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Analysis on the Integrated Development of Traditional Information and Rural Tourism based on Remote Sensing Image Data Analysis

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***Abstract*— Analysis on the integrated development of the traditional information and rural tourism based on remote sensing image data analysis is conducted in this paper. Texture reflects the spatial variation characteristics of pixel gray level, and is a pattern that is regularly arranged in the entire image or a certain area in the image. Using traditional methods for the remote sensing image feature extraction can not avoid the defect of large deviation of feature segmentation results caused by broken cloud clutter, hence, the wavelet analysis is combined. Further, the integrated development of traditional information and rural tourism is selected as the application scenario. Through different sets of the simulations, the efficiency is shown.**

Keywords*— *Remote Sensing; Image Analysis; Traditional Information; Data Structure; Data Mining

I. INTRODUCTION

In the field of remote sensing, image quality is defined as a measure of an image, and its pros and cons are evaluated based on optical consistency, feature detection capability, and maximum exposure scale. In the process of remote sensing image acquisition, it is often disturbed by the sky uncertain cloud, which will then greatly reflect the remote sensing rays, resulting in the presence of broken cloud clutter in the remote sensing image, resulting in the fuzziness and loss of the key features in the remote sensing image [1, 2, 3].

The traditional image segmentation algorithm sets the filter value according to a single threshold, which is difficult to establish an effective filtering model for this random broken cloud clutter interference, resulting in the large deviation of feature segmentation results, which reduces the accuracy of the feature extraction of remote sensing image [4, 5, 6]. Therefore, the finite ridge wavelet transform can be used to perform primary decomposition of the image to realize the rotation invariance and also translation invariance of the image, and then use the binary wavelet transform with the function of the differential operator to perform multi-level decomposition of the result to obtain the signal at different scales [7, 8, 9].

Graph and detail subgraphs, as well as the modulo values and directions of the signal image gradients at all levels at different scales, are used to combine feature vectors of image textures. Remote sensing image feature extraction method. It is the core issue in the field of remote sensing [10, 11].

Using traditional methods for the remote sensing image feature extraction can not avoid the defect of large deviation of feature segmentation results caused by broken cloud clutter, which reduces the accuracy of remote sensing image feature extraction. In the figure 1, we then present the analytic model.

Fig. 1. The Remote Sensing Analytic Model

Besides the image extraction, the transmission of the data is also essential. After the solar radiation is well transmitted through the atmosphere, it is mainly the combined effects of reflection, absorption and scattering that attenuate the basic radiation intensity. The remaining part is the transmitted part. If cloudless weather is selected for passive remote sensing, the attenuation of solar radiation by the atmosphere will only consider atmospheric scattering and absorption [12, 13].

Usually, electromagnetic waves are less reflected, and absorbed or scattered when they pass through the atmosphere! The band with higher transmittance is called the atmospheric window. The atmospheric window is then mainly visible light, infrared band, followed by microwave, ultraviolet band, and the selection of remote sensor imaging band Strictly controlled by the atmospheric window. Stereoscopic images are highly specialized for extracting elevation information. This article will not describe them in detail, but will mainly discuss the theories and techniques of the remote sensing image data processing related to the latter's general and stronger remote sensing images used as terrain surface texture maps, including: data selection, core geometric correction, mosaic, projection transformation, the 3D visual display, etc. Then, the proposed model will be applied to the scenarios of the traditional information and rural tourism.

II. THE PROPOSED METHODOLOGY

A. The Remote Sensing Image Collection and Processing

Spectral features are the most basic features of the remote sensing images, and also the traditional remote sensing image classification algorithm is based on the spectral features. The purpose of the spectral enhancement is usually to make some features clearer in an image by increasing the contrast [14-18].

Depending on the features to be extracted and their bands, spectral enhancement for one band may not be suitable for other bands. Therefore, spectral enhancement of multi band images is then usually regarded as a series of the single band enhancement. Using the basic remote sensing image feature extraction method, the features in the remote sensing image can be extracted, so as to provide a data basis for remote sensing image applications in different fields. In the lemma 1, the model is defined.

$$w = \frac{\eta(\varepsilon - b_j)}{N^2\sqrt{P^2 - 1}} \tag{1}$$

Nonlinear spectral enhancement can be used to gradually increase or decrease the contrast over the range without the same amount of slope.

In general, nonlinear enhancement amplifies the contrast in one region while reducing the contrast in other regions. In the figure 2, the image collection steps are defined.

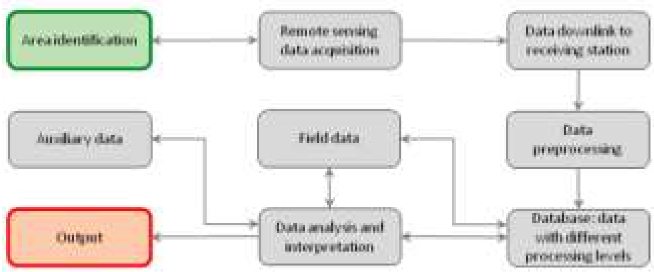

Fig. 2. The Image Collection Steps

According to the known pixel data, the parameters are obtained, the forms of the various discriminant functions are determined, and then the unknown pixels are classified by the discriminant function.

The classic supervised classification methods include the maximum likelihood method, the minimum distance method, and also spectral angle classification method. Unsupervised classification is classified according to the characteristics of category clusters in the feature space. The classification results only reach a certain level for different categories, and the category attributes are analyzed by post-event analysis of the spectral response curves of various categories as below.

$$Con = \sum_i \sum_j (i-j)^2 p(i,j) \tag{2}$$

Histogram equalization can also separate cells into distinct groups if there are few output values over a wide range. This has rough classified visuals [19, 20]. The underlying grid computing nodes provide different services, including the restoration algorithm services, computing processing services, and also transmission services.

In the middle, a virtual processing platform is mainly constructed to shield the service resources of the different locations and structures provided by the underlying nodes, and to provide users with a unified processing platform. In the figure 3, the processing pipeline is defined.

Fig. 3. The Processing Pipeline

B. The Remote Sensing Data Transmission Model

Structural features including ruffles, faults, cuts, linear structures, etc., which are represented or reflected by surface outcrops of bedrock, or by the distribution of vegetation, are important information that provide thermal motion, liquid matter, carbohydrates and Mineral detection clues [21-23].

Tectonic field mapping is in the operational demonstration stage. Airborne SAR has been used for the detection of the carbohydrates. Interpretation of the radar images revealed the structural complexity of the unmapped area and played a guiding role in the exploration plan.

Unsupervised classification is a classification process of classifying objects according to the statistical characteristics of the image itself and the distribution of natural point groups without prior knowledge of primary categories supervised classification can effectively develop data content, but also requires sufficient information It can determine the prior probability of surface information, not only the selection of the supervision and classification training sample area requires a variety of rich knowledge and experience, but also some specific information on the local land cover. In the formula 3, we define the cluster centers [24-26].

$$center(k+1) = \frac{1}{N_j}\sum_{x \in f_j(k)} x \tag{3}$$

The number of cluster centers k, the selection of initial cluster centers, the order of sample input, and the geometric characteristics of the core samples all affect the process of the averaging algorithm. Although it is impossible to prove the convergence of this algorithm, when the pattern classes are between the results obtained by this algorithm are satisfactory when they are far away from each other. The arrangement of the codeword length and the probability of the symbol are strictly reversed in the order of the codeword length of the Hodamann code. It has been theoretically proved that the average code length is the shortest, so it is called the optimal code. The basic idea is to use a codeword with a short word length for information with a high probability of occurrence, and use a codeword with a long word length for information with a small probability of occurrence, so as to shorten the average code length, thereby realizing the r data compression. In the figure 4, we define the coding process.

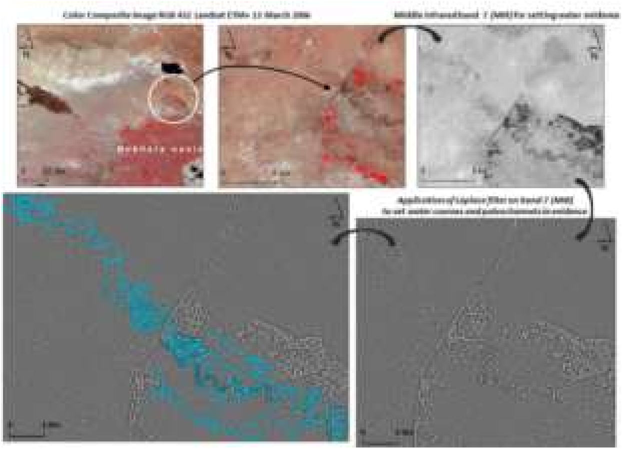

Fig. 4. The Coding Process

During the mosaicing process, even if the two images have undergone image-enhanced tone adjustment, the tone at the seam between the two images cannot be completely consistent, and due to the existence of GCP error in geometric correction, the image after geometric correction will not be completely consistent. The edges are still not completely tight, and the same feature on the adjacent images is dislocated. In the figure 5, the data transmission pattern is defined.

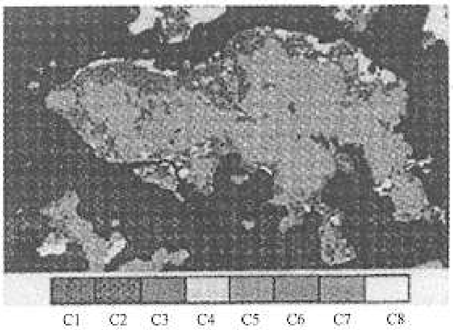

Fig. 5. Data Transmission Pattern

C. *The Integrated Development of Traditional Information and Rural Tourism*

Agricultural landscape is the basis for the development of sightseeing agriculture, and agricultural landscape has the dual characteristics of natural landscape and cultural landscape. Sightseeing agriculture caters to the market demand with its location advantage and ecological and cultural characteristics adjacent to the city, so it is favored by tourists. Village is the creation of human beings to adapt to the environment for a long time, and has accumulated thousands of years of culture and art. It is also a unique cultural tourism resource and a materialized expression of regional culture. The resources of ancient villages include not only material cultural heritage such as the planning of ancient villages, various buildings, historical sites, etc., but also intangible cultural heritage such as various folk customs, national languages, living dwellings, folk skills, and production methods [27]. The vast rural areas of China still maintain extremely rich historical memories and roots, as well as rich cultural relics. With the remote sensing image integration, the proper analysis will be done.

III. THE SIMULATION AND VERIFICATION

Image algebraic operations refer to any type of algebraic function applied to data file values for one or more bands. The result of the function is output to another image file, another band in the same file, or to a color gun on the display device. This simulation will be based on that model to calculate. The figure 6 shows the simulation result.

41	173	25724
45	180	24601
34	146	23524
49	230	23280
40	171	22934
35	150	22900
32	141	22122
30	136	21678
38	164	21581
60	396	21324
46	181	20754
58	357	18508
27	116	17959
31	138	17865
21	90	13805
57	352	13600
29	133	12325
28	131	12111
17	73	10903
23	101	10494
39	168	10262
48	198	9432
42	174	8452
24	103	8219
16	65	7947
33	143	7827
20	84	7327
37	160	7181
55	324	6949

Fig. 6. The Simulation Result for Referring

IV. CONCLUSION AND PROSPECT

Analysis on the integrated development of the traditional information and rural tourism based on remote sensing image data analysis is then conducted in this paper. The description method of this texture feature needs to divide the image into rhodin partitions, and the partition size needs to be determined through experiments. If the partition is too large or too small, it cannot accurately reflect the texture features. If the partition is too large, the influence of the adjacent land cover type will increase, and the classification accuracy will decrease. Further, the different application scenarios are considered for the simulation. In our future study, the different applications will be integrated to test the robustness.

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