CHINESE GEOGRAPHICAL SCIENCE
Volume 12, Number 1, pp. 68 – 72, 2002
Science Press, Beijing, China

THE METHODS OF EXTRACTING WATER INFORMATION FROM SPOT IMAGE

DU Jin-kang, FENG Xue-zhi, WANG Zhou-long, HUANG Yong-sheng, RAMADAN Elnazir
(Department of Urban and Resource Science, Nanjing University, Nanjing 210093, P. R. China)

ABSTRACT: Some techniques and methods for deriving water information from SPOT – 4(XI) image were investigated and discussed in this paper. An algorithm of decision-tree (DT) classification which includes several classifiers based on the spectral responding characteristics of water bodies and other objects, was developed and put forward to delineate water bodies. Another algorithm of decision-tree classification based on both spectral characteristics and auxiliary information of DEM and slope (DTDS) was also designed for water bodies extraction. In addition, supervised classification method of maximum-likelyhood classification (MLC), and unsupervised method of interactive self-organizing dada analysis technique (ISODATA) were used to extract waterbodies for comparison purpose. An index was designed and used to assess the accuracy of different methods adopted in the research. Results have shown that water extraction accuracy was variable with respect to the various techniques applied. It was low using ISODATA, very high using DT algorithm and much higher using both DTDS and MLC.

KEY WORDS: water body; decision tree algorithm; accuracy assessment

CLC number: TP751. 1 Document code: A Article ID: 1002-0063(2002)01-0068-05

Extraction of water information from digital satellite images has been studied broadly in recent twenty years. The methods of identifying waterbodies such as thresholding, segment, Landsat chromaticity coordinates, proportion estimation, and descriptive algorithm based on knowledge of water spectrum feature, have been put forward and applied to a variety of satellite data for management of water resources and monitoring of floods. SHIH (1985) used Landsat MSS data to delineate the water surface area from the surrounding land. In his research he indicated that both techniques of density slicing from band7(near infrared) and ELAS classification with combination of bands 5 and 7 could successfully assess the water-surface area. The deviation of the surface area assessment between two techniques was within 3%. LU Jia-ju(1992) used techniques of thresholding, Landsat chromaticity coordinates and "proportion estimation" to extract water bodies based on Landsat CCT data, and found that the proportion estimation approach can distinguish smaller water bodies effectively. SHENG Yong-wei *et al.* (1994) tried to discriminate water bodies using FY—1B VHRSR data, they indicated that water bodies could be identified if the ratio of CH2 and CH1 be used. ZHOU Cheng-hu *et al.* (1996) and Du Yun-yan *et al.* (1998) developed a descriptive model for automatically extracting and recognizing water bodies based on the knowledge of water spectrum feature using NOAA/AVHRR data. YANG Chun-jian *et al.* (1998) designed a algorithm to extract water bodies from Landsat TM. Based on their analyzed results that the sum of TM2 and TM3 were larger than that of TM4 and TM5 for water bodies, they used the algorithm to distinguish water bodies from shadows effectively in mountainous areas. Other methods were used to extract water information from different satellite data By BARTON I J *et al.* (1989), LIU Jian-bo *et al.* (1996), XIAO Qian-guang *et al.* (1987). Due to the different spatial resolutions of satellite data and geographical characteristics of study area, a method or technique can only be adopted based on the deep analysis of satellite data, the physical-geographical features of the study area and the spectral characteristics of water and other objects. In this paper, some techniques of extracting water infor-

---

Received date: 2001-11-15
Biography: DU Jin-kang(1964 –), male, a native of Muping County, Shandong Province, associate professor. His research interests include hydrological modeling, application of GIS and Remote Sensing to hydrology.

mation from SPOT – 4 data were investigated. An algorithm of decision-tree (DT) classification with several classifiers based on spectral responding values was designed to derive water information. Another algorithm of decision-tree classification algorithm based on both spectral responding values and auxiliary information of DEM and slope (DTDS) was developed. Supervised classification method of maximum-likelyhood classification (MLC) and unsupervised classification method of interactive self-organizing dada analysis technique (ISODATA) were also used to extract water information in the same area. The results and accuracy of the methods were compared and evaluated.

1 THE SPECTRAL RESPONDING CHARACTERISTICS OF WATER BODIES

The Jiangning County of Jiangsu Province was selected as study area and the SPOT – 4 image(XI, 1999. 1) with four bands of B1(0. 59 – 0. 59μm), B2 (0. 61 – 0. 68μm), B3(0. 78 – 0. 89μm), and SWIR (1. 58 – 1. 75μm) was used for the study.

The original SPOT – 4 image was rectified with known GCPs obtained by GPS and from relief map of 1∶50000. The nearest neighbor interpolation algorithm was used to re-sample the Digital Number(DN) value of each pixel.

The image mainly recorded the information of reflection and radiation of the objects. For the different structures, components, physical and chemical characteristics of objects, the reflection and radiation are varied in the electromagnetic wave bands. In natural condition, even when the water is very shallow, water bodies absorb nearly all incident energy in both the near-infrared and middle-infrared wavelengths, and there is very little energy available to be reflected. That leads to water feature having a significant and distinctly lower reflectance than either vegetation or soil throughout the reflective infrared portion of the spectra. In infrared image, and for the same reason, water appears dark while soil and vegetation appear bright. Thus it's easy to derive water form other objects using thresholding in infrared band. Unfortunately, in mountainous area, the objects under the shadow of mountain also reflect little energy and appear dark in image, it's difficult to extract water bodies by the use of thresholding in infrared band. In visible light band, the reflected information of water in image mostly come from matters in water surface, inside water, and at water bottom, which could be used to recognize the deepness, quality and bedload content of water. In order to extract water bodies effectively from image in mountainous area, both information from infrared and visible bands could be used to identify the difference between water bodies and shadows.

In SPOT image of the study area, five typical land cover classes were determined and training sampling were taken to calculate means and standard deviations of their spectral responding values (Std. Dev.) (Table 1), which are re-sampled DN values. The coincident spectral plot (mean plus and minus two standard deviations for the five types in each band) was drawn in Fig. 1. In this figure it was clear that the ranges of spectral values of water and other objects were overlapped in B1 and B2. In B3 the range of water spectral values also overlapped with that of shadows, but they were lower than that of other three classes and shadows have little overlapped area with plants. There was a clear distinction between the group of water, shadow and the remaining three classes in SWIR, but there is still a big overlapping area between water and shadow. Based on the analyzed spectral characteristics of five land cover classes in SPOT (XI) image, the following different approaches were used for extracting water information and the results were evaluated.

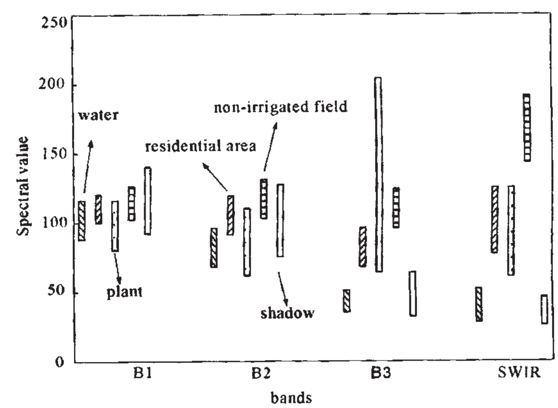

Fig. 1 The coincident spectral plot of five typical spectral classes

2 THE METHODS OF EXTRACTING WATER INFORMATION FROM SPOT IMAGE

2. 1 The Decision Tree Method Based on Spectral Values(DT)

Since the spectral values of water were less than those of other objects in band SWIR, the thresholding technique could be used to extract water information. The histogram of SWIR was built to determine the threshold. It is clear from the histogram that there were

Table 1 The statistic index of samples

Type	B1		B2		B3		SWIR	
	mean	Std. Dev.	mean	Std. Dev.	mean	Std. Dev.	mean	Std. Dev.
Water	102	7	82	7	43	4	40	6
Plant	98	9	86	24	134	35	93	16
Residential area	110	5	105	7	82	7	101	12
Shadow	116	12	101	13	48	8	36	5
Non-irrigated field	114	6	117	7	110	7	167	12

two peaks between water and other objects, and smooth dip between the peaks. The threshold value of 85 was selected , which was little close to the edge of the peak of other objects so that the water would not be lost. The extracted water image using thresholding was overlaid on the color image of B2, B3, SWIR. By flicking the two images, we found that nearly all water pixels were selected, Some of them were not belong to water, but to the shadows of mountains(Fig. 2).

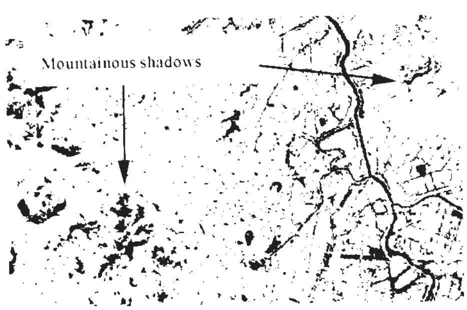

Fig. 2 Water image extracted using thresholding in SWIR

In order to discard shadows from the image of extracted water, sampling of water and shadows were taken from the water image. It could be seen from Spectral responding curves of the two types of samples that most spectral values of water pixels were greater than that of shadow pixels in B1. The threshold technique could be adopted to discard shadows, nearly all shadow pixels were discarded if threshold level of 100 was used, but some of water pixels were lost.

To withdraw the lost water pixels, water and shadow samples on discarded shadow image were collected to find if the difference of spectral responding exist between water and shadows. It was clear from the analysis that the spectral values of most water pixels were: 1) great 83 in B1; 2) great 60 in B2; 3) less 55 in B3; 4) less 50 in SWIR. The lost water pixels could be taken out from shadows image if they met the following set of conditions:

B1> 83 and B2> 60 and B3 <55 and SWIR <50

The water image obtained through the above steps was shown in Fig. 3. It could be seen that nearly all water pixels were obvious and few shadow pixels were found in water image by flicking the water image and color composition image of B2, B3, SWIR. The steps of extracting water bodies could be taken as decision tree algorithm (Fig. 4), at each step a classifier was designed, and more pure classes were obtained.

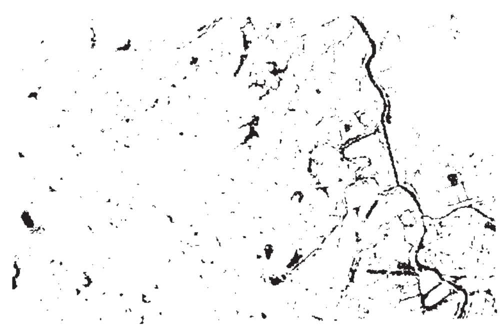

Fig. 3 Water image extracted using DT

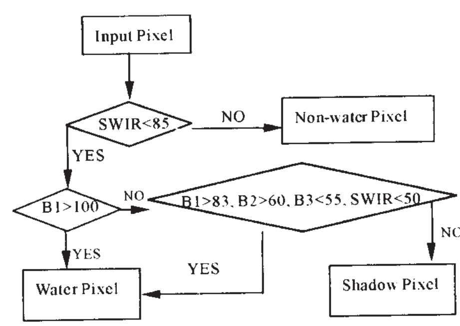

Fig. 4 The decision tree diagram of extracting water

2. 2 The Decision Tree Method Based on Both Spectral Value and Auxiliary Information of DEM and Slope (DTDS)

Auxiliary information such as DEM and slope can be used to improve the accuracy in land cover/use classification. we attempt to use these auxiliary information to identify water information using decision tree algorithm.

Thresholding

Thresholding technique could be used to withdraw water pixels from the image by using the threshold value of 85 in band SWIR. The water image have had some shadow pixels needed to be discarded. The DEM obtained from topographic map and slope derived from DEM are added to the water image as other auxiliary bands. Sampling was taken to analyze the differences of DEM and slope between water and shadows pixels. It was found that most DEM values of water pixels were less than 110 and the values of slopes less than 6, therefore the classifier of DEM <110 and slope <6 could be used to separate the water image into water and shadow ones. The procedure of the method was shown in Fig. 5.

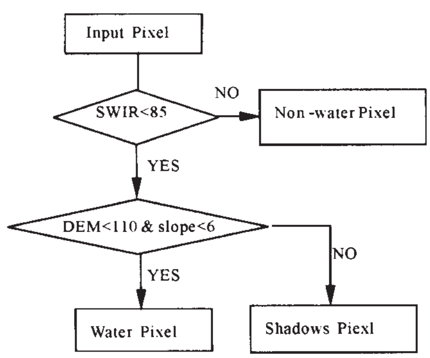

Fig. 5 The decision tree diagram of extracting water with auxilary information of DEM and slope

2. 3 Supervised Classification Method of Maximum Likelyhood Classification (MLC)

It was easy to find visually the differences between water and shadows in stretched water image derived using threshoding technique in band SWIR, in which some shadow pixels existed. Therefore, the method of maximum likelyhood classification (MLC) could be used to classify the water image. The block-training strategy in which a number of contiguous pixels were used as the training samples was employed for training. After training, statistics (signitures) of water and shadow were obtained. The water and shadow were classified using the MLC method, and the water bodies were extracted.

2. 4 Unsupervised Classification Method

The easiest way to extract water bodies without any spectral analysis is the use of unsupervised classification technique. In this study, the unsupervised classification method of interactive self-organizing data analysis technique (ISODATA) was adopted to classify the information of SPOT XI into 15 classes. The water, as one of the classes, was withdrawn.

3 ACCURACY ANALYSIS

Usually, accuracy assessment is done through a comparison of test pixels. Sample pixels are selected within a square window using one of the random, stratified random and equalized random strategy. Kappa coefficient is derived from confusion matrix produced by comparing the classification results for the test samples with the reference data. For accuracy assessment of water extraction methods, only two types of pixels (water and non-water) were contained on the thematic water image, when non-water pixels occupy a large parts of the image, the estimated Kappa coefficients for all methods would retain high values with little differences, leading to the failing to reflect the accuracy of each method. A new assessment approach was developed to attempt to evaluate each method effectively. The procedure of the assessment was to compare the reference water image with those extracted using other methods throughout all pixels on the image. Generally, water surface area varies with time, it is difficult to obtain ground truth data about water area. The method was supposed to be with high accuracy, if the water bodies extracted using the method have a good visual agreement with original image. The DT method achieved best results by comparison, therefore, the results obtained by DT method can be used as the reference water image in accuracy assessment. The accuracy of each method could be assessed by calculating the user-accuracy coefficient K and computation-accuracy coefficient C, which were defined as follows:

$$K = WATER/(WATER + WATER+)$$

$$C = 100-(WATER- + WATER+)/WATER(REF)$$

where: WATER — number of pixels which are labeled with water both on reference map and compared map; WATER- — number of pixels which are labeled with water in reference map and non-water in compared map; WATER+ — number of pixels which are labeled with non-water in reference map and water in compared map; WATER(REF) — number of pixels which are labeled with water in the image obtained using DT. Table 2 was the results obtained by comparing all pixels on reference image with compared image. The results showed that the higher accuracy of deriving water bodies from SPOT(XI) could be reached by using the methods of DT, DTDS, and MLC. The unsupervised ISODATA technique could make significant differences and has low accuracy.

Table 2 The accuracy assessment of four methods

Methods	WATER	WATER-	WATER+	K(%)	C(%)
DT	1220488	0	0	100	100
DTDS	1201883	18605	93025	93	91
MLC	1194441	26047	78141	94	91
ISODATA	1209325	11163	271633	82	77

4 DISCUSSION AND CONCLUSION

It is difficult to extract water bodies effectively from SPOT image by applying single technique such as the thresholding in mountainous area due to the effects of shadows. The framework of decision tree classification could be taken as an effective tool for deriving water bodies because of it's high accuracy, but the designing of classifier creates difficulties, which requires detailed spectral analysis of the image.

Such auxiliary information as DEM and slope could be used to discard shadows from extracted thematic image of water bodies using thresholding technique, but the designed classifier based on the information of DEM and slope also requires sampling and analysis to find the differences of DEM and slope between pixels of water and other objects.

The supervised MLC method is an alternative approach for it's simple operation procedure and relatively higher accuracy. It is easy to perform sample training in stretched image of water bodies obtained by threshoding approach.

The unsupervised classification method could produced the results with low accuracy, which could not be used as the final products.

The thresholding technique is not recommended to be used to obtain the final results in mountainous area, but it could be used with other methods, therefore it is a significant method to be used in water extraction.

REFERENCES

BARTON I J, *Bathols* J M, 1989. Mornitoring floods with AVHRR[J]. *Remote Sensing of Environment*, 30 (1): 89–94.

DU Yun-yan, ZHOU Cheng-hu, 1998. Automatically Extracting Remote Sensing Information for Waterbodies[J]. *Remote Sensing of Environment*, 2(4): 264–268. (in Chinese)

LIU Jian-bo, DAI Chang-da, 1996. The Application of TM Image in Reservoir Situation Monitoring[J]. *Remote Sensing of Environment*, 11(1): 53–58. (in Chinese)

LU Jia-ju, LI Shi-hong, 1992. Improvement of the Techniques for Distinguishing Water Bodies from TM Data[J]. *Remote Sensing of Environment*, 7(1):17–23. (in Chinese)

SHENG Yong-wei, XIAO Qian-guang, 1994. Waterbody Identification in Cloud-Contaminated NOAA/AVHRR Image[J]. *Remote Sensing of Environment*, 9(4): 247–255. (in Chinese)

SHIH S F, 1985. Comparison of ELAS classifications and density slicing Landsat data for water surface area assessment[A]. In: JOHNSON A I (ed). *Hydrologic Applications of Space Technology* (Publication No. 160)[C]. Wallingford: IAHS Press, 91–97.

XIAO Qian-guang, *et al.*, 1987. NOAA Imagery Application for Monitoring Songhua River Flood[J]. *Remote Sensing Information*, (4): 26–27. (in Chinese)

YANG Cun-jian, Xu Mei, 1998. Investigation on Extracting the Waterbody from Landsat TM[J]. *Geographical Research*, 17 (supplement): 86–89. (in Chinese)

ZHOU Cheng-hu, DU Yun-yan, LUO Jian-cheng, 1996. A Description Model Based on Knowledge for Automatically Recognizing Water from NOAA/AVHRR[J]. *Journal of Natural Disasters*, 5(3): 100–108. (in Chinese)