

THE DECISION TREE ALGORITHM OF URBAN EXTRACTION FROM MULTI-SOURCE IMAGE DATA

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ABSTRACT:

Extraction of urban land is one of the necessary process in the change detection of urban growth. This Paper build a unified conceptual model to make the extraction more effectively and accurately based on the model of V-I-S (Vegetation- Impervious surface- Soil). The unified conceptual model uses the Decision Tree Algorithm with characteristics of spectrum and texture, etc. Using this model, we found common and unique indices from multi-source image data according to their similarity and dissimilarity. These indices were to remove the other land-use information (e.g. vegetation and soil), then leave the urban information as the result. They follow the same procedures conducted by the decision tree. The TM-5 image (30m) and the SPOT-4 image (20m) from Chaoyang (Beijing) were used in this paper. The analysis results show that the overall accuracy of TM- extraction is 88%, while the SPOT- extraction 86.75%. It provides an appropriate method to meet the demand of the change detection of urban growth.

1. INTRODUCTION

As the needs of long-term urban monitoring increases, how to use multi-source data to extract urban land has become a hot issue. Urban land is complicated mixture which consists of the buildings, roads, green land, unused land and other land-use types. As building materials, structures are different, the extraction of urban land is also a difficult problem in the field of remote sensing.

Post-classification method is the commonly used method in urban extraction. The manual intervention in the process leads to time-consuming and low accuracy. In order to find a more rapid and accurate methods, domestic and foreign experts and scholars in related fields have been doing a lot of exploration and research. Cun-Jian Yang et al (2000) had an analysis of the separability of different land use at TM bands, they proposed a simple and practical model based on the relationship between bands and used threshold method to recognize cement-roofed and Tile-roofed house of in the central region of Fuqing, Fujian. Masek et al (2000) used unsupervised classification and NDVI index to get the growth and change information in Washington in 1973-1996. Zhang (2002) introduced the the road information, to improve the accuracy of the extraction. Qing-Xiang Jiang and Hui-Ping Liu (2004) used texture analysis methods to separate different land use type from high-resolution images in Fengtai, Beijing. Han-qiu XU(2005,2007) did a lot of research on Urban Extraction based on normalized indices. They had studied deeply on the remote sensing indices to extract and separate urban land..

Decision tree is a hierarchical processing structure in remote-sensing classification, the basic idea is to do some bipartite work and refinement on the original dataset according to a number of judgments. Each bifurcation point represents of a decision-rule and it has two child nodes, representing the conditions of satisfaction and dissatisfaction categories. This method does not rely on any a priori statistical assumptions,

also, would facilitate the use of the knowledge other than brightness. As a result, it has been widely used in remote sensing classification and thematic information-extraction (Marct, etc., 2000). Ping Zhao (2003) used the decision tree method to find urban land from SPOT images in Jiangning, Nanjing. In this paper, we used band math and threshold segmentation method according to decision tree principle. For remote sensing images, we generally use the spectral characteristics. Spectral information is usually considered a good material in computing. However, due to the distinctiveness of multi-source data, spectral information can't meet the need of extraction. It's necessary to introduce other features. Take TM and SPOT images as an example, TM images have abundant spectral information, so we use spectral-extraction method in decision tree. But SPOT images have less bands, which are almost visible band. It's difficult to do the extraction without other information. Because of the characteristics of their high resolution, appropriate texture information can be introduced as indices of the decision tree. Here, we chose indices according to the characteristics of different sensors, put the spectral information, normalized indices, and textures into the decision tree in order to complete the extraction.

2. METHODOLOGY

Ridd (1995) presented the VIS model when doing urban research, each pixel in urban image is treated as a linear combination of vegetation - impervious surface - soil, which are three representative land cover types in urban area. Water is introduced into this model based on the research condition. In this article, the urban land refers to impervious surface. So the purpose is to reject the information for vegetation, soil and water. In the decision tree, each bifurcation point represents the indicator be selected for the rejection. As a result, three indices related to vegetation, water and soil are the main bifurcation. Then, a unified conceptual model for multi-source data was

built up under a same frame, the specific process as shown in Figure 1.

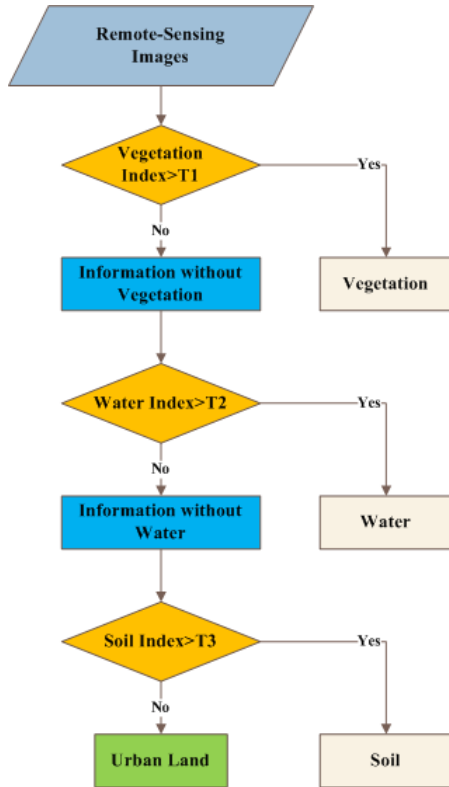


Figure 1 Unified Conceptual Model In Multi-Source Extraction

Select the indices step by step according to the model.

2.1 Vegetation Index

Vegetation has a low reflectivity in red band, while a high reflectivity in near-infrared band. The two bands were selected for computing as vegetation index. Generally, most remote-sensing images, such as TM, SPOT, and HJ-1, contain these two bands. Therefore, in this step, we can adopt the same vegetation index algorithm.

NDVI (Normalized Difference Vegetation Index) is commonly, the formula is as follow:

$$NDVI = (NIR - RED) / (NIR + RED) \quad (1)$$

where NIR = near-infrared band value
RED = red band value

NDVI assumes that the study area has the same soil type, but in actual study, the soil inconsistency could affect the result. Huete (1988) proposed the Soil Adjusted Vegetation Index (SAVI) for the extraction of vegetation.

$$SAVI = [(NIR - RED) (1 + l)] / (NIR + RED + l) \quad (2)$$

where l = soil adjusted factor, value between 0 and 1. Here, we chose 0.5 to eliminate the impact of different background.

2.2 Water Index

Water has a higher reflection in green band than in near-infrared band. Because of this, Mcfeeters presented a normalized difference water index (NDWI) in 1996.

$$NDWI = (GREEN - NIR) / (GREEN + NIR) \quad (3)$$

Where GREEN = green band value

As the turbidity of water increases, the reflection curve of water gradually moves to long-wave, lead to abnormal reflex in the mid-infrared region (Hanqiu Xu, 2005). In urban area and its surround, the major water such as rivers, lakes are more or less pollution. In order to better respond to the water, a Modified Normalized Difference Water Index (MNDWI), with mid-infrared instead of near-infrared band was raised (Hanqiu Xu, 2006).

$$MNDWI = (GREEN - MIR) / (GREEN + MIR) \quad (4)$$

MNDWI has higher accuracy, but it needs more spectral information. TM images contain mid-infrared band information, therefore, MNDWI was selected. On the contrary, Spot images lack of it, NDWI was the only choice.

2.3 Soil Index

In the Urban land area and its surround, soil always refers to unused land or bare land, which is more uniform in its internal nature and has more regular shape. Textures can be soil index to extract information when other promiscuous types have been removed (e.g. Crop land has been removed by Vegetation Index). The texture characteristics contain contrast, entropy, correlation, etc. (Qing-Xiang Jiang, Hui-Ping Liu, 2004).

However, this method is usually useful in high-resolution images, in which the textures are evident (e.g. SPOT). The experiment proves that the method is less effective in TM images. Low-resolution images usually have more spectral information relatively. For the reason, we tried to find a solution from the view of spectrum.

Yong Cha (2003) proposed a Normalized Difference Building-up Index (NDBI) based on the rule that the building-up area has higher reflection in mid-infrared band is higher than in near-infrared band.

$$NDBI = (MIR - NIR) / (MIR + NIR) \quad (5)$$

where MIR = mid-infrared band value

This index can extract part of information of building-up area, but the index is not as significant as vegetation index (e.g. NDVI). In other words, after extraction it is still mixed with other types (e.g. Vegetation and Water). On Condition that the vegetation and water information has been rejected, we can use the index to remove the mixed soil in urban area.

3. RESULTS

Under the Unified Conceptual Model (UCM), we use in Landsat -5 30m images and SPOT - 4 20 m multispectral images in Chaoyang, Beijing at the year of 2007 as experimental data to do the extraction.

TM images have seven bands, which contains the visible, near-infrared, mid-infrared bands useful for urban extraction. In addition, in the resolution of 30m, the majority of land-use types (such as crop land) do not have significant texture features. Therefore, the indices based on band math are important

information to classify images in the process. In accordance with the decision tree in Figure 1, select SAVI as vegetation index, MNDWI water index, NDBI as soil index. In every step, use the threshold segmentation method to get binary image, and finally result in a relatively pure urban area.

SPOT images have higher resolution but less spectral information than TM images, so the effect of texture features becomes more prominent. Take SPOT - 5 20m multi-spectral data as an example, these images contain a total of four bands, three bands of visible (B1, B2, B3) and short-wave infrared (SWIR). As limit of bands, select SAVI as vegetation index, NDWI as water index, and introduce homogeneity index as soil index, which is a texture characteristic, the formula is:

$$U = -\sum_{i=0}^{L-1} p^2(z_i) \quad (6)$$

where L = distinguish factor of gray level
 Z = random variable represents gray level
 p(z_i) (i = 0,1,2, ..., L-1) = corresponding histogram

3.1 TM Image Extraction

The results of NDBI, SAVI, MNDWI of TM image are shown in Figure 2. As can be seen from the images, the specific features in different images have a significantly different value. NDBI image shows a significantly higher value in urban area than in other area, while water has the lowest value. SAVI image shows a much higher value in vegetation area than other. And in MNDWI image water has the highest value. These features allow us to use the threshold method for urban extraction.

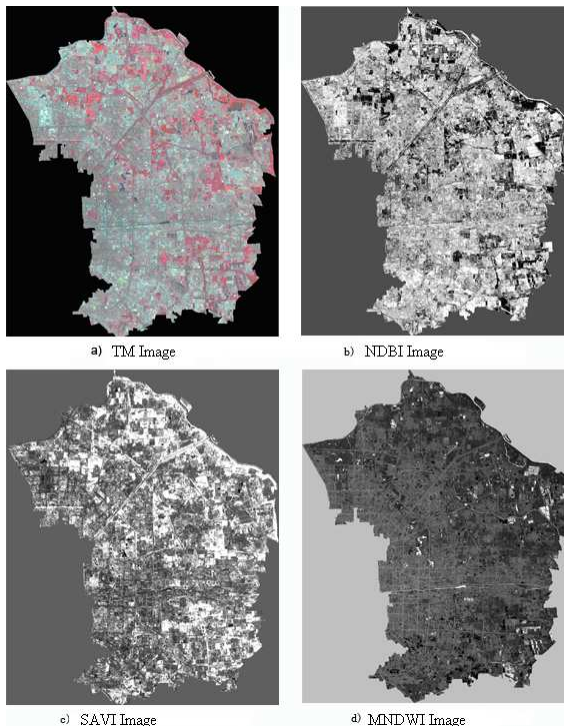


Figure 2 Process Data of TM Image Extraction

By choosing the threshold from the above three images, the land-use information could be extracted. As a result, the urban land map was gained, as shown in Figure 3.

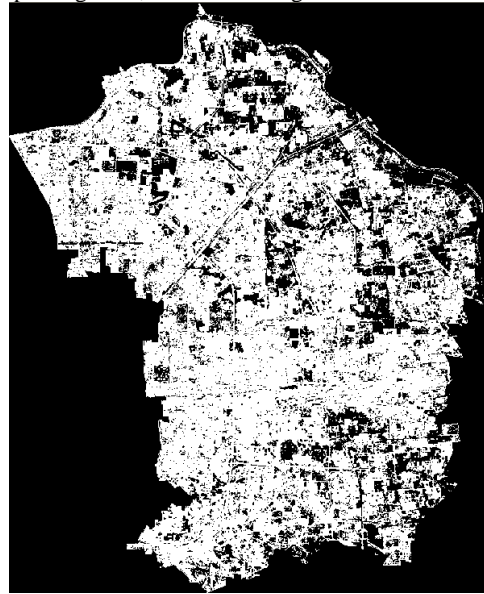


Figure 3 Result Image of TM Image Extraction

3.2 SPOT Image Extraction

The SPOT image resolution (In this paper, 20m) is higher than TM image, the texture homogeneity (Figure 4) had more effects on the extraction.



Figure 4 Homogeneity of SPOT Image

SPOT image using the decision tree extraction method resulted in the final image as shown in Figure 5.

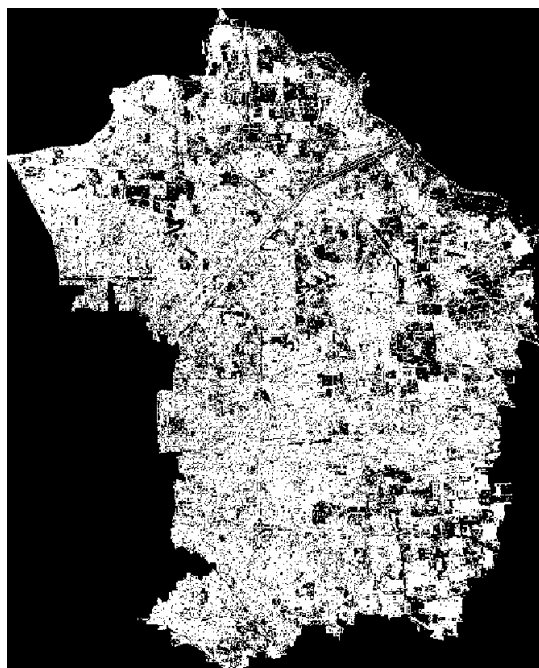


Figure 5 Result Image of SPOT Image Extraction

4. ACCURACY ASSESSMENT

Accuracy assessment has two major method in general: field validation and visual interpretation by higher resolution images. In this paper, we used the second one, set SPOT 10m pan images and QUICKBIRD images as reference data. Select 400 random point in proportion to each category (i.e., urban and non-urban).

		True Data		Total	User Accuracy
		Urban	Non-Urban		
TM Image	Urban	304	47	351	86.61%
	Non-Urban	1	48	49	97.96%
	Total	305	95	400	
	Producer Accuracy	99.6%	50.5%		OverAll: 88%
SPOT Image	Urban	241	30	271	88.93%
	Non-Urban	23	106	129	82.17%
	Total	264	136	400	
	Producer Accuracy	91.2%	77.9%		OverAll: 86.75%

Table 1 Error Matrix

We can See from Table 1 that the overall Accuracy of TM image is 88%, while SPOT image is 86.75%.

5. CONCLUSION

We have Summed up a unified conceptual model to extract urban land from multi-source remote sensing data. The model is based on the VIS model proposed by Ridd (1995) in accordance with the principle of decision tree method. In the VIS model urban is divided into vegetation, soil, impervious surface (the urban land used in this article). In addition, we add water for

research. In each bifurcation point of the decision tree, the corresponding index was used to extract information by threshold segmentation method. This method can be operated more quickly and more simply than the traditional post-classification comparison method. Also it is conducive to urban extraction of multi-temporal and multi-source remote sensing images.

When deciding indices used in the model, we need to select the same indices as far as possible according to the similarity and difference among different types of images. If unable to meet the targets in the same conditions, select distinct indices due to the specific characteristics of images. This embodies the unity and separation of urban extraction from multi-source data.

In addition, the application of decision tree lead the extraction process to be a completely automated one after determined the thresholds in the manual. It is simple to facilitate the realization by programming or modeling. Several indices were mixed-used in the decision tree to overcome the shortcoming brought by one single index. It is a doddle to achieve a high accuracy. In the process of index-extraction, we took artificial methods to determine the thresholds, which would result in the emergence of personal error. And it's also a little bit hard. However, It is more flexibility, and can be a specific regulation according to specific circumstances.

In this paper, we used TM image and SPOT image as data source, respectively, discussed the two types of images to do urban extraction using decision tree method. TM image has rich spectral information, and its resolution is in middle-level. So the band math was taken for computing. To make full use of various types of spectral features, we introduced three indices to the extraction: SAVI, MNDWI and NDBI. These three indices represent the major land-use types of urban area: vegetation, water and urban land. Results shows that the overall accuracy is 88%, higher than the general post-classification method. SPOT image has higher resolution, but poorer spectral information. Because of that a texture characteristics was taken, finally resulted in the overall accuracy of 86.75%. The extraction accuracy of SPOT image is slightly lower than TM image, but we could consider the advantages of high resolution in further study.

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