutrient interval and is recorded as c_1.
(4) In the hyperspectral data, the corresponding pixels in the airspace are removed from the hyperspectral data, and the initial cut-off frequency of second nutrient contents is set at d_2, Repeat step 3 until c_2 is obtained.
(5) Repeat step 4 and step 3 until the five levels of nutrient content are generated by c_3, $c_{4,}$ and c_5.

4 Black Soil Nutrient Data and Information Extraction

4.1 Data

Data are obtained from the CASI/SASI aviation hyperspectral imaging system. The spectral range is 380–2450 nm, the spatial resolution is 4 m, the continuous spectrum channel number is 137, and the spectral bandwidth is 12.5 nm. The experimental data are collected on April 10, 2017, with a length of 9.27 km and a width of 5.36 km, with an area of about 50 km^2 and a flight altitude of 3 km (Fig. 1). The black and white cloth is laid on the ground. The calibration spectrum is obtained by ASD Field Spec spectrometer. The spectral range is 350–2500 nm, and the spectral resolution is 1 nm.

The sampling point is 60, the coordinates of sample 1 are 132.747E, 47.232N, and the coordinates of sample 60 are 132.857E, 47.272N, and the soil samples are collected at 0.75 km intervals. The surface of the survey area is a black humus layer, thick 30–60 cm, thickest than 1 m, and many cylindrical or granular structures. On the same day, the soil samples of the surface 0–20 cm are collected synchronously, and the large plant residue and stone and other debris are removed. The soil samples are

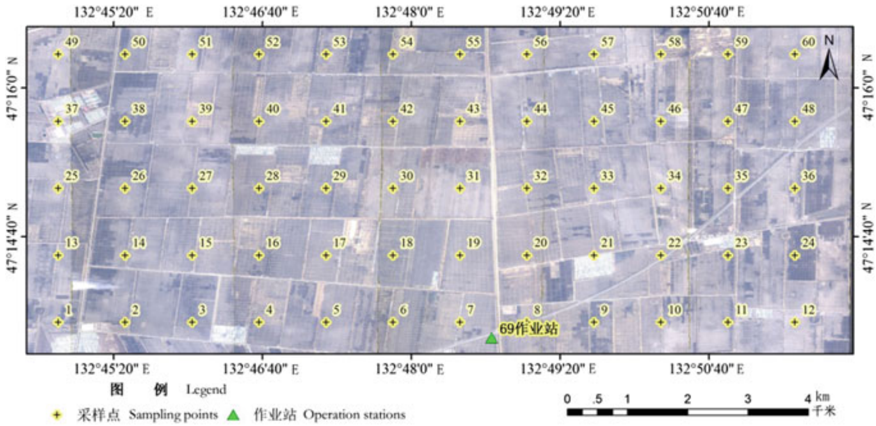

Fig. 1 Aeronautical data acquisition area and sampling point distribution map

Table 2 Information table of black soil organic matter content at different sample points

Sample class		Minimum/(g kg^{-1})	Maximum/(g kg^{-1})	Average/(g kg^{-1})	Standard deviation/(g kg^{-1})
Soil organic matter	Modeling samples	3.39	4.46	3.85	0.23
	Prediction samples	3.30	4.14	3.79	0.24
	All samples	3.30	4.46	3.83	0.23

used in the laboratory to dry and grind, and 0.15 mm screening is used to determine the content of the soil. The organic matter is determined by potassium dichromate volumetric external heating method. In soil nutrient content determination, sample 1–45 is used for training set, and the remaining 15 samples are used for evaluation accuracy (Table 2).

4.2 *Extraction of Nutrient Information from Black Soil*

The values of initial variance σ_1 and e_1 of residual value are 0.1 and 1.5, respectively. The adaptive Gauss low-pass filter is used to calculate the variance value and gradually reduce the residual value. The nutrient test data of the black land in the measured area are brought into Formula 4, and the grade assessment map of the 5 levels of nutrient content is obtained.

The adaptive Gauss low-pass filtering algorithm combines the results of the ground test data. By optimizing the whole energy function, the spatial information of the image is transformed into the space item in the energy function, and the spectral information is converted into the spectral term in the energy function. When constructing the energy function, it is assumed that the adjacent eight neighboring center pixels are identical to the results of the ground test data.

Although the increase of variance σ can improve the classification accuracy of the pixel-level filter in the smooth region, the probability of misclassification of pixels at the edge of the block is also increased. Different from the variation of variance, the algorithm based on Gauss low-pass filter is used to evaluate the difference between the adjacent pixels by the residual value, and the probability optimization is carried out by the residual value. The higher the residual value is, the lower the similarity of gray value of adjacent pixels is, the lower the probability of being labeled as the same category.

Therefore, residuals can play a positive role in the detection of pixels on the edge of the plot. Therefore, on the basis of reasonable initial variance of σ_1 and residual value e_1, the adaptive Gauss low-pass filtering algorithm not only improves the accuracy of the pixel classification accuracy of the smooth region but also makes the edge detection of the soil nutrient content more accurate in the classification results.

5 Black Soil Nutrient Extraction Precision Analysis

5.1 Precision Evaluation Method

The ground test data points are scored by kriging interpolation, and the soil nutrient grading map is obtained as the basis for evaluating the accuracy of information extraction. The total accuracy ($P_c = \Sigma_{k=1}^{n} P_{kk}/P$), mapping precision ($P_{Ai} = P_{jj}/P_{j+}$), leakage error ($1 - P_{ui}$), user accuracy ($P_{ui} = P_{ii}/P_{\mathrm{i}+}$), and error ($1 - P_{Ai}$) between the image information extraction results of different initial variance σ_1 and residual e_1 are calculated, and the objective evaluation results are obtained.

5.2 Extraction Precision Analysis Results

The error confusion matrix table is constructed, and the five quantitative indexes of different initial variance σ_1 and residual value e_1 are calculated, respectively.

(1) Overall accuracy evaluation (Fig. 2). The parameters of the overall accuracy and Kappa coefficient are set to $\sigma_1 = 0.5$ and $e_1 = 1.1$, respectively, 92.24% and 0.8933, respectively. The parameters with the lowest extraction accuracy are $\sigma_1 = 0.1$ and $e_1 = 1.5$, 40.51% and 0.2566, respectively.
(2) Determination of the best information extraction parameters for each nutrient level. The best initial parameters for 1–5 level are: $\sigma_1 = 0.1/e_1 = 1.5$ (100%), $\sigma_1 = 0.5/e_1 = 1.1$ (91.10%), $\sigma_1 = 0.5/e_1 = 1.1$ (91.47%), $\sigma_1 = 0.6/e_1 = 1.0$

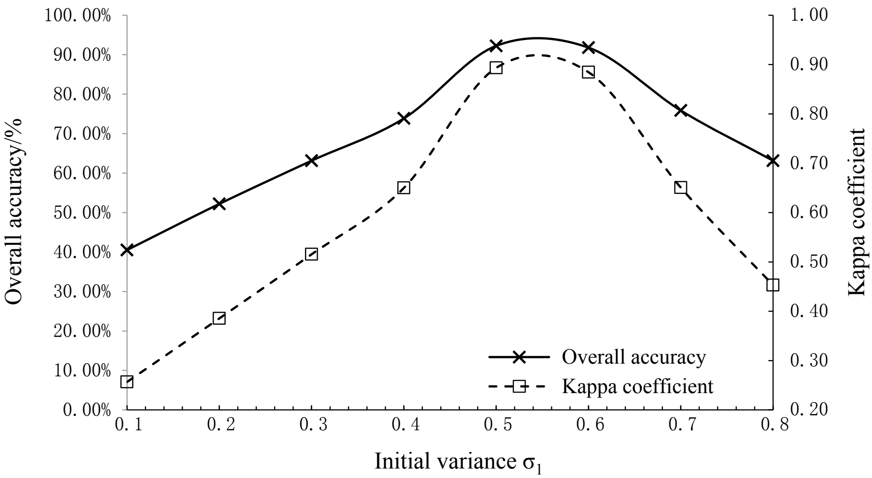

Fig. 2 Comparison of black soil nutrient extraction accuracy with eight initial parameters

(89.24%), and $\sigma_1 = 0.6/e_1 = 1.0$ (99.95%). It is concluded that for the black soil with higher nutrient content, the initial parameter is set to $\sigma_1 = 0.6/e_1 = 1.0$, and the extraction accuracy is higher.

(3) Targeted analysis of nutrient extraction grades of black soil under eight parameter settings. The $\sigma_1 = 0.3/e_1 = 1.3$ in extraction content grade 1, $\sigma_1 = 0.3/e_1 = 1.3$ in extraction content grade 1, $\sigma_1 = 0.4/e_1 = 1.2$ in extraction content grade 1, $\sigma_1 = 0.5/e_1 = 1.1$ in extraction content grade 1, $\sigma_1 = 0.6/e_1 = 1.0$ in extraction content level 5, $\sigma_1 = 0.7/e_1 = 0.9$ in extraction content level 5, $\sigma_1 = 0.8/e_1 = 0.8$ in extraction content level 5, the user accuracy is more higher. It is found that the setting of initial parameters is mainly related to the lowest and two highest nutrient levels.

5.3 Extraction Results

The parameters of the highest precision and Kappa coefficient are set up $\sigma_1 = 0.5$, and $e_1 = 1.1$ are applied to extract nutrient in black land. After classification, the nutrient content of each level is given according to the ground analysis data, and the spatial distribution of nutrient content in black soil is obtained (Fig. 3).

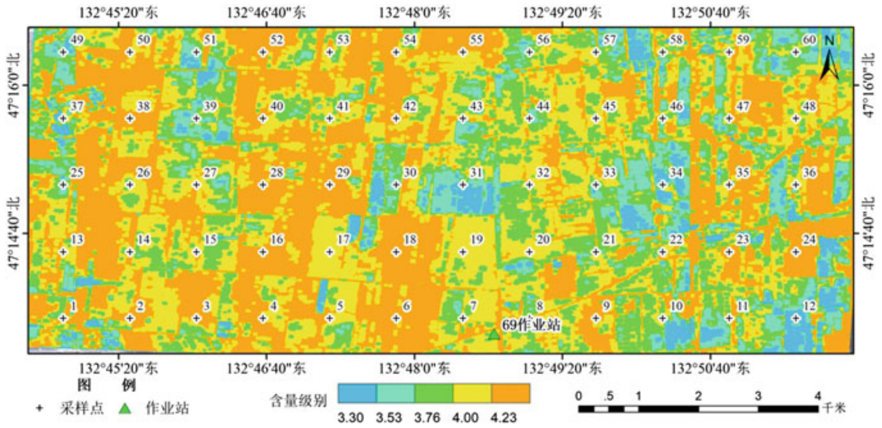

Fig. 3 Spatial distribution of black soil nutrient content by optimal initial parameters

6 Conclusion and Discussion

On the basis of the research of traditional spectral method and object-oriented target recognition method, the feasibility of combining hyperspectral image space and spectral information is explored to improve the accuracy of nutrient recognition in black land [18]. According to the characteristics of black land texture, the amplitude spectrum and phase spectrum characteristics of the typical black land are studied. On this basis, an adaptive classifier based on Gauss filter is designed for the hyperspectral space spectrum joint analysis algorithm, and a space spectrum classification framework based on the ground test data optimization is constructed, and the spatial information of the image is extracted from the frequency domain information. The spatial information and spectral information are scientifically integrated through the smoothing filtering of plots.

Using the data of CASI/SASI aerial hyperspectral imaging system, the proposed adaptive high and low-pass filtering algorithms are tested. The results show that the smooth filtering of the massif can effectively combine the spatial and spectral information of the image. On the basis of effectively removing the salt and pepper noise similar to the traditional classification method, the contour of the black land in the classification result is basically consistent with the real black land plot contour.

Compared with the traditional hyperspectral classification algorithm, the frequency domain recognition and extraction algorithm proposed in this chapter are more efficient. After defining the level of nutrient content, the result data of each level can be quickly calculated. Frequency domain method can partly solve the uncertainty of information extraction, because it expresses hyperspectral data from a new perspective. In the future, this method may be able to break through the traditional atmospheric correction and radiation correction factors and bring new methods.

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