Classification of High Spatial Resolution Remote Sensing Images Based on Decision Fusion

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***Abstract*—With the development of earth observation technology, a series of high spatial resolution remote sensing satellites has been successfully launched. The earth observation data, especially high spatial resolution remote sensing image, is becoming more accessible. Therefore, the ability and efficiency of high spatial resolution remote sensing image classification has become a prominent problem for its further applications. This paper presents an object-based image classification framework based on decision fusion for high spatial resolution remote sensing image. This framework mainly included three steps. Firstly, high spatial resolution remote sensing image was segmented by multi-resolution segmentation method. Secondly, the multi-source features of segmented regions were extracted and classified by Support Vector Machine classifier, respectively. Finally, the multi-source classification results were integrated by decision fusion and reclassification strategy. Quick-bird satellite data was performed to classify the land surface using the proposed classification framework; and the classification results using different feature spaces were compared. The results show that the classification method based on decision fusion takes fully advantage of multi-source region features and finally obtain higher classification precision.**

***Index Terms*—high spatial resolution remote sensing image, image segmentation, image classification, decision fusion**

I. Introduction

With the development of remote sensing technology, high spatial resolution remote sensing data had been more easily acquired and widely applied. High spatial resolution remote sensing data contains more spatial texture and details [1]. They have been widely used for urban change detection, forest dynamic monitoring, land cover classification, ecological environment monitor and so on. Remote sensing image classification is the foundation of these applications. Therefore, the classification of high spatial resolution satellite remote sensing image is becoming a hotspot.

Comparing to low and medium spatial resolution remote sensing images, more details were contained in high spatial resolution images. However, the improvement of spatial resolution increases the internal spectral variability of each land cover class and decreases the spectral variability between different classes [2]. In decades, many classification methods have been proposed to improve classification precision of high spatial resolution remote sensing images. These methods can be divided into different groups based on different standards. According to the size of basic processing unit, classification methods can be divided into pixel-based and object-oriented. The early traditional classification methods were pixel-based methods. The pixel was considered as the minimum basic processing unit. The shape, texture and contexture characteristics around the central pixel were not fully considered. And the application of traditional pixel-based classification methods in high spatial resolution remote sensing images have been proven to have some drawbacks, such as low classification accuracy, the derivation of very limited spatial information, and salt and pepper effects [3]. With the development of image analysis technologies, the object-based analysis method was introduced into the classification of high spatial resolution remote sensing images. High spatial resolution remote sensing images were firstly segmented and the objects replace the pixels as the minimum processing unit. Object-based image analysis technology is very effective for high spatial resolution remote sensing image classification. More and more object features were mined and used for classification. Chen et al. proposed a modified object-oriented classification method for high spatial resolution remote sensing images [3]. Multi-source features of image objects were computed and the fuzzy-logic classifier was used to divide the feature space. Zhang and Zhu presented a knowledge-rule-based classification method for high spatial resolution remote sensing images [4]. The spectral features, texture features, and shape features were integrated to establish classification ruler. From the above, the multi-source features were simply combined together and straightly classified. The characteristics of multi-source features were not considered separately.

In view of the characteristics and problems of high spatial resolution remote sensing image classification, an

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object-based image classification framework based on the decision fusion has been proposed. The regional spectral, texture and vegetation index features were extracted through the corresponding extraction methods, and classified by Support Vector Machine classifier, respectively. The multi-feature classification results were fused by decision fusion mechanism. In the presented classification framework, the multi-scale characteristics of the image and multi-source region features were integrated by decision fusion and reclassification mechanism and finally got high classification precision.

II. METHOD

This section introduced the framework of decision fusion classification for high spatial resolution remote sensing images. The image segmentation, the multi-source feature extraction, classification and decision fusion mechanism were detailed. The flowchart of the proposed method is shown in Fig. 1.

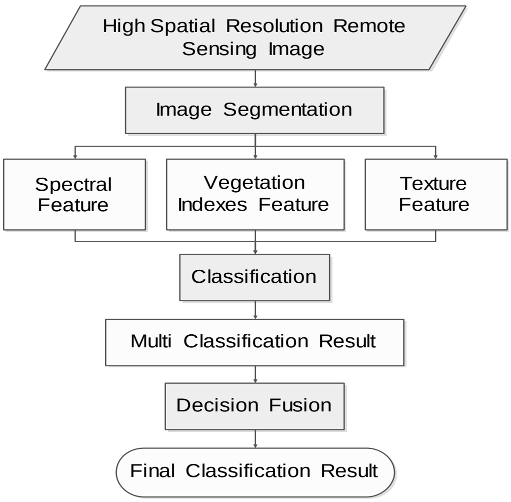

Figure 1. The flowchart of the proposed classification method.

A. Image Segmentation

High spatial resolution remote sensing images contain more spatial information of ground objects and show great diversity of them. Image segmentation is an essential step for object-based analysis of high spatial resolution remote sensing images [5]. Image segmentation is a process of dividing an image into meaningful homogenous regions.

Many segmentation approaches have been proposed for segmentation of high spatial resolution remote sensing images. There are some representative segmentation methods, such as the clustering method, the mean shift, the wavelet transform method, the active contours method, the watershed transform method and so on. The segmentation methods can be divided into different categories based on different classification standards. The segmentation methods can be classified into single-scale and multi-scale classes according to whether or not to use the multi-scale image information.

The multi-scale segmentation technique is one of the most important techniques for image segmentation. The region-based multi-resolution segmentation method available in eCognition software was used. The segmentation process was controlled by the scale, shape and compactness parameters specified by users. The most suitable parameters were determined by experimenting and users' subjective assessment.

B. Multi-source Feature Extraction

After image segmentation, the regional spectral, texture and vegetation index features were extracted using the corresponding calculation methods. The regional spectral vector was calculated by the mean spectral vector of pixels contained in each region.

Texture is an important feature in identifying interest regions in image. In 1973, Haralick introduced the grey-level co-occurrence matrix and texture features for rock image classification [6]. The grey-level co-occurrence matrix is one of the effective techniques for image texture analysis. The texture features based on co-occurrence matrix were widely used for different images analysis tasks.

The co-occurrence matrix was controlled by the move window size, move step length and direction parameters specified by users. Texture features were calculated based on the grey-level co-occurrence matrix. Eight statistical indicators of texture information, namely mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment and correlation, were selected for composing the object texture feature space.

The vegetation indexes were defined by referring to the calculation formula of normalized difference vegetation index (NDVI). The NDVI computation formula is as follows:

$$NDVI = \frac{Band_1 - Band_2}{Band_1 + Band_2} \tag{1}$$

where band 1 stands for the near-infrared band of high spatial resolution remote sensing image, and band 2 represent the red band of high spatial resolution remote sensing image.

For high spatial resolution remote sensing image, generally, it has four spectral bands, and then six imitated vegetation indexes can be obtained from every two bands.

C. Multi-source Features Classification

With the development of artificial intelligence and machine learning, a lot of new machine learning algorithms were brought into the classification of high spatial resolution remote images. Each algorithm had its unique advantages and weaknesses.

Support vector machine (SVM) is a supervised nonparametric statistical learning technique. A hyperplane or set of hyperplanes were constructed in a high-dimensional space by SVM, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class. The larger the distance means the lower the generalization error of the classifier. SVM is very good at solving nonlinear, high dimensional and limited training samples, and widely applied to classification of remote sensing images [7]. There are many kinds of kernel functions used for space transform. The Gaussian radial basis function (RBF) kernel was employed for all experiments. In order to integrate the characteristics of different features, the spectral, texture and vegetation indexes were classified separately.

D. Multi Classification Results Decision Fusion

Decision fusion is the process of fusing information from individual sources [8]. The spectral, texture and vegetation index features were classified separately. The multi classification results were fused by decision fusion mechanism. The decision fusion scheme can be considered to be two-stage processes, including soft majority voting and reclassification.

Firstly, the classification results provided by the different features were aggregated by majority voting. The final decision was assigned with the majority class. The soft majority voting can reject regions if either the majority or all of the classification labels for the region do not agree on one class.

After soft majority voting, the unclassified regions will be reclassified based on spectral and context information. The minimum distance classification method was used to classify the unclassified regions to the closest class. The Euclidian distance between the mean of a class and an unclassified region in the n dimensional spectral feature space is given as [9]:

$$D_{ED} = \left(\sum_{i=1}^{n} (x_i - C_i)^2 \right)^{1/2} \tag{2}$$

where n is the dimensionality of feature space, x_i is the mean spectral value of i_{th} feature of the unclassified region, and C_i is the mean spectral value of the i_{th} feature of one class. The unclassified region is then assigned to the class where D_{ED} is minimal. All unclassified regions are classified to the most similar class.

III. EXPERIMENTS AND DISCUSSION

To evaluate the performance of the proposed decision fusion classification approach, one subset of Quick-bird satellite remote sensing image is employed to classify the land surface. The Quick-bird dataset includes one panchromatic band with resolution of 0.6 m and four multispectral bands with resolution of 2.4 m. The size of multispectral image is 256 × 256, while the size of the panchromatic image is 1024 × 1024.

The SVM classifier with Gaussian radial basis function (RBF) kernel was applied for all experiments. The optimal parameters C (parameter that controls the amount of penalty during the SVM optimization) and γ (parameter that describes the spread of the RBF kernel) were chosen by fivefold cross validation [10]. Table I reports the optimal parameters of all SVM classification experiments.

To assess classification accuracy of different methods, the confusion matrixes are constructed. The reference classification image is generated through a precise manual interpretation on fusion images. The producer, user and overall classification accuracies are calculated from the confusion matrix.

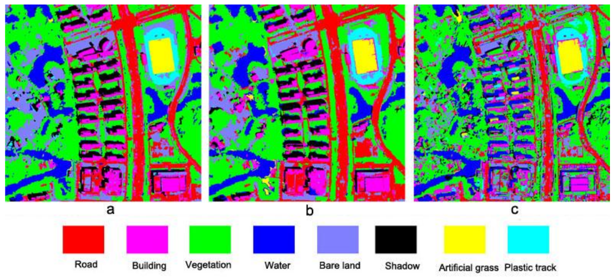

Figure 2. Classification results using different feature space. (a) is the classification result based on spectral space, (b) is classification result using vegetation index features, (c) shows the classification result of texture features.

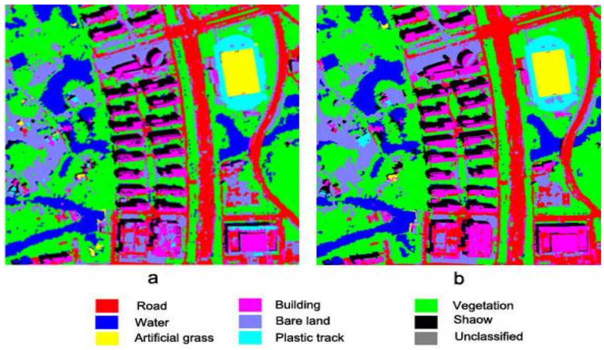

Figure 3. Classification results by different method. (a) is the classification result based on combined all feature space, (b) shows the classification result through decision fusion.

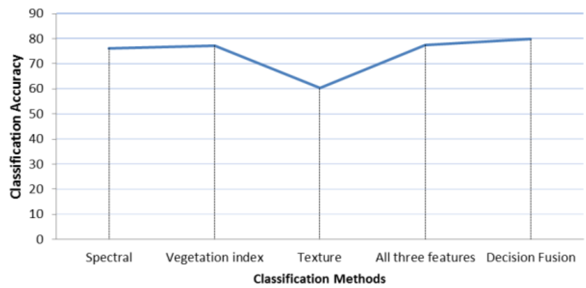

Figure 4. Accuracy comparison of different classification methods.

By comparing the accuracies of the various classification results, the proposed decision fusion method obtained the best classification result than other methods. Fig. 4 shows the comparison of different classification methods.

TABLE I. OPTIMAL PARAMETERS OF ALL SVM CLASSIFICATION EXPERIMENTS

Methods	Optimal Parameters	
Features	C	γ
Spectral	32768	0.125
Vegetation Indexes	8	2
Texture	2048	0.5
All three features	32768	0.001953125

TABLE II. PRODUCER AND USER CLASSIFICATION ACCURACIES BASED ON SPECTRAL FEATURES

Features	Spectral feature	
Class	Producer's Accuracy %	User's Accuracy %
Road	73.3096	73.1361
Building	58.4647	68.3494
Vegetation	79.4007	91.4669
Water	89.4212	77.3080
Bare land	68.7800	45.7508
Shadow	79.0754	69.5187
Artificial grass	92.1739	93.3921
Plastic track	94.0000	75.2000
Average Accuracy	79.3282	74.2652
Overall Accuracy	76.1782	

TABLE III. PRODUCER AND USER CLASSIFICATION ACCURACIES BASED ON VEGETATION INDEXES FEATURES

Features	Vegetation Indexes feature	
Class	Producer's Accuracy %	User's Accuracy %
Road	81.7912	65.6667
Building	63.4681	69.1561
Vegetation	81.6479	92.7660
Water	86.6267	76.6108
Bare land	57.4448	51.8198
Shadow	74.8175	75.6458
Artificial grass	83.4783	80.0000
Plastic track	93.5000	78.9030
Average Accuracy	77.8468	73.8210
Overall Accuracy	77.2630	

TABLE IV. PRODUCER AND USER CLASSIFICATION ACCURACIES BASED ON TEXTURE FEATURES

Features	Texture feature	
Class	Producer's Accuracy %	User's Accuracy %
Road	54.3298	68.2563
Building	42.4949	44.2857
Vegetation	71.4107	76.6756
Water	83.7325	45.0591
Bare land	40.5379	38.0523
Shadow	21.4112	38.0952
Artificial grass	86.0870	83.1933
Plastic track	86.0000	48.1793
Average Accuracy	60.7505	55.2246
Overall Accuracy	60.2436	

TABLE V. PRODUCER AND USER CLASSIFICATION ACCURACIES BASED ON ALL THREE FEATURES

Features	All three features	
Class	Producer's Accuracy %	User's Accuracy %
Road	72.3013	75.1541
Building	55.6546	72.1137
Vegetation	83.3749	92.3059
Water	89.8204	78.4656
Bare land	73.0067	45.7831
Shadow	75.4258	77.0186
Artificial grass	91.3043	88.6076
Plastic track	95.0000	61.6883
Average Accuracy	79.4860	73.8921
Overall Accuracy	77.5209	

Table II, III and IV showed that different feature space produced different classification accuracies. The accuracy using vegetation indexes was higher than that of spectral and texture. As shown in Table V, the classification accuracy by combining multiple features together was higher than that of single feature. From Fig. 4, it can be found that the proposed decision fusion method obtained highest overall accuracy; the overall accuracy was 79.86%, increased by about 2.5% than the best single feature space classification. It can be concluded that the presented decision fusion classification framework can make full use of multi-source region features and improve the final classification precision.

TABLE VI. PRODUCER AND USER CLASSIFICATION ACCURACIES OF PROPOSED METHOD

Features	Decision fusion	
Class	Producer's Accuracy %	User's Accuracy %
Road	76.9276	74.4119
Building	66.5524	73.8965
Vegetation	84.4361	92.1226
Water	89.4212	81.9013
Bare land	70.0288	51.5924
Shadow	76.5207	78.5268
Artificial grass	91.3043	95.0226
Plastic track	95.5000	74.9020
Average Accuracy	81.3364	77.7970
Overall Accuracy	79.8595	

IV. CONCLUSION

An object-based image classification framework based on decision fusion has been presented. Quick-bird satellite data was performed to classify the land surface using the proposed classification framework; and the classification results using different feature spaces were compared. Experimental results show that the classification accuracy using all features is higher than that of single feature, and the classification accuracy using decision fusion strategy is higher than that of simply combining the multiple features. It is concluded that the proposed decision fusion method can be effectively improve the classification accuracy of high spatial resolution remote sensing images.

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REFERENCES

[1] G. Z. Wang, J. B. Liu, and G. J. He. A method of spatial mapping and reclassification for high-spatial-resolution remote sensing image classification. The Scientific World Journal. [Online]. pp. 192982-192988. Available: http://www.hindawi.com/journals/tswj/2013/192982/

[2] L. Bruzzon and L. Carlin, “A multilevel context-based system for classification of very high spatial resolution images,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 44, no. 9, pp. 2587-2600, 2006.

[3] Z. Chen, G. Y. Wang, and J. G. Liu, “A modified object-oriented classification algorithm and its application in high-resolution remote-sensing imagery,” *International Journal of Remote Sensing*, vol. 33, no. 10, pp. 3048-3062, 2012.

[4] R. Q. Zhang and D. L. Zhu, “Study of land cover classification based on knowledge rules using high-resolution remote sensing images,” *Expert Systems with Applications*, vol. 38, pp. 3647–3652, 2011.

[5] Y. Liu, Q. H. Guo, and M. Kelly, “A framework of region-based spatial relations for non-overlapping features and its application in object based image analysis,” *ISPRS Journal of Photogrammetry & Remote Sensing*, vol. 63, pp. 461–475, 2008.

[6] R. Haralick, K. Shanmugam, and I. Dinstein, “Textural features fo r image classification,” *IEEE Trans. on Systems, Man and Cybern etics*, SMC–3(6):610–621, 1973.

[7] G. Mountrakis, J. Im, and C. Ogole, “Support vector machines in remote sensing: a review,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 66, no. 3, pp. 247–259, 2011.

[8] J. A. Benediktsson and I. Kanellopoulos, “Classification of multisource and hyperspectral data based on decision fusion,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 37, no. 3, pp. 1367-1377, 1999.

[9] A. G. Wacker and D. A. Landgrebe, “Minimum distance classification in remote sensing,” 1972, LARS Technical Reports. Paper 25.

[10] Y. Tarabalka, J. Chanussotk, and J. A. Benediktsson, “Segmentation and classification of hyperspectral images using minimum spanning forest grown from automatically selected markers,” *IEEE Transactions on Systems, Man, and Cybernetics—Part b: cybernetics*, vol. 40, no. 5, October 2010.

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