A Highly Efficient Method for Training Sample Selection in Remote Sensing Classification

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Abstract—**Remote sensing classification is an important way to obtain land cover information, and the selection of classification training samples for most of the classification method is an expensive and time-consuming task. However, the traditional training samples selection method is a direct selection based on two-dimensional (2D) images, therefore, training sample selection efficiency is always low in the regions with complex terrain and landscape fragmentation, and the ROI (region of interest) separability is unsatisfactory for classification. This study aims at the low efficiency and low ROI separability for traditional training sample selection method put forward a new training sample selection method using a three-dimensional (3D) terrain model that was created by OLI image fusion digital elevation model (DEM) to select ROIs, which departs from the traditional method based on a two-dimensional image. A Landsat-8 OLI image of the Yunlong Reservoir Basin in Kunming was used to test this proposed method. Study results showed that the proposed method obtained ROI separability that was greater than 1.9, and with most reaching 2.0; while the ROI separability of traditional method still had unqualified situation, which showed the new method was more effective.**

Keywords- Remote sensing classification; Training samples; 3D terrain; ROI separability; ImageFusion

I. INTRODUCTION

Remote sensing classification is an important way to quickly and accurately obtain the land cover information. It has been widely applied in the fields of land use / land cover (LULC), disaster monitoring and evaluation, environment monitoring, and so on. Training sample selection is the most important component of most remote sensing classification methods, and assessing the quality of ROI (region of interest) is also needed for improving the classification accuracy [1]. However, the quality of ROIs is often overlooked when training samples are selected with high priori knowledge. High-quality classification training samples (with high ROI separability) determines the classification accuracy in a certain extent [2]. Good classification algorithm can improve the classification accuracy, but the premise needs good training samples, especially for the supervised classification.

Supervised classification usually needs selecting ROIs from remote sensing images in advance, then uses selected ROIs to train classification algorithm, finally completes the whole study area's classification [3]. Supervised classification algorithms include minimum distance (MD), maximum likelihood (ML), parallelepiped (P), spectral angle mapper (SAM), mahalanobis distance (MaD) and binary encoding (BE) classification, and all algorithms must need training samples to take part in classification.

At present, common classification method based on machine learning, including artificial neural network (ANN), support vector machine (SVM) and decision tree (such as classification and regression tree (CART), quick unbiased, efficient statistical tree (QUEST) ,See5.0/C5.0), even object-oriented classification methods, which are related to the selection of training samples[4,5].

The traditional training sample selection method is a direct selection based on two-dimensional (2D) images. Classification accuracy is largely determined by ROI separability. However, for low or medium-resolution images or in regions with landscape fragmentation or complex terrain, ROI separability is often unsatisfactory [6]. In recent years, it has been proposed using the automatic training samples selection method instead of artificial selection in order to improve the efficiency and accuracy of sample selection[7,8]; Some studies also used auxiliary data to optimize the training samples and reduce noise samples[9,10]. Because of the limitation of sensor resolution, landscape fragmentation and complex terrain make the obvious phenomenon of “different objects with same spectra and same objects with different spectra” ,which results in low efficient of ROIs selection. Traditional method and automatic selection method have been unable to meet the requirements of high ROI separability. Therefore, we need to explore an efficient method to select high-quality classification training samples urgently, so as to improve the classification accuracy.

In this paper, a new training sample selection method was proposed using a 3D terrain that was created by OLI image fusion DEM to select ROIs, which departs from the traditional

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method based on a two-dimensional image. The 3D terrain training sample selection utilizes the principle of color synthesis and integrated terrain from various angles (looking down, looking up, from top, from side) to select ROIs, and it can improve the efficiency and separability of samples to a great extent.

The following of the paper is organized as follows. Section 2 introduces study area and data source. Section 3 presents the proposed approach. Section 4 describes the results. Section 5 concludes and discusses the paper.

II. *STUDY AREA AND DATA SOURCES*

A. *Brief Introduction of Study Area*

Yunlong Reservoir Basin (102°22′30″ ～ 102°32′18″ E, 25°5′16″～25°58′6″ N), with a total runoff area of 745 km^2, is located in the northern Kunming City, Yunnan Province, China [6] (Fig. 1). The basin primarily belongs to a karst-tectonic origin canyon landform, a valley that was caused by mountainous tectonic erosion, and its landscape is fragmented. Yunlong Reservoir houses 70% of the total water supply for Kunming City and is responsible for maintaining sufficient drinking water for Kunming and its surrounding areas. Forest cover (including arboreal forest, shrubs, and herbs) makes up more than 70% of the basin [11].

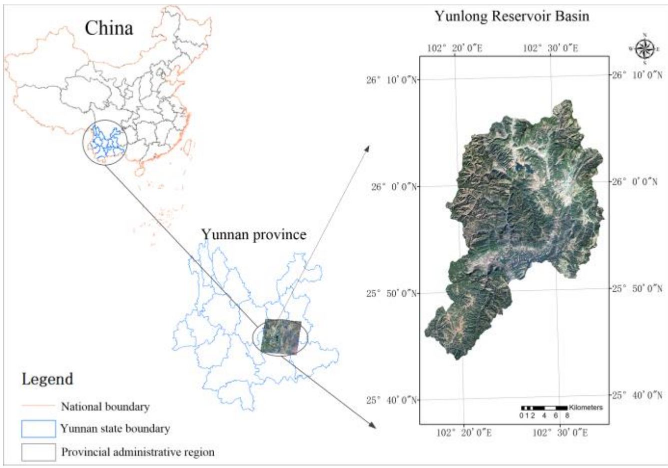

Figure 1. Location of Yunlong Reservoir Basin

B. *Data Sources*

The date includes Landsat-8 OLI image and DEM. A Landsat-8 OLI image acquired on 4 August 2017 covering the study area was downloaded from the USGS Global Visualization Viewer (GloVis, https://glovis.usgs.gov/). It has seven multispectral bands with 30 m resolution, one panchromatic band with 15 m resolution, and two thermal infrared bands with 100 m resolution. The DEM of study area with a resolution of 30m was downloaded from the GloVis platform, and it is a subset of ASTER GDEM (Advanced Space borne Thermal Emission and Reflection Radiometer Global Digital Elevation Model) on 4 August 2017.

III. METHODS

The proposed methodological framework for training sample selection (Fig. 2) includes, Gram-Schmidt (GS) image fusion, 3D terrain creation, training sample selection and sample-expanding.

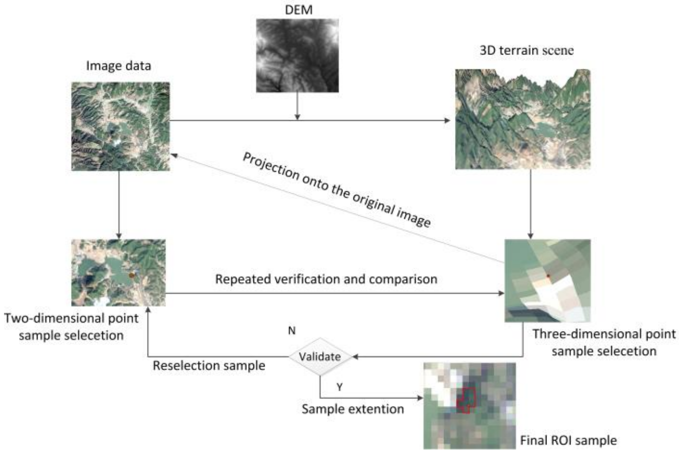

Figure 2. The methodological framework for 3D terrain aided ROIs selection

A. *Gram-Schmidt Image Fusion*

Landsat OLI multi-spectral bands fuse with panchromatic band to improve spatial resolution and preserve spectral information while improving the accuracy and efficiency of ROIs selection. At present, the commonly used image fusion methods include HSV (hue, saturation, brightness value) transform, PCA (principal component analysis), energy separation , Brovey transform and Gram-Schmidt (GS) fusion [12], but using GS fusion method, the spatial resolution of multispectral bands can be improved while maintaining a wealth of spectral information [13, 14]. Unlike other fusion methods, each component produced by GS transform is orthogonal, and the amount of information between them is not obviously different from the amount of the maximum spectral difference that is preserved (Fig. 3).

（a）　（b）　（c）

Figure. 3 Comparison of Gram-Schmidt images fusion before and after

B. *3D Terrain Creation*

The ArcScene module developed by Environmental Systems Research Institute (ESRI) is a 3D terrain visualization tool, which has a powerful 3D terrain building function. In this study, ArcScene was used to construct three-dimensional terrain. DEM image with 30m spatial resolution was resampled to15m so that it can match with the fused Landsat-8 OLI image with 15m spatial resolution. With 3D rendering and rendering, 3D terrain scenes was generated, adding shadow on the topographic map to make the 3D scene more sensitive and stereoscopic (Fig. 4), which was convenient for the selection of training samples.

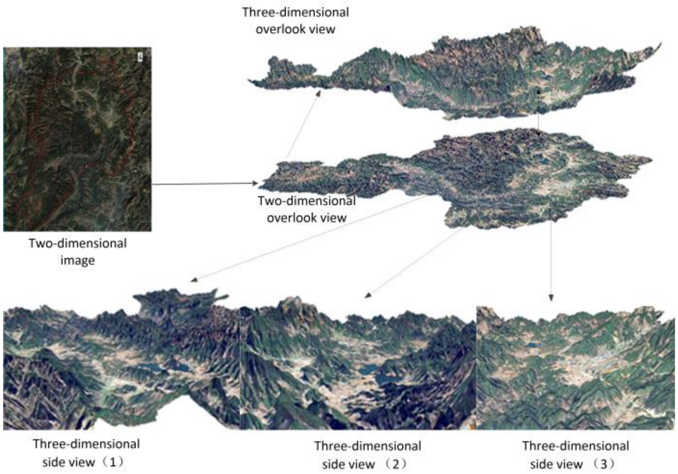

Figure 4. 3D terrain generating scene

TABLE. 1. ROI SAMPLES OF LULC IN THIS STUDY

First class	Second class	Third class
01farming land	012 arable land	--------
02 garden	--------	--------
03 forest land	031 arbor forest	0311broad-leaved forest 0312 coniferous forest
	032 sparse forest	--------
	033 sparse shrub	--------
04 grassland	041 natural grassland	0411high coverage grassland 0412 medium coverage grassland
05 building region	--------	--------
06 roads	--------	--------
07 structure	071 hardened surface	0711 revetment
	072hydraulicfacilities	0721 dams
	073 other structures	--------
08 artificial piling and digging land	--------	--------
09 desert and bare surface	--------	--------
10 water	--------	--------

Note: "--------" for ROIs only to the upper class in this study, not selected into "--------" types.

When selecting training samples, different band combinations can be adopted, it's helpful for different ROIs recognition. Band combination can be divided into true color synthesis, simulated true color synthesis and pseudo color synthesis. The traditional method directly drawn on the regular or irregular polygon in two-dimensional images; the new method selecting ROIs from the 3D terrain by using annotated points, which did not generate projection distortion. Then annotated points will be projected onto a two-dimensional image for sample expansion.

C. Training Sample Selection

We used traditional training sample selection method and the new training sample selection method to select training samples, and take training samples of land use / land cover types in study area as an example. Considering the "Contents and Indices of the First National Geographic Survey in Yunnan", the actual conditions in the study area and the limited spatial resolution of Landsat OLI image, the LULC classification system of Yunlong reservoir basin was determined (Tab. 1).

D. Sample-expanding

The selected annotated points require sample extension for point - to - surface, and the following patterns are usually used: (1) Point-centered outward expansion or linear pattern expansion based on pixels; (2) Point-centered outward expansion with regular or irregular polygons; (3) Point-centered outward expansion with circles or ellipses. In applications, the ROIs expanding combination with the above 3 patterns are more effective (Fig. 5).

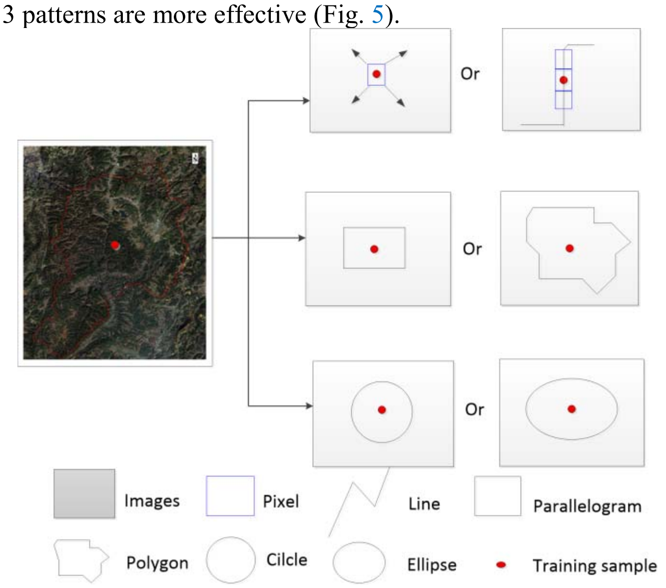

Figure 5. Training sample extension models

IV. *RESULT ANALYSIS*

ROI separability is an important index to evaluate the accuracy of training samples. The ROI separability was determined by using the "Jeffries-Matusita and Transformed Divergence separability" measures, and a separability index was computed between each pair of training samples [15, 16]. The values of ROI separability range from 0 to 2, and the value greater than 1.8 is often considered to be a high quality training sample [17].The proposed method obtained ROI separability was greater than 1.9, and most of them reached 2.0, while the ROI separability of traditional method still has unqualified situation (Table2, 3), which shows that the 3D terrain aided ROIs selection is more effective.

TABLE. 2 THE ROI SEPARABILITY OBTAINED BY TRADITIONAL METHOD

ROIs types	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	__															
2	1.800	__														
3	2.000	1.999	__													
4	2.000	1.999	1.850	__												
5	2.000	2.000	1.900	1.900	__											
6	1.999	1.999	1.899	1.899	1.780	__										
7	2.000	2.000	2.000	2.000	2.000	1.988	__									
8	2.000	2.000	2.000	2.000	2.000	1.999	1.950	__								
9	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	__							
10	1.999	1.800	2.000	2.000	1.999	1.999	2.000	2.000	1.888	__						
11	1.999	1.999	1.999	2.000	2.000	2.000	2.000	2.000	1.880	1.788	__					
12	2.000	2.000	2.000	2.000	2.000	1.999	2.000	2.000	1.977	1.930	1.900	__				
13	1.999	1.999	2.000	2.000	2.000	2.000	2.000	2.000	1.789	1.800	1.760	1.799	__			
14	1.980	2.000	2.000	2.000	2.000	2.000	2.000	2.000	1.789	1.900	1.830	1.785	1.760	__		
15	1.980	1.999	2.000	2.000	1.999	1.789	2.000	2.000	1.899	1.788	1.999	1.990	1.999	1.860	__	
16	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	_

TABLE. 3 THE ROI SEPARABILITY OBTAINED BY PROPOSED METHOD

ROIs types	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	__															
2	1.900	__														
3	2.000	2.000	__													
4	2.000	2.000	1.950	__												
5	2.000	2.000	1.999	1.999	__											
6	2.000	2.000	1.999	1.999	1.900	__										
7	2.000	2.000	2.000	2.000	2.000	1.988	__									
8	2.000	2.000	2.000	2.000	2.000	1.999	1.950	__								
9	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	__							
10	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	1.988	__						
11	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	1.990	1.950	__					
12	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	1.977	1.930	1.900	__				
13	1.999	1.999	2.000	2.000	2.000	2.000	2.000	2.000	1.999	1.999	1.999	1.999	__			
14	1.999	2.000	2.000	2.000	2.000	2.000	2.000	2.000	1.989	1.900	1.930	1.905	1.890	__		
15	1.999	1.999	2.000	2.000	2.000	1.999	2.000	2.000	1.999	1.988	1.999	1.999	1.999	1.960	__	
16	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	_

Note, 1: arable land, 2: gardens, 3: coniferous forest, 4:broad-leaved forest, 5: sparse forest, 6: sparse shrub, 7; medium coverage grassland, 8: high coverage grassland, 9: building region, 10: roads, 11: dams, 12: revetment, 13: other structures, 14: artificial piling and digging land, 15: desert and bare surface, 16: water.

Table 2and 3 showed that the ROI separability obtained by traditional method and proposed new method has some differences in some LULC types, ROI separability of new method was higher than that of the traditional method to a certain extent, most of the samples' ROI separability reached 2, there was no case of less than 1.8, so all the samples were qualified; The lowest value of ROI separability belonged to artificial piling and digging land (1.890), the rest of the samples' ROI separability were more than 1.9, which are high-quality training samples. As for the traditional method, there were some samples' ROI separability were lower than 1.8, which were unqualified, for example, the ROI separability of other structures, dams and artificial piling and digging land were the lowest (1.760); sparse shrub and sparse forest, dams and roads were 1.780 and 1.788, respectively; it is worth noting that the two methods obtained ROI separability for other structures and dams , artificial piling and digging land and other structures , sparse shrub and sparse forest, gardens and arable land were relatively low, but the proposed method obtained ROI separability were qualified.

V. CONCLUSIONS *AND DISCUSSION*

In this paper, we aimed at the low efficiency and low ROI separability for traditional training sample selection method put forward a new training sample selection method using a 3D terrain model, which was created using an image fusion DEM, to select training samples, and improve ROI separability. The 3D terrain training sample selection utilizes the principle of color synthesis and integrated terrain from various angles (looking down, looking up, from top, from side) to select ROIs, and it could improve the efficiency and separability of samples to a great extent. In this study, the ROI separability was greater than 1.9, and most of them reached 2.0. Almost all samples selected by proposed method are qualified, even high quality samples to a great extent; this method solved the difficult situation selecting training samples in the landscape fragmentation and complex terrain areas, which has a good application prospect. Although new method was effective and obtained a high ROI separability, only the Landsat-8 OLI image was tested, while other images, such as Quickbird, SPOT, Sentinel, GF-1 MODIS, were not tested. Future works should be carried out to test this method using different image date in other regions.

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