Urban Area Extraction using Variogram texture analysis and OTSU Threshold Segmentation in TerraSAR-X SAR image

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***Abstract*—This paper presents a new method for unsupervised urban area extraction from SAR imagery. The image segmentation method combines variogram texture feature extraction with OTSU threshold segmentation method, to obtain the result as good as traditional classical algorithm and have much higher computational efficiency. TerraSAR-X image is used to validate the proposed method, and experimental results show that the proposed segmentation approach can obtain accurate urban area delineation.**

Keywords-Urban, variogram, OTSU,TerraSAR-X

I. INTRODUCTION

Nowadays the analysis of information about urban areas from remotely sensed images is essentially accomplished by Optical sensors with the contribution of ground surveys. The improvement of SAR spatial resolution now taking place (to a spatial resolution of 1 m) has awakened the interest of people working in urban areas. But the development of reliable and robust algorithms to extract information from the images of cities is difficult due to the complexity of the urban landscape and SAR speckle.

This paper presents a new method to extract urban area from high spatial resolution SAR images. The image segmentation method combines variogram texture feature extraction with OTSU threshold segmentation method, and an example is given by using TerraSAR-X images. The results show that it is as good as traditional classical algorithm and have much higher computational efficiency.

II. TEXTURE ANALYSIS BASED ON VARIOGRAM

A. Defination of Variogram

In spatial statistics, the theoretical variogram 2γ(x,y) is a function describing the degree of spatial dependence of a spatial random field or stochastic process Z(x). It is defined as the expected squared increment of the values between locations x and y [1]:

$$2\gamma(x,y) = E\left(\left|f(x) - f(y)\right|^2\right) \tag{1}$$

where γ(x,y) itself is called the semivariogram. In case of a stationary process the variogram and semivariogram can be represented as a function $\gamma_s(h) = \gamma(0,0+h)$ of the difference h = y − x between locations only, by the following relation [1]:

$$\gamma_s(y-x) = \gamma(x,y) \tag{2}$$

B. The Optimal Variable Range Calculation

For practical applications, the variogram is not directly available, usually to be estimated by (3),

$$\gamma^*(h) = \frac{1}{2N(h)} \sum_{1}^{N(h)} \left\{ f(x_k) - f(x_k + h) \right\}^2 \tag{3}$$

Where, $N(h)$ is the number of couple points whose distance is h in observation data .

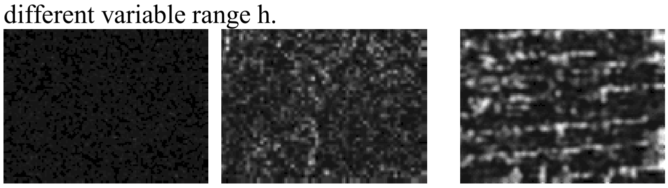
Currently, to obtain the parameters of periodic variogram, there are two main methods. One is a mathematical fitting model, the other is to obtain the parameters by use of maximum and minimum value without considering a specific analysis formula of variogram. In this paper, the second method is used.

In the calculation of variogram, h contains both the direction information and spacing information. Taking into account the complexity and Variability of the actual surface distributions and arrangements in high-resolution SAR image, four-directional variogram is used to replace all the traditional fixed-directional variogram, to extract texture information. The formula of four-directional variogram is shown in (4),

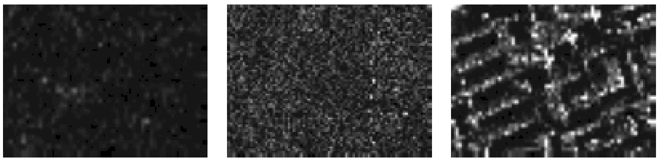
$$\begin{aligned}
\gamma_h^{*,0}(x_0,y_0) &= \frac{1}{2N_0(h)} \sum_{x=x_0-d}^{x_0+d} \sum_{y=y_0-d}^{y_0+d-h} \left[f(x,y) - f(x,y+h) \right]^2 \\
\gamma_h^{*,45}(x_0,y_0) &= \frac{1}{2N_{45}(h)} \sum_{x=x_0-d}^{x_0+d-h} \sum_{y=y_0-d}^{y_0+d-h} \left[f(x,y+h) - f(x+h,y) \right]^2 \\
\gamma_h^{*,90}(x_0,y_0) &= \frac{1}{2N_{90}(h)} \sum_{x=x_0-d}^{x_0+d-h} \sum_{y=y_0-d}^{y_0+d} \left[f(x,y) - f(x+h,y) \right]^2 \\
\gamma_h^{*,135}(x_0,y_0) &= \frac{1}{2N_{135}(h)} \sum_{x=x_0-d}^{x_0+d-h} \sum_{y=y_0-d}^{y_0+d-h} \left[f(x,y) - f(x+h,y+h) \right]^2
\end{aligned} \tag{4}$$

Normally, it is best to select 0 °, 45 °, 90 ° and 135 ° directions as the direction of the fixed points.

In 2006, Ismail proved that in the plotted variogram curves of different sections of same target area in a SAR image , The firsts to reach the peak of the variable range are equal[2].Take samples of water, vegetation and build-up area from TerraSAR-X (Figure 1), and draw Variogram curve (Figure 2) through calculating the value of Variogram $\gamma^*(h)$ with different variable range h.



I: (a) water (b) vegetation (c) build-up area



II: (a) water (b) vegetation (c) build-up area

Figure 1 Two sets of samples from TerraSAR-X image

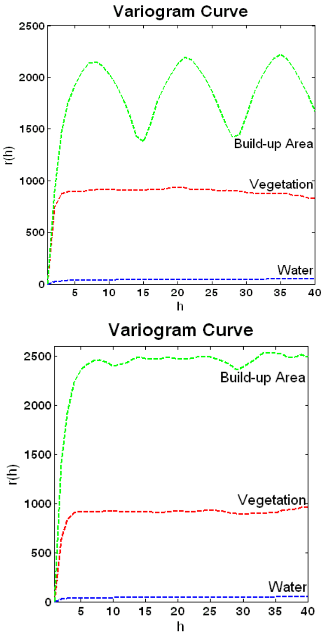


Figure 2. The variogram curve of Figure 1

From Figure 2, the variogram curves of water, vegetation and build-up area, can be clearly differentiated. For the regulation of curve, because of mirror reflection, echo of water is weak and even, which is similar to a straight line. The curve of vegetation becomes stable after a few pixels, since its non-similarity increases while distance increases. The curve of build-up area theoretically shows periodic change, and appears peaks and troughs while the value of h increases. However, the value of peaks may not strictly equal to each other and so do the value of troughs, because of the irregular arrangement of buildings. For the non-similarity of curve, as the build-up area in high-resolution SAR images are usually orderly arranged, and a large number of strong reflection may be caused by sloping roof and corner reflector spots inside, among which exist black plaque caused by roads and shadows, such formed a certain period of light and shade texture and lead to strong non-similarity. Thus results in the variogram curve of build-up area should be significantly higher than vegetation and water.

III. DYNAMIC OTSU SEGMENTATION METHOD

Suppose the gray level of the original image is L, the pixel number in gray level i is n_i, and the total number of pixels is N , then the probability of each gray is $p_i = n_i / N$. Set the threshold t, the gray scale is divided into two categories $C_0 = \{0,1,\cdots t\}$ and $C_1 = \{t+1,\cdots L-1\}$ .The probabilities and the mean values of C_0 and C_1 are of is given by the following:

$$\omega_0 = P_r(C_0) = \sum_{i=0}^{t} p_i = \omega(t)$$
$$\omega_1 = P_r(C_1) = \sum_{i=t+1}^{L-1} p_i = 1-\omega(t) \tag{5}$$

$$\mu_0 == \sum_{i=0}^{t} \frac{ip_i}{\omega_0} = \mu(t)/\omega(t)$$
$$\mu_1 == \sum_{i=t+1}^{L-1} \frac{ip_i}{\omega_1} = \left(\mu_T(t)-\mu(t)\right)/\left(1-\omega(t)\right) \tag{6}$$

Where,

$$\mu(t) = \sum_{i=0}^{t} ip_i$$
$$\mu_T(t) = \mu(L-1) = \sum_{i=0}^{L-1} ip_i \tag{7}$$

From (7), it is not difficult to draw that for any t value, the following formula can be established,

$$\omega_0\mu_0 + \omega_1\mu_1 = \mu_T \quad , \quad \omega_0 + \omega_1 = 1 \tag{8}$$

The variance of C_0 and C_1 are,

$$\sigma_0^2 = \sum_{i=0}^{t} \left(i-\mu_0\right)^2 p_i / \omega_0$$
$$\sigma_1^2 = \sum_{i=t+1}^{L-1} \left(i-\mu_1\right)^2 p_i / \omega_1 \tag{9}$$

The intra-class variance, the interclass variance, and population variance are shown as

$$\sigma_\omega^2 = \omega_0\sigma_0^2 + \omega_1\sigma_1^2$$
$$\sigma_B^2 = \omega_0\left(\mu_0-\mu_T\right)^2 + \omega_1\left(\mu_1-\mu_T\right)^2 = \omega_0\omega_1\left(\mu_1-\mu_0\right)^2 \tag{10}$$
$$\sigma_T^2 = \sigma_\omega^2 + \sigma_B^2$$

Introduce the following decision criteria,

$$\lambda(t) = \sigma_B^2 / \sigma_\omega^2$$
$$\eta(t) = \sigma_B^2 / \sigma_T^2 \tag{11}$$
$$\kappa(t) = \sigma_T^2 / \sigma_\omega^2$$

Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance [3], So using $\eta(t)$ as a criterion, the optimal threshold t^* is expressed as,

$$t^* = \arg \max_{0 \le t \le L-1} \sigma_B^2 \qquad (12)$$

Since the method is no need to make any assumptions of PDFs of object and background, only based on the statistical characteristics of gray histogram and then using the mean and variance to express the two probability density functions, the processing speed is very fast. The only drawback of this method is that it is failure when the area ratio between the target class and background class is too small. For urban area extraction, this problem does not exist, and the algorithm can satisfy the basic needs of the present study.

IV. EXPERIMETS AND RESULTS

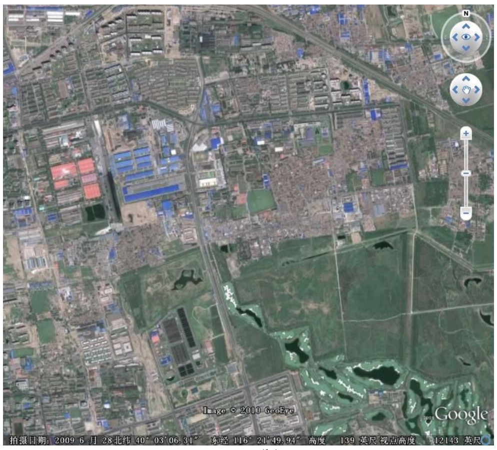
In this paper, one scene of TerraSAR-X HH image is used to validate the proposed algorithm. The scene locates in Olympic Park, Beijing, China, collected on March 4, 2008, shown in Figure3.

So, choose the value of h, when the variogram curve of build-up area reach the peak at the first time, to achieve the variogram feature map extraction, and operate OTSU threshold segmentation after then, urban area may be extracted from Figure 3(a). The segmentation result is shown in Figure 4.

In Figure 4, white area is urban area, and black area represents water and vegetation.

Next, we use the receiver operating characteristic (ROC) curve to verify its performance. In signal detection theory, a receiver operating characteristic (ROC), or simply ROC curve, is a graphical plot of the sensitivity, or true positives, vs. (1 − specificity), or false positives, for a binary classifier system as its discrimination threshold is varied. In 2003, Inglada expanded the ROC curve to the performance evaluation of SAR image change detection methods [4]. Since the larger area below ROC curve is, the better effect the detector would be. Selecting five Characteristic quantities form 14 GLCM features, including mean, variance, entropy, contrast, and correlation, compared with virogram, the ROC curves is shown in Figure 5.

(a)



(b)

Figure 3 (a) TerraSAR-X image; (b) The corresponding optical images from Google Earth

Figure 4 The segmentation result by the proposed method

From Figure 5, we can see that the performance of the proposed method (red line) is best, mean factor (blue line) followed, and correlation factor (black line) worst.

To further analyze the effectiveness of the method, the method will be compared with the fuzzy C means clustering method. Figure 6 is the result by using fuzzy C means clustering method, and Table 1 shows overall accuracy and Kappa coefficient for two results.

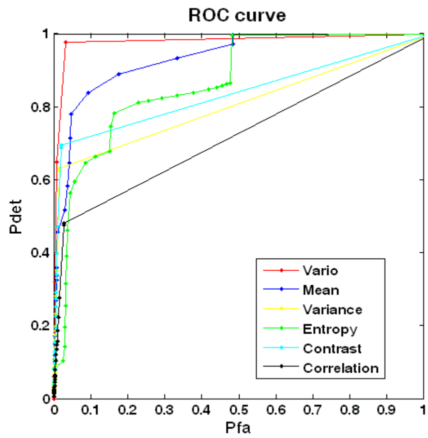


Figure 5 The ROC curves of variogram and five GLCM factors

Figure 6 The segmentation result by the fuzzy C means clustering method

TABLE 1 ACCURACY ASSESSMENT

The proposed Method			fuzzy C means clustering method		
Class	Urban area	background	Class	Urban area	background
Urban area	0.919	0.149	Urban area	0.892	0.134
background	0.081	0.851	background	0.108	0.866
overall accuracy	0.876		overall accuracy	0.876	
Kappa coefficient	0.742		Kappa coefficient	0.744	

From accuracy assessment in Table 1, the Kappa coefficients for two results are greater than 0.74, and the overall accuracies both reach 0.876. From a holistic point of view, the effect of the chosen method is a little better than the fuzzy C means clustering method.

V. CONCLUSION

In This paper, we present a new method for unsupervised urban area extraction from SAR imagery. The image segmentation method combines variogram texture feature extraction with OTSU threshold segmentation method, to obtain the result as good as traditional classical algorithm and have much higher computational efficiency. TerraSAR-X image is used to validate the proposed method, and experimental results show that the proposed segmentation approach can obtain accurate urban area delineation.

The further optimization and efficiency of this method, as well as the further integration with image feature extraction algorithm will be the focus of the study in the next step.

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REFERENCES

[1] Cressie, N., *1993,* “Statistics for spatial data,”, *Wiley Interscience*

[2] Ismail Ben Ayed, Hennane N and Mitiche, A. “Unsupervised Variational Image Segmentation/Classification Using a Weibull Observation Model”, *IEEE Transactions on Image Processing,* 2006, 15(11):3431-3439.

[3] Nobuyuki Otsu. “A threshold selection method from gray-level histograms”, IEEE Trans. Sys., Man., Cyber. 9: 62–66.

[4] Inglada J,. et al., “Change detection on SAR images by susing a parametric estimation of the Kullback-Leibler duivergence”, *Proc. IGARSS2003*, Toulouse, France, 2003, 4104-4106