AN OBJECT-ORIENTED CLASSIFICATION TECHNIQUES FOR HIGH RESOLUTION SATELLITE IMAGERY

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ABSTRACT

Land cover plays a pivotal role in impacting and linking many parts of the human and physiography. Monitoring land cover and its change thus are of critical significance. Remote sensing techniques are gaining more and more importance for land cover classification and urban analysis. And the most common approach of classification is pixel-based supervised classification to classify various land use types. The pixel-based supervised classification approach is to classify the image using spectral features, which form the classification feature space. With the recent availability of commercial high resolution remote sensing multispectral imagery we cannot get high accuracy of land cover classification expected just using pixel-based approach. In this paper a hierarchical support vector machine object-based classification scheme is introduced. By combining spatial information and spectral information, the amount of overlap between classes can be decreased, thereby yielding higher classification accuracy and more accurate urban land cover maps. Initially, the image is segmented with a multi-scale segmentation technique. Then image objects are subsequently classified with hierarchical support vector machine classifier.

1. INTRODUCTION

Remote sensing research focusing on image classification has long attracted the attention of the remote sensing. Classifying remotely sensed data into a thematic map remains a challenge because many factors, such as the complexity of the landscape in a study area, selected remotely sensed data, image processing and classification approaches, may affect the success of a classification.

With the recent availability of commercial high resolution remote sensing multispectral imagery from sensors such as IKONOS and QuickBird, it is possible to recognize small scale features such as individual roads and buildings in urban environments. And in the high resolution image, there exists much more legible information such as distinct land cover, clear texture, and visible edge and so on.

The most common approach of classification is pixel-based supervised classification. The pixel based supervised classification approach is to classify the image using spectral features, which form the classification feature space and in this classification scale we can't make full use of information provided by the high resolution image. In this paper we introduce a new approach of image classification that is a hierarchical support vector machine object-based classification scheme. The analysis of result indicates that it can improve the accuracy.

Object-based approaches do not operate directly on individual pixels but on objects consisting of many pixels that have been grouped together in a meaningful way by image segmentation. In addition to spectral and textural information for pixel-based classification methods, image objects also allow us to get shape characteristics and neighborhood relationships is used for the object's classification.

2. METHODOLOGICAL FRAMWORK

2.1 Image segmentation

Image segmentation is the subdivision of an image into separated regions. There are lots of algorithms used in the field of remotely sensed imagery segmentation. Based on investigation of several algorithms we notice that the watershed algorithm has a significant accuracy result.

In geography a watershed is the ridge that divides areas drained by different river systems. A catchment basin means in this sense an area from which rainfall flows into a river or reservoir. The watershed transform applies these ideas to the gray-scale image processing to get enable solution of a variety of image segmentation problems. Understanding the watershed transform requires us to consider a gray-scale image as a topological surface, where the values of f(x,y) are interpreted as height. The watershed transform finds the catchment basins and ridge lines in such a grayscale image (Rafael C. Gonzalez and Rafael E Woods, 2002).

The gradient magnitude is used often to preprocess a gray-scale image prior to using watershed transform. The gradient magnitude image has high pixel values along object edges, and has low pixel values in the other parts. The gradient magnitude is computed using linear filtering methods, in this case we use Sobel horizontal and vertical edge filter.

We start by computing the gradient on individual planes and using results to form a composite gradient image then we compute the watershed transform of the gradient. The resulting segmentation is not good as it is very sensitive to oversegmentation. So we must smooth the gradient image before computing its watershed transform. Here we use some *morphology operations* such as *closing* and *h-minima* transform. Morphology operation *imclose* fills the gaps between pixels and smoothes their outer edges. Oversegmentation occurs because of local minima, even if it's tiny and insignificant, but it still forms its own catchment basin. We use *h-minima* transform to remove minima that are too shallow (suppresses all minima in the intensity image whose depth is less than h, where h is a scalar).

2.2 Support Vector Machines

Recently, particular attention has been dedicated to Support Vector Machines (SVM) as a classification method. SVMs have often been found to provide better classification results that other widely used pattern recognition methods, such as the maximum likelihood and neural network classifiers. Thus, SVMs are very attractive for the classification of remotely sensed data.

SVM is a general class of learning architecture inspired from statistical learning theory that performs structural risk minimization on a nested set structure of separating hyperplanes. Given a training data, the SVM training algorithm obtains the optimal separating hyperplane in terms of generalization error (Nello Cristianini *et al*, 2000).

The SVM approach seeks to find the optimal separating hyperplane between classes by focusing on the training cases that are placed at the edge of the class descriptors. These training cases are called support vectors. Training cases other than support vectors are discarded. This way, not only an optimal hyperplane is fitted, but also less training samples are effectively used; thus high classification accuracy is achieved with small training sets. This feature is very advantageous, especially for remote sensing datasets and more specifically for object-based image analysis, where object samples tend to be less in number than in pixelbased approaches (Angelos Tzotsos, 2006).

2.3 Feature selection

Because of the complex nature and diverse composition of land cover types found within the urban environment, classification of high-resolution multispectral satellite imagery is a difficult task. The goal of this paper was use the classification techniques for extraction of urban area geospatial information produced from high-resolution satellite imagery. The urban land cover classes used in this study were *Road*, *Building*, *Grass*, *Tree*, *Bare Soil*, *Water* and *Shadow*.

The *Road* and *Building* classes, the *Water* and *Shadow* and the *Grass* and *Tree* classes in the image are spectrally similar and have a significant amount of spectral overlap. This is the primary reason for the large number of misclassifications between these classes. Traditional supervised classification methods that only take into account spectral information, such as maximum likelihood, are unable to differentiate between these classes with a high degree of accuracy. Consequently, methods that utilize spatial information in addition to spectral information are needed to produce more accurate land cover classifications of high-resolution image data over urban areas.

There is plenty of geometrical information such as object feature, shape feature, texture, and contextual relation feature and so on. And the feature of object-based classification is object feature from segmented image. In this paper we add other feature information into feature space, which is area, entropy, shape index and contextual relation feature.

Area feature: The area of an image object is the number of pixels forming it. While the *Water* and *Shadow* classes can have similar spectral signatures, areas in the image covered with *Water* larger than *Shadow* covered areas.

Entropy feature: With the *Grass* and *Tree* classes, areas in the image covered with grass appear much more homogeneous than tree-covered areas. This difference in homogeneity between regions can be used to decrease the confusion between the classes. Several of the other statistical texture measures show increase in the accuracy of these classes, but not as large as the increase found when using the entropy measure. Entropy texture measure are calculated as follows:

$$entropy = -\sum_{i=0}^{L-1} p(z_i)\log_2 p(z_i)$$

Where L is the number of distinct gray levels, z is a random variable denoting image gray levels and $p(z_i)$ is the normalized graylevel histogram.

Shape feature: We use shape feature as follows (Xinliang Li *et al*, 2007):

$$L = \sqrt{S}/P$$

In this formula, S is the area of a certain polygon object and P is the perimeter. L is called shape index of object. Shape index of rectangle or square is bigger than linear object. Spectrally similar between roads and buildings in urban space, we can distinguish each other by shape index.

***Adjacency feature**:* The adjacency feature is intelligent understanding to the image. For instant, the objects of buildings and roads have the same object features, and we cannot distinguish these types commendably. But there exist visible shadow objects in some direction around high buildings, so we can distinguish these two objects by the adjacency information.

***Relation feature**:* We define relation feature as follows: if object A and B are two adjacent objects and A and B are the same class then A has relation with B. If B has relation with C and C is not adjacent with A then A has relation with C. Relation feature is the number of objects has relation with A. Because the road and river is continuous and building and shadow objects are discrete in the image, so we can distinguish which by relation feature.

3. IMPLEMENTATION OBJECT-BASED CLASSIFICATION

The spatial information extracted from objects can help to decrease the number of misclassifications between the spectrally similar *Road/Building, Water/Shadow* and *Tree/Grass* classes.

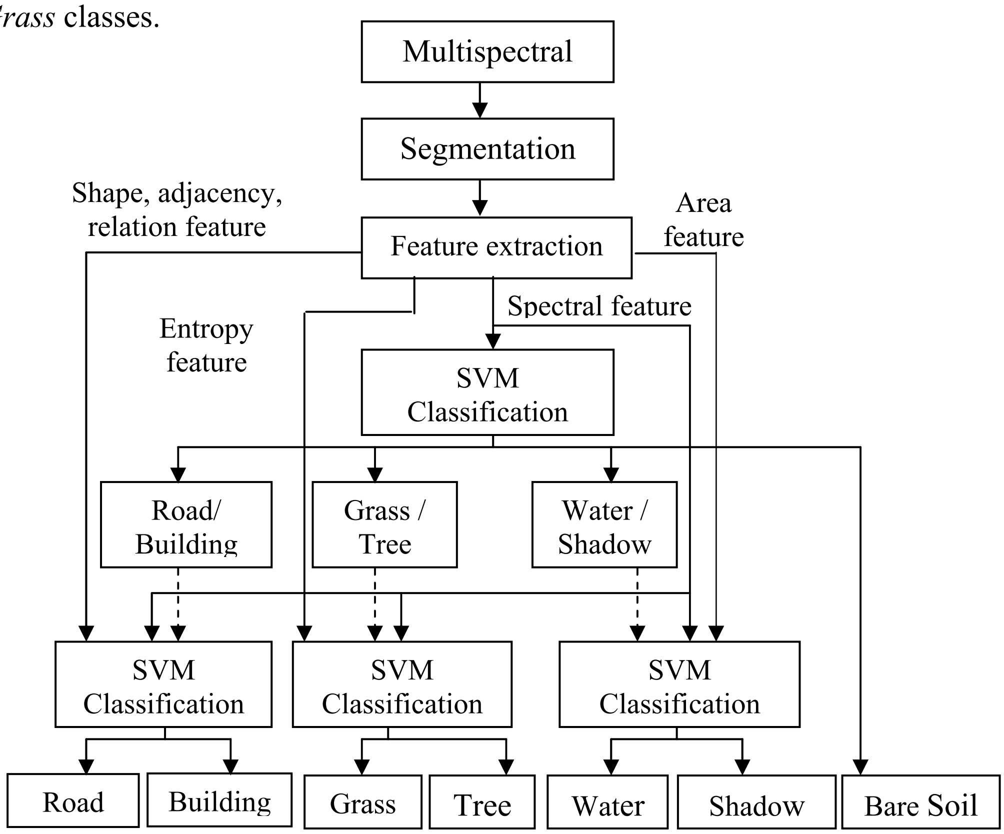


Figure 1. Block diagram of hierarchical SVM classification scheme.

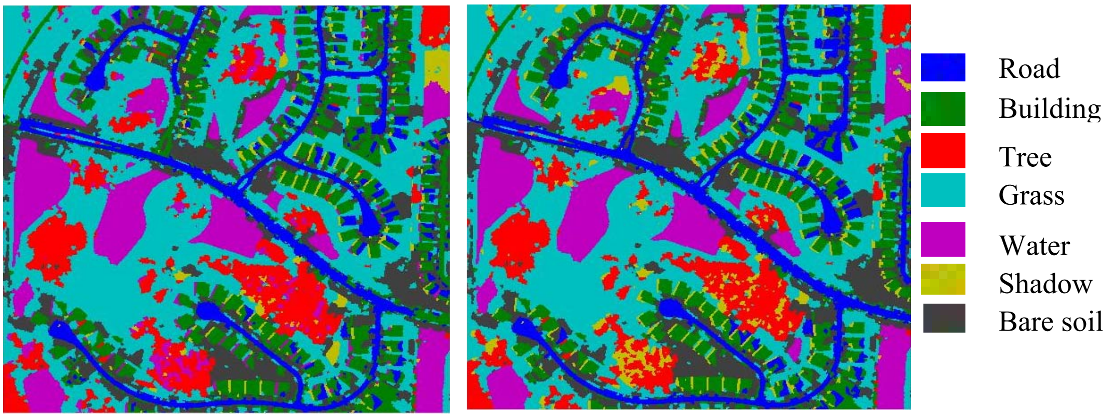
However, while one spatial feature might increase the classification accuracy between one set of classes, it might decrease the accuracy between another set using traditional classification methods. So that different classes should only be classified using the spatial measures best suited for those classes. We developed a support vector machine classification scheme that allows the image to be hierarchically classified using different spatial measures for different sets of classes.

First, the spectral information of the objects is used to split the objects into four initial sets: *Grass-Tree*, *Road-Building*, *Water-Shadow*, and *Bare Soil*. In this step we find four hyperplane (w, b) where the margin is largest to separate these sets. And then entropy feature measure is used addition for the *Grass-Tree* set to find the hyperplane which separate *Grass* and *Tree* class, the shape, adjacency and relation feature are used for both the *Road-Building* set, the area feature is used for *Water-Shadow* set.

For the evaluation of the developed approach, the classification was carried out in two image in the figure 2.

Figure 2. Two true color image was used to classification

To compare the approach, we also classify the same image using pixel-based classification. The first classified map are as follows (Figure. 3).



A: pixel-based classification B: object-based classification

Figuge 3. The classified maps of the first image. A is done based on the image pixel and B is classified based on the segmented objects.

The confusion matrix, the overall accuracy was computed for each classification.

Table 1: Pixel based classification confusion matrix of the first image.

	Road	Building	Tree	Grass	Water	Shadow	Bare soil
Road	173112	33361	0	0	0	0	0
Building	30684	90234	0	4938	0	0	4180
Tree	0	0	37743	6136	2014	0	0
Grass	0	0	13424	97708	0	0	6712
Water	0	0	0	0	407473	0	0
Shadow	0	1774	391	0	6197	7928	0
Bare soil	0	984	0	17845	0	0	15491

Table 2: Object based classification confusion matrix of the first image.

	Road	Building	Tree	Grass	Water	Shadow	Bare soil
Road	33	0	0	0	0	0	0
Building	6	104	0	0	0	0	1
Tree	0	0	45	2	0	2	0
Grass	0	0	0	31	0	0	3
Water	0	0	0	0	13	0	0
Shadow	0	0	1	0	0	53	1
Bare soil	0	0	0	3	0	0	15

The overall accuracy was computed by dividing the number of correctly classified reference pixels or objects by the total number of reference pixels or objects. The approach object-based can get higher accuracy than pixel-based approach. The overall accuracy is 93%, while the accuracy of pixel-based approach is only 86% for the first image and the overall accuracy is 92%, while the accuracy of pixel-based approach is only 84% for the second image.

4. CONCLUSION

High resolution images provide much more knowledge of land cover with the spatial features. So we can get much higher classification accuracy by fully use of that knowledge. The approach of object-based classification can improve the accuracy of classification. In addition to spectral and textural information for pixel-based classification methods, an additional information like image objects also allow us to get shape characteristics and neighborhood relationships is used for the object's classification. However, the success of object-based classification approaches is very dependent much on the quality of the image segmentation and the classification method. A good feature of SVMs is that only a small training set is required to achieve good results, because only the support vectors are of importance during training. In the future work we will compare several types of SVM kernels for object oriented image classification.

5. REFERENCE

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