A NEW APPROACH TO OBJECT RECOGNITION ON HIGH RESOLUTION SATELLITE IMAGE*

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ABSTRACT

The data of satellite remote sensing can provide the object information of the earth's surface accurately. Now the commercial satellites can provide the satellite images with the resolution between 1 meter and 10 meter. With those high spatial resolution images, shape features and texture features of the ground objects are very clear. With the characters of the high resolution satellite image, we will use the recognition of the type of water bodies as example, begin with the extraction of the spectrum features of the ground objects from the satellite digital images , separate water bodies from background and recognize it through the classification of the image. After the tracing of boundary we extract and describe the shape features of water bodies and implement the recognition of various water bodies on the partition of areas. The experiments of the recognition in the satellite image prove this recognizing approach is feasible for high spatial resolution satellite images.

1 INTRODUCTION

The traditional method acquiring the object's information from the satellite image is through visual interpretation. The method needs the interpreter has abundant geo-science knowledge and visual interpreting experience and the interpreter takes a lot of time to interpret it. Its labor intensity is high. The quality of interpretation is affected by the interpreter's experience and the familiarity of the region etc. In order to solve this problem, a few exports begin to try to classify with computer using the spectrum features of the ground objects from 1970s. Now the commercial satellites can provide the satellite images with the resolution between 1 meter and 10 meter. With these high spatial resolution images, shape features and texture features of the ground objects including large buildings in city ,roads, rivers, lakes and other man-made objects is very clear. With the characters of high resolution satellite image, we describe and recognize the water bodies in satellite image with two level during the recognition of water bodies with computer in this research. The low level describing object is pixel, and the value every pixel corresponding to is the spectrum feature value of this ground object. We can recognize the

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ground objects with different components and different internal structures with classification. Using this, we can distinguish water bodies with background. Because different types of water bodies have same components and internal structures, it is impossible to recognize the water body is a river or a lake with spectrum features. It needs the shape features to help recognition. Because the objects of water bodies has been recombined in classification and the image is consisted with recognizing units on water bodies, we can recognize water bodies with different shape features with the extraction and description of the shape features of the objects. We discuss the recognizing approach to various types of water bodies as follows .

2 EXTRACTION OF SPECTRUM FEATURES OF GROUND OBJECTS AND THE CLASSIFICATION OF IMAGE

The main basis of remote sensing image classification is the spectrum features of ground object. The spectrum features of ground objects are the regulation of the object's reflecting and scattering ability with the wave length. The spectrum features of ground objects have a close relation with the objects' components and internal structures . In general different objects have different spectrum features. Figure 1 presents the SPOT image of Beijing used in this paper and Figure 2 shows the spectrum curve features of main type ground objects in the image. In Figure 2 the feature value of curve is the average of namy pixels' measuring values in every ground object types.

Figure 1. SPOT Image of Beijing(local) in the experiments of the recognition

(Black is various types of water bodies)

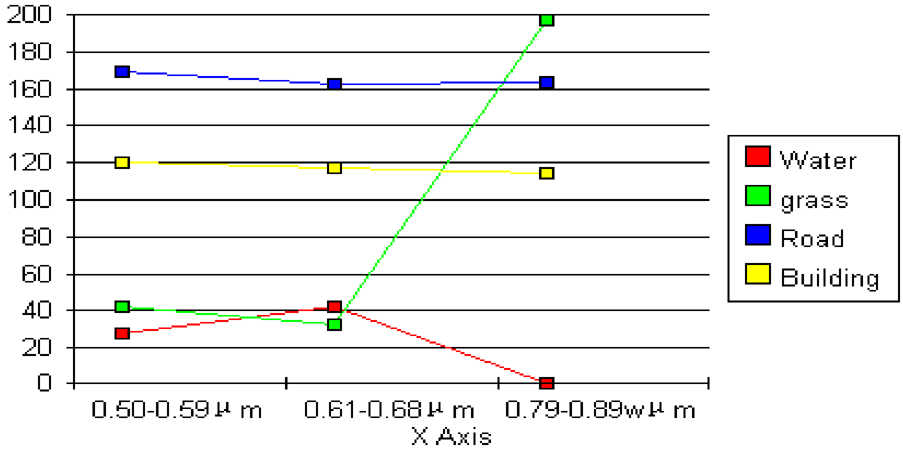

Figure 2. The Spectrum Curve Features of Ground Object Types on the SPOT Image

The radiation measuring values of various objects can be used as the feature variable of the image classification. We will classify the objects and ground with maximum likelihood classifier.

The maximum likelihood classifier is a method that calculates the attaching probability of every pixel belonging to every class and distributes the pixel to the class the attaching probability of which is max. If the condition probability of observing x in class k is P(x|k), the attaching probability L_k can be represented as follows:

$$L_k = P(k \mid x) = P(k) \times P(x \mid k) / \sum P(i) \times P(x \mid i) \qquad (1)$$

In Eq.(1) x is the pixel being classifying , P(k) is prior probability of class k which is determined by training areas.

The maximum likelihood classifier assumes that the spectrum features of the objects in the train area approximately obeys normal distribution like most of random phenomena in nature[1].With train area we can acquire feature index like mean ,variance and co-variance, and infer prior probability density function of collectivity. Now the attaching probability L_k pixel X being classified to class k can be represented as follows: (Here the data items having no relation to class is omited)

$$L_k(x) = \left\{2\pi^{n/2} \times (\det \Sigma_k)^{1/2}\right\}^{-1} \exp\left\{(-1/2) \times (x-\mu_k)^t \Sigma_k^{-1} (x-\mu_k)\right\} P(k) \qquad (2)$$

In Eq. (2): n = The dimension of feature space;

$P(k)$ = The prior probability of class k ;

$L_k(x)$ = The attaching probability of pixel X being classified to class k;

X = The pixel vector

μ_k = The mean vector of class k(n dimension column vector).

det = The determinant of matrix A.

Σ_k: = The variance, co-variance matrix of class k(n×n matrix).

Note: The training data of every class must be 2 or 3 times of feature dimension at least, then we can acquire the mean and variance, co-variance with high precision. If there is more than 2 bands with high pertinence, the inverse matrix of variance and co-variance matrix may be nonexistent or very unstable. When the training samples are almost same values of homogenous data group, this will also occur. Now by primary component transformation we can reduce the dimensions to the independent bands and acquire variance and co-variance matrix.

It must be pointed out that in order to separate the water bodies with the background we choose the water bodies as recognizing object and the buildings, green lands, roads, and the other types as background during choosing the training area. The buildings, green lands, roads, and the other types must be included in choosing training areas. After classification it is needed to de-noise the image. The noise the area of which is smaller than 8 pixels is classified to background. The image classified result of the maximum likelihood classifier is illustrated in figure 3.

In figure 3 the lakes on left from down to up were Beijing's Nanhai(South lake), Zhonghai(Middle lake), Beihai(North lake), Qianhai(Front lake) and Houhai(back lake). They are all small lakes. The lakes on right is the man-made Tongzi river of the Imperial Palace. The four entrances of the Imperial Place as Wumen, Donghuamen, Shengwumen, Xihuamen separate the Tongzi river . It is hard to recognize those two types of different water bodies with their spectrum features but can be classified with their shape features.

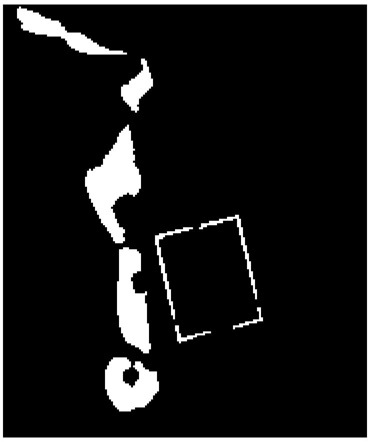

Figure 3. Classificatory result of maximum likelihood classifier(White is water bodies)

3 THE TRACING OF BOUNDARY AND THE RECOGNITION OF SHAPE FEATURES

We note that the shape feature of objects is presented by its boundary information. The premise of ac quiring the object's shape feature is to trace the object's boundary. We con-sider the boundary of the obj ects is between the object and the background, so the tracing route of boundary should be located in th e middle of two neighboring object's boundary pixels[2]. Now we will make a discussion of the tracing method of boundary based on the boundary tracing of two types of ground objects.

At first the boundary tracing need to distinguish the boundary points of different objects and the interi or points of the same object. The boundary points and the interior points of one object are defined as f ollows:

If G_1 is the first kind object, and G_2 is the second one, Pixel A_0, A_1, A_2, A_3 would have neighbori ng relations in the spatial distribution of the two-dimension image (Fig.4)

A_0	A_1
A_2	A_3

Fig.4 The neighboring relation of four pixels in the window of 2X2

If $A \in G_1$ or $A \in G_2$, $A=\{A_0, A_1, A_2, A_3\}$, The middle point of those four pixels in the window of 2X2 (The center of the window) is a interior point. If existing $A\,i \in G_1$, $A_j \in G_2$, $i \neq j$, the middle point is a boundary point. The boundary tracing of the objects is to locate boundary points and connect those points belonging to the same ground object. The detail approach to boundary tracing of the object would be discussed as follows:

The definition of the starting point. If the image has m rows and n columns, a row or a columns is added to the image all around. The value of pixels added is -1, then the image size is $(m+2)\times(n+2)$ now. Finishing this, The pixels of the original image's boundary are all boundary pixels now. We define the coordinate center is the boundary point of the first object, then the coordinate center is the starting point now. We will record the coordinate of the starting point at the beginning of the tracing and scan the image orderly and find the boundary point.

The definition of the next tracing point: The key point of locating the next tracing Point is the definition of the next tracing point's direction. Analyzing the possible states which the object's boundary point could appear in image window, we find when searching in anti-clockwise direction, the current area's next boundary point is exclusive. The direction of the current area's next boundary point depends on the location of the current point and the distribution of the neighboring pixels in the image windows. Knowing the direction, we could locate the current area's next boundary point easily. Figure 5 gives the distribution of the neighboring pixels in the image windows and the searching direction of the next boundary point.

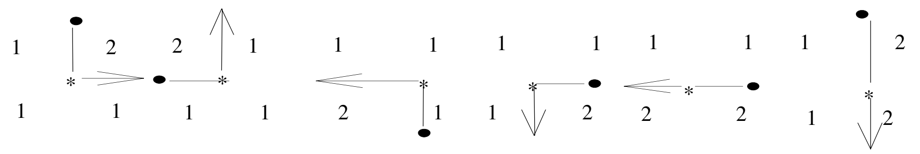

Figure5. the distribution state of the neighboring pixels in the 2X2 image window and the searching direction of the next boundary point.

In figure.5, The measuring values of first two pixels of the first line and which of the second one comprise a 2X2 image window. The measuring values of the third pixel and the fourth pixel of the first line and which of the second one comprise another 2X2 image window and so on. There will be six different stages of boundary windows. "1"or"2" in the window represents the object type the image pixel belongs. In this paper they will be water bodies and backgrounds."□" represents the previous location in the tracing process. "*" represents the current location in the tracing process. "$\longrightarrow$" represents the next boundary point's direction.

Knowing the next boundary point's direction from the current boundary point, we can confirm the location of next boundary point in the object boundary. Using the direction and locating the next boundary point, we will distinguish whether the coordinate of this point is same to the starting point. If they are different, we will continue to locate the next point of current object. If they are same, we will record the information of the boundary point during tracing, produce a data record of the object, and begin to trace the next boundary point of the object with the same method until all objects in the image were traced.(Figure. 6)

The extraction and description of shape features. We can acquire a sequence of ordered boundary poi nts by boundary tracing. These points provide a lot of information about the shape features of the object s. The description and extraction of shape features can adapt many methods. We will adapt chain code t o record and describe the boundary of every ground object.

Chain code is a ordered sequence of directional signed code, $A = a_1, a_2, \cdots, a_n$. it is defined by the direction in which the center pixel point to its 8 neighboring points. We will define the code of direction in anti-clockwise, and the value is in [0，7]. The value begins with 0, and increase 1 when the direction rotates 45 degrees in anti-clockwise. It is convenient and practical to choose chain code to record the boundary of objects while tracing the object. The chain code could be used to represent the location between neighboring pixels in one boundary line and to control the test sequence of the pixel's neighboring points during tracing.

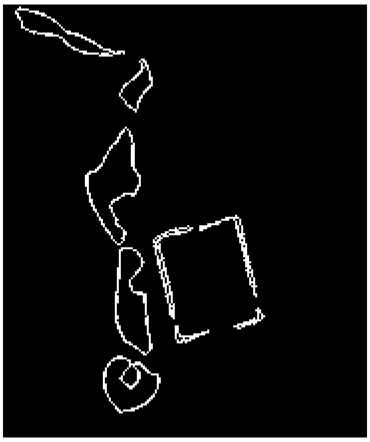

Figure. 6 The result acquired by the boundary tracing of different types of water bodies

The features extraction of the shape of the water body. The shape features of the water body can be described by the formula related with the perimeter and the area of the water body. The calculation of the perimeter P of the water body:

The perimeter of the object whose boundary is recorded in chain code can be extracted as follows: If the length of neighboring pixels recorded in chain code is：

$$L_n = \left(\sqrt{2}\right)^n \qquad (3)$$

In Eq.(3)， $n = Mod(2, a_i)$, $i =$ 0,1,2,…7. is the directions of the chain code。

$P = \sum L_j$ ， is the number of the object's boundary pixels 。

The calculation of the area S of the water body:

First let's calculate the area S_k of the water body in each line. The equation is

$$S_k = (x_j - x_i) \times \Delta s \qquad (4)$$

△s is the area of every pixel corresponding to , x_i , x_j (x_j >x_i) is x geographic coordinates of the same object's boundary points in same line.

$$S = \sum S_k \quad (5)$$

We can acquire the perimeter and area of every water body basing on these equations.

The calculation of the shape index C of the water body[3]:

$$C = \frac{P^2}{4\pi \times S} \quad (6)$$

In Eq.(6) C is the shape index of the water body. S is the area of the water body. P is the perimeter of the water body.

Now we can calculate the perimeter, area and the shape feature of every water body. In order to distinguish the lakes with the man-made rivers, we establish a recognizing function $F(C)$:

$$F(C) = \begin{cases} \text{Man - made river} & C \geq 6.0 \\ \text{Lake} & C < 6.0 \end{cases} \quad (7)$$

With this recognizing function we can recognize every feature of the water body . The results of calculation and recognition is illustrated in Table 1.

Ground Object No.	Area	Perimeter	Strcutual Freaturec	Class in Fact	Class After Recognition
1	374	160	5.447	Lake	Lake
2	199	90	3.239	Lake	Lake
3	783	200	4.065	Lake	Lake
4	105	152	17.51	Man-made River	Man-made River
5	109	146	15.562	Man-made River	Man-made River
6	588	154	3.21	Lake	Lake
7	31	54	7.485	Man-made River	Man-madeRiver
8	39	60	7.346	Man-made River	Man-made River
9	488	148	3.572	Lake	Lake

Table 1. The results of calculation and recognition.

(the perimeter and the area in Tab.1 are measued by pixels in SPOT, they are not real)

4 DISCUSSION

Table 1 shows the five small lakes(Nanhai, Zhonghai, Beihai, Qianhai and Houhai) and four parts of the Tongzi river around the Imperial Place are recognized correctly basing on the shape features based on the shape features. The recognizing correcting ratio of the types of water bodies reaches 100% in Beijing SPOT image, it presents that the approach is feasible.

we consider that most of ground objects have clear shape features in high spatial resolution image, the correcting ratio can be improved with using the spectrum features and the shape features synthetically in the recognition of ground objects. We will improve this mathed in mulit-objects recognition of high spatial resolution satellite imagery.

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