Classification of High Resolution Remote Sensing Images Based on PCA, HSV and Texture Feature

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Abstract: Land cover classification of high spatial resolution data integrating textural information and spectral features remains limited, and the traditional extraction methods of high spatial resolution image have shortcomings of low accuracy and classification efficiency. In order to explore the practical application methods and effects of high-resolution remote sensing images in vegetation classification, this paper presents a support vector machine classification method for high-resolution image classification, combined using the spectral, principal component, HSV color space and texture features of the study object, which is based on the image data of Wuwei, one city in Gansu Province, China. The threshold values of NDVI are determined to separate vegetation area and non vegetation area. Surface objects in vegetation area mainly include special medicinal herbs, wheat, sorghum, sunflower and fruit tree. The overall classification accuracy is measured as high as 96.01%, and the Kappa coefficient is 92.49%. The results of ground truth check show that the method has high precision and good effect, which can be used to distinguish the vegetation of the same species. Meanwhile, the method could be used to extract the vegetation coverage information accurately and quickly, which can provide a reference for high resolution image classification. This method would have an extensive application prospect in crop information extraction from mass satellite data.

1 INTRODUCTION

Remote sensing technology is used to obtain the target information through analysis and interpretation on electromagnetic radiation data of surface reflection or ground object emission. With the development of remote sensing technology, a large number of high-spectral-resolution and high-spatial-resolution satellites have been launched, and their data gradually become the main data source for remote sensing applications. High-resolution images are not only rich in spectral information, but also have prominent features such as structure, shape and texture. They provide vivid and effective data sources for ecological environment protection, land survey and fine agriculture (Zhao et al., 2015;Wu et al., 2016;Lu et al., 2015). However, due to the richness of detailed information, the influence of interference factors such as small target and boundary becomes more obvious. At the same time, spectral features are used to classify high-resolution remote sensing images because of the phenomenon of "same objects with different spectra" and "different objects with the same spectrum" will cause lower classification accuracy, and "Salt and Pepper" phenomenon is more serious in classification.

With the development of remote sensing technology, the classification methods for high resolution remote sensing images are getting more and more attention, especially based on combination of texture and spectrum. A large number of studies show that the comprehensive utilization of the spectrum and texture features can contribute to improving the feature extraction (Blaschke, 2010;Chen et al., 2008;Li et al., 2006). Zhang Sen et al. studied on classification with spectral images, texture features of objects and corresponding DEM information, and the results show that the texture can effectively improve the classification accuracy

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(Zhang et al., 2016). Zhao Liang comprehensively utilized the spectrum and the texture features to achieve a high accuracy extraction (Zhao et al., 2016).

As mentioned above, this paper takes the Worldview-3 multispectral remote sensing imagery as data source, and its principal component analysis and color space transformation images. On this basis, the multi-scale texture features of the principal component analysis results are discussed. Finally, fusion multispectral, principal component analysis, color space transformation and texture feature for feature extraction.

2 STUDY AREAS

The study area locates in the southeast of Wuwei City, Gansu Province, China. The remote sensing data of WorldView-3 was acquired on June 19, 2016. The 'WorldView-3' is the fourth generation of high resolution optical satellite developed by the Digital Global corporation, and is the world's highest resolution commercial remote sensing satellite. WorldView-3 high resolution images include three kinds of image data: full-color images (0.3m), Vis-NIR multi-spectral image (1.24m) and SWIR multi-spectral image (3.7m). This paper uses its 1.24m Vis-NIR multi-spectral image (shown in Figure 1), including bands of coastal zone (427.4nm), blue (481.9nm), green (547.1nm), yellow (604.3nm), red edge (722.7nm), near-infrared 1 (824.0nm), near-infrared 2 (913.6nm).

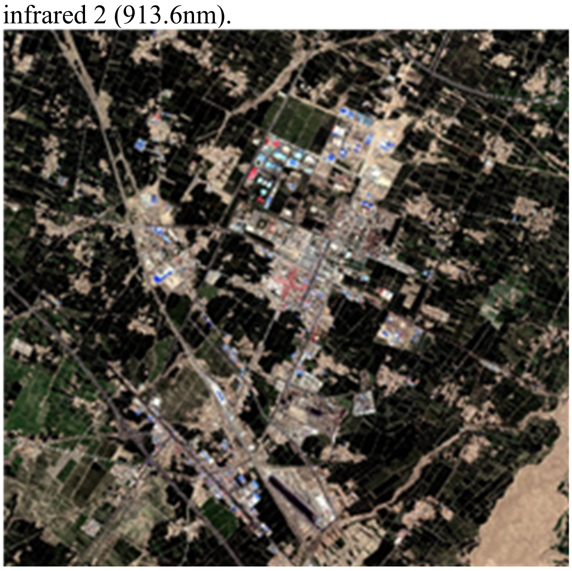

Figure 1: The study area.

3 RESEARCH METHODS ANDRESULTS

Firstly, remote sensing image preprocessing is performed on the Worldview-3 image in the study area, including radiometric calibration, geometric correction and cropping. The radiometric calibration coefficient adopts the latest absolute radiometric calibration coefficient released by the United States Digital Earth Corporation on February 22, 2016. After preprocessing, the principal component transform of the multispectral data in the experimental area was performed. The gray scale co-occurrence matrix method was utilized to extract the multi-scale texture feature of the first principal component of PCA. At the same time, the HSV color space transform, finally multi-scale texture feature data fusion multispectral data for SVM classification and accuracy evaluation.

3.1 Principal Component Analysis

Principal component analysis is also called K-L transform. By performing a linear transformation on the multispectral image, the spectral space X composed by the multispectral image is multiplied by a linear transformation matrix A to generate a new spectral space Y, i.e. a new Multi-spectral image. Its expression is:

$$Y=A*X \tag{1}$$

In the formula: X is the pixel vector of multi-spectral feature space before transform;

Y is the pixel vector of transformed multispectral feature space;

A is an n × n linear transformation matrix.

A large number of studies have shown that after PCA transform, the components of multispectral images will have the least correlation between them, which can help to highlight the main information, suppress the noise and enhance the image, which is beneficial to feature selection. The first principal component of the transformed feature space concentrates the largest amount of information, often accounting for more than 80%, followed by the second principal component. Principal component analysis can effectively reduce the data set dimensions. The first two components of the image of the study area are shown in Figure 2.


a) pc1

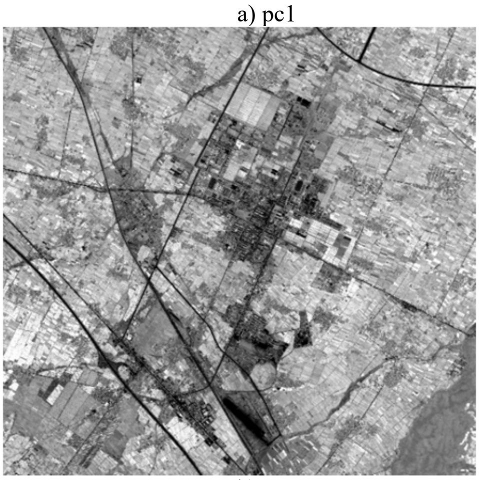
b) pc2

Figure 2: Principal components after PCA.

3.2 Gray Level Co-Occurrence Matrix

Gray Level Co-occurrence Matrix is the most important texture feature extraction method based on statistical analysis, which calculates the probability that two pixels of a certain direction and a certain distance in an image transition from one gray level to another, then reflects the image comprehensive information in the interval, direction, change rate and speed etc. (Xu, 2010). Its expression is as follows:

$$P(i,j,d,\theta) = \{[(x,y),(x+d,y+d)] | f(x,y) = i, f(x+d,y+d) = j\}$$
$$x = 1,2,\cdots,N_x,\ y = 1,2,\cdots,N_y, i,j = 0,1,\cdots,L-1 \quad (2)$$

Grayscale co-occurrence matrix texture information mainly includes mean value, variance, entropy, angle second moment, homogeneity, contrast, dissimilarity, correlation and partial texture information. In this paper, the principal component analysis of multispectral images is performed in advance, then the first principal component is selected for texture feature extraction. The size of the moving window in the gray level co-occurrence matrix analysis is 3 × 3, and the moving step takes 1 pixel. Parts of the texture features are shown in Figure 3.


a) homogeneity


b) contrast

Figure 3: Gray level co-occurrence matrix.

3.3 HSV Transformation

The HSV color model has three basic elements: Hue (H), Saturation (S) and Value (V). The HSV color feature can express the global features of an image. It is also one of the classic color features used in image classification (Zhong, 2015). In this paper, we select the near-infrared 1, red and blue bands of the image to do HSV transformation. The spectral characteristics of green plants in the near-infrared band are high reflectance, which is the key area of their spectral study. The spectral absorption zone of vegetation in red band can enhance the contrast between vegetation and no-vegetation coverage, and at the same time enhance the contrast between different types of vegetation. Blue band is a strong absorption area of vegetation, which can effectively distinguish the flowering vegetation from others. The transformed image is shown in Figure.4. In the transformed image, vegetation appears as a pink, yellow, green and other bright colors due to different types and different growth stages; non-vegetation roads, houses, etc. appear blue.

Figure 4: HSV color space model.

Masking operation can effectively remove the effects of irrelevant data. In this paper, the main research object is cropland. At the same time, because the study area is located in the inland of northwestern China, there are insufficient vegetation on the ground besides the crops, so we choose the best vegetation growth state indicator factor NDVI to do the masking operation. After testing, when the threshold of NDVI is set as 0.3 in the study area, it can effectively remove the buildings, roads and bare land. If the NDVI value of a local object is less than 0.3, it is considered as a non-research object, and the NDVI masking of the image is shown in Figure 5 (the black area is the mask area).

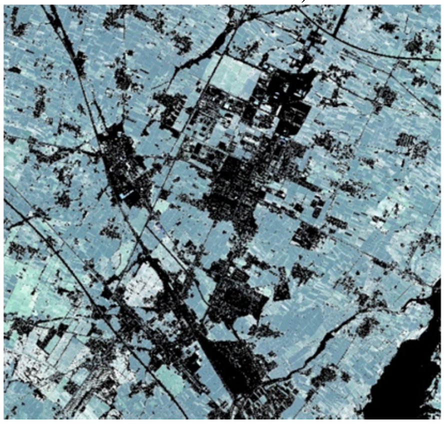

Figure 5: Masking.

3.4 Support Vector Machine (SVM)

SVM is a machine learning algorithm based on statistical learning theory. The core idea of SVM is to transform the linearly inseparable problem of low-dimensional space into a high-dimensional space for accurate classification by using kernel transformation. It can minimize the empirical error and maximize classification interval, thereby enhancing the generalization ability of the model. A large number of studies show that SVM classifier has obvious advantages over other remote sensing image processing methods in feature adaptation, learning speed and training sample requirements (Mountrakis et al., 2011).

Table 1: Accuracy evaluation.

		Reference image					
		Sorghum	Special medicinal herbs	sunflower	wheat	total	User accuracy (%)
Classification results	Sorghum	58361	98	390	2886	61735	94.53%
	Special medicinal herbs	5	4087	39	0	4131	98.93%
	sunflower	319	8	8257	13	8597	96.05%
	wheat	0	0	0	19735	19735	100.00%
	total	58685	4193	8686	22634	94198	
	Production accuracy (%)	99.45%	97.47%	95.06%	87.19%		

The first three principal components and eight common texture features of the first principal component are analyzed by the gray level co-occurrence matrix (GLCM), which are composed of HSV images converted by bands 7 (near red), 5 (red), 2 (blue), and original multispectral image is converted into a multi-dimensional image that combines spectral features and texture features. Finally, the image is introduced into the classification of Support Vector Machine (SVM) classification.

3.5 Results

The masked samples in the study area mainly include the main types of special medicinal herbs, wheat, sorghum, sunflower and orchard. The types of masks are set as others. The samples are selected and the study area is classified by using the SVM classification method. The kernel of the classification selection is Radial Basis Function. The results are shown in Figure 6, and the classification accuracy of the classified results was evaluated using the ground survey plots (Table 1):

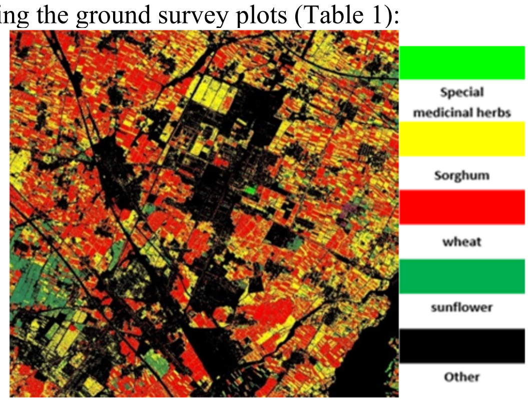

Figure 6: Classification result.

Orchard shows spectral mixture in remote sensing images, due to intercropping techniques, and can not be effectively evaluated for classification accuracy. The classification accuracy was evaluated only for four main crops: sorghum, special medicinal herbs, sunflowers and wheat. The production accuracy of sorghum, special medicinal herbs, sunflower and wheat by ground truth test can reach 99.45%, 97.47%, 95.06% and 87.19%, respectively (see Table 1). Sorghum, special medicinal herbs and sunflower are highly distinguishable from other vegetation, and wheat and sorghum have a certain degree of confusion. However, the confusion areas are mainly concentrated in the upper spectral mixing area of field ridge and boundary, thus have little effect on the overall classification accuracy. Since the accuracy verification uses the ground survey area and the coverage area is small, the classification result evaluation accuracy is high, and the verification accuracy of the whole image will be slightly lower.

4 CONCLUSIONS

Based on the principal component analysis of the image of the study area, this paper combines the texture features of the first principal component of PCA transform, the second and third principal components of PCA transform, multispectral and color space transform. Image classification is conducted using SVM classifier. Overall accuracy of the classification can reach 96.01%. Kappa coefficient is 0.9249. The results show that:

The SVM classification method based on multi-scale texture features of PCA and spectral information data can be effectively applied to high-resolution vegetation classification and fine recognition. The result can achieve higher classification accuracy.

The SVM classification method based on multi-scale texture features of PCA and spectral information data is relatively simple, fast and adaptable. It can be used in remote sensing applications such as emergency response and disaster relief with rapid classification and interpretation requirements.

Due to the mixed spectrum of field ridge or boundary, wheat and sorghum are partially misclassified when they are classified using the proposed method. The future work is to further improve the classification accuracy by introducing more features and pre-performing image segmentation, and to explore significant image features of various types of objects to improve processing speed and efficiency of classification method.

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