An Adaptive and Iterative Method of Urban Area Extraction From SAR Images

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***Abstract*—This letter presents a new method for unsupervised urban area extraction from synthetic aperture radar (SAR) images based on the ffmax algorithm proposed by C. Gouinaud specially for acquiring urban areas in SPOT imagery. According to the statistical characteristics of urban areas, an adaptive and iterative method based on the low-level extraction given by the ffmax algorithm using a large window is proposed. Experimental results on real SAR images show that the proposed automatic method works quickly and can preserve the borders of urban areas as well as avoid the disturbance of other classes and the extractions of urban areas are reliable and precise.**

***Index Terms*—Adaptive and iterative (AI), ffmax algorithm, synthetic aperture radar (SAR) image, urban area extraction.**

I. Introduction

SYNTHETIC aperture radar (SAR) plays an important role in remote sensing for its high spatial resolution and freedom from the influence of weather and sunlight. As SAR represents a powerful observation tool for monitoring geophysical resource globally, SAR images could be used for land description and scene analysis. SAR images with high resolution have also proven their usefulness and been widely used in many applied fields (such as agriculture, geology, and ecology). Actually, various applications specifically require the detection and the analysis of urban areas from original SAR images. For instance, one needs such results for monitoring the land-use, studying the urban expansion in the process of development as well as the pressure it gives on forests and agriculture. Such information can also be used in communication management and military intelligence [1]. This letter addresses the problem of extracting the urban areas from SAR images with high resolution.

Owing to the typical speckle signal of SAR images and the complex structures of urban areas, most classical image processing techniques fail to extract urban areas. Weigl *et al.* [2] developed a novel extraction method by combining the Fourier transform and neural network classification algorithm together. Gouinaud and Tupin [3] proposed an extraction algorithm named ffmax filter, which provided a low level but robust extraction result with rough boundaries, based on the local statistical characteristics of SAR images. Yu *et al.* [4] proposed an integrated approach to extract urban areas of SPOT images with the aid of a map information of the same scene as well as *a priori* knowledge about the contextual information of images. Tison *et al.* [5] proposed a more precise statistical model combined with a Markov random field (MRF) model for urban areas in high-resolution SAR images, which can provide good classification results. As urban areas may have special textures, many extraction approaches based on textural information are proposed [6]–[8]. At the same time, with various data are available for Earth observation such as the increasing volumes of interferometric and polarimetric SAR images, many compound or fused extraction methods based on these data are established [9]–[12]. Among these method, some need relative prior knowledge (e.g., method of Yu), some have a heavy complexity (e.g., methods of Weigl), and some cannot provide high precision.

In this letter, aiming at conquering the drawbacks of existing methods and improving the precision of the extraction results, we propose a new method for unsupervised urban area extraction from SAR images, using an adaptive and iterative (AI) method based on ffmax algorithm proposed by Gouinaud and Tupin [3]. Our method is an iterative scheme that consists of two steps: to extract urban areas using ffmax algorithm with a large fixed window and to compute the adaptive window of each pixel with local statistical characteristics. The Kolmogorov–Smirnov (K–S) test is used to find the adaptive window.

The remainder of the letter is organized as follows. In Section II, the statistical model of backscatter of urban objects and the estimation of parameters are presented. In Section III, the ffmax algorithm is briefly described. In Section IV, the proposed urban extraction method is presented in detail. In Section V, some experimental results for real SAR images are analyzed. Section VI contains the conclusions.

II. Statistical Model of Urban Areas

According to [3] and [13], for urban objects, depending on their geometry and roughness as well as their effects on the local statistical characteristics of images, they could be classified into three sets: smooth surfaces, rough surfaces, and conductor surfaces. The backscatter law of smooth surfaces are close to Snell–Descartes' ones. Rough surfaces represent irregularities on the scale of wavelength, and conductor surfaces are mainly metallic ones, which are never plan and

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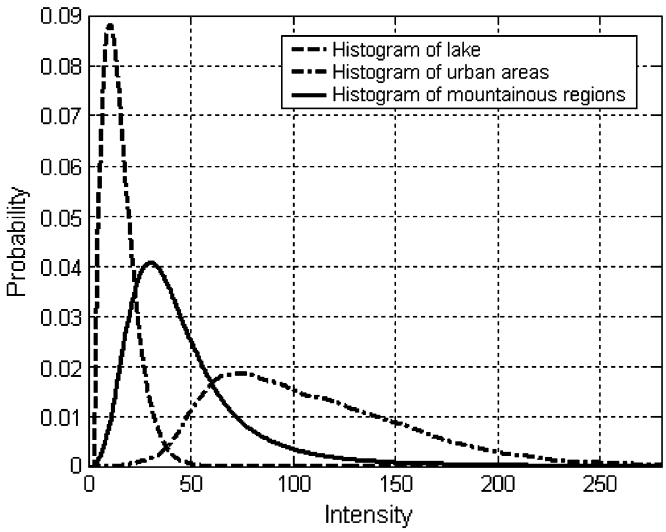


Fig. 1. Histogram of different kinds of categories in a SAR image.

act as periodic lattices [3]. The composition of the three previous effects determines the characteristics of the global backscattering law: 1) there are more dark pixels, because of the Snell–Descartes responses in an unfavorable configuration; 2) there are more bright pixels, because of the Snell–Descartes responses in a favorable configuration; and 3) the intermediate values around the mean caused by speckle are not so much modified. These properties can be described by statistical models well.

In this letter, square-root Gamma distribution is adopted to model SAR amplitude data. Its probability density function can be written as follows:

$$P(A) = \frac{2L^L}{(2\alpha^2)^L \Gamma(L)} A^{2L-1} e^{-\frac{LA^2}{2\alpha^2}} \tag{1}$$

where $\Gamma(\cdot)$ is the Gamma function, A is the amplitude of pixels, L is the number of looks, and α is the parameter of the law. We can get a consistent unbias estimation of α [14]

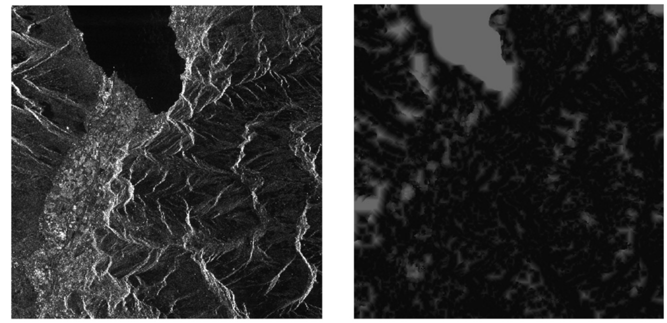
$$\widehat{\alpha} = \frac{\Gamma(L)}{\Gamma(L+1/2)} \sqrt{\frac{L}{2}} \cdot \frac{1}{N} \sum_{i=1}^{N} x_i \tag{2}$$

where N is the number of the pixels which belongs to the window used for estimating the parameter α.

III. FFMAX Algorithm

According to the backscatter characteristics of urban areas, different kinds of areas in SAR images have different local statistical characteristics and so do their parameters. For example, in a SAR image, which includes urban zones, mountainous regions, and lakes, the local statistical characteristics of the three categories are different from each other, as shown in Fig. 1.

Based on the local statistical characteristics of images and using χ distribution to describe the urban zones, Gouinaud and Tupin [3] proposed the ffmax algorithm that consists of two parts: dealing with the detection of bright points characterizing industrial areas and dealing with more homogeneous regions like large towns.



(a) (b)

Fig. 2. (a) X-SAR image and (b) adaptive windows of (a) (Black: small window size; White: large-window size. The window sizes vary from 5 to 60, the smaller the window, the lower the pixel level).

The extraction rule of ffmax algorithm is as follows: With assumption that A, the amplitude of pixels, takes value from $[0, g-1]$, where g is the maximum gray level of the SAR image, to cut the local histogram (on 60 $\times$ 60 window) into two parts using a threshold s, $s \in [0, g-1]$. In the high part, the sum of the probability of this section $\sum = P(A > s)$ is computed and compared to the highest statistical frequency $f_{\max}$ of the low part (the maximum value of the low part). When $\sum > f_{\max}$, the central pixel receives s as its current value, or else the threshold should be decreased. The process is iterated until all the pixels are classified.

There are several characteristics of ffmax algorithm: 1) extraction rule is robust; 2) rule not only extracts the urban zone but also permits the urban agglomeration density measures; and 3) extraction results just provide low-level description of urban zones with no precise borders, as shown in Fig. 4(b).

Based on ffmax algorithm, we will show below an AI urban extraction method, which preserves the advantages of ffmax algorithm as well as provides precise borders and agglomeration density measures of urban zones.

IV. Proposed Method of Urban Area Extraction

A. Adaptive Urban Area Extraction

The main reason that ffmax algorithm cannot provide a high-level description of urban zones with precise borders is that uniform large-scale window (e.g., 30 $\times$ 30 or 60 $\times$ 60) is adopted in the extraction process, by which it can prevent other categories from disturbing the extraction results but make the borders ambiguous. After many studies, it shows that the scale of windows in ffmax algorithm should be adaptive, that is to say, the optimal goodness of fit (GF) can be obtained in some scale window. The data obtained from the window with a better GF are more reliable, and the extraction results of the urban zones will be more precise. Here, we take the K–S test for GF to get the adaptive windows [15]. For example, the adaptive window data of an X-SAR image is shown in Fig. 2, with the window sizes vary from 5 to 60.

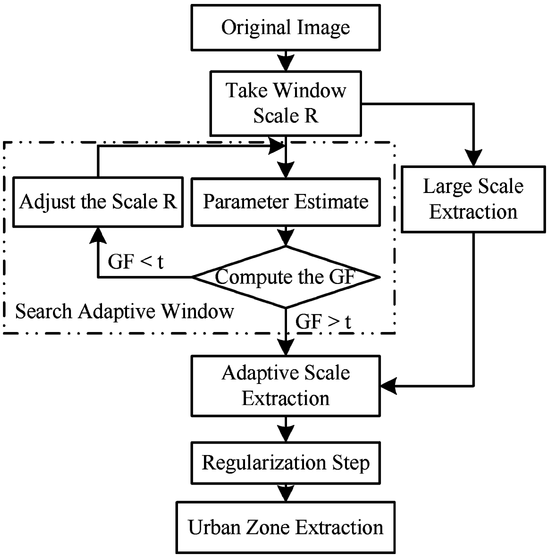


Fig. 3. Framework of the proposed extraction method.

Obviously, the local statistical characteristics on the optimal windows are unconspicuous and the extraction of urban zones will be disturbed by other categories (such as the bright ridges) in the image, which lead to a less robust ability. To conquer this disadvantage, we propose an AI method of urban area extraction, which can improve the precision of the extraction results in a robust way.

B. AI Method of Urban Extraction

In this letter, we use the square-root Gamma distribution to model SAR amplitude data. The framework of the proposed extraction method is shown in Fig. 3, which can be realized by four main steps.

Step 1) *Fixed large-scale ffmax extraction*. We extract urban areas from SAR images using ffmax algorithm (as shown in Section III) with fixed large-scale window (e.g., 60 $\times$ 60). This step provides us a low-level but robust extraction result.

Step 2) *Search adaptive window*. In order to find the adaptive window of every pixel, we take the K–S test for GF. With designing an initialization window scale R to every pixel in the image, we estimate the parameter α by (2) and fit the data using square-root Gamma distribution on the window. Then, we test the GF of the distribution with certain significance level t. If GF $> t$, we accept current scale as the optimal window, otherwise we adjust the window scale and repeat this step until GF $> t$. The search will not stop until every pixel has its optimal adaptive window.

Step 3) *Iterative extraction*. This step includes two parts: 1) do ffmax algorithm with optimal adaptive windows on the urban areas of the low-level extraction result obtained in Step 1); and 2) do ffmax algorithm with fixed large-scale windows on the no-urban areas of the low-level extraction result.

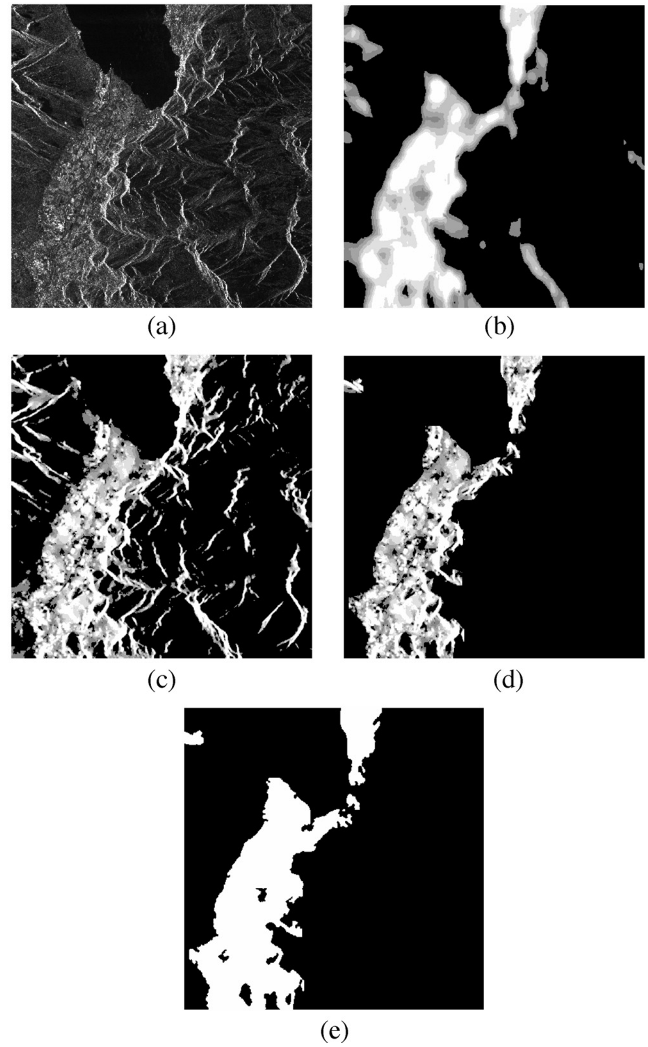


Fig. 4. Urban area extraction experiments on an X-SAR image. (a) Three-look original X-SAR image with the size of 1024 $\times$ 1024. (b) Extraction result of (a) using the Dffmax algorithm. (c) Extraction result of (a) by the Affmax algorithm. (d) Extraction result of (a) by the AIffmax algorithm. (e) Regularization result of (d) using the iterated maximum selecting approach.

Step 4) *Regularization*. After Step 3), we find that there are some fragments in the results. To solve this problem, a strategy named iterated maximum selecting approach [16] is introduced: With assumption that there are k classes in the image, for pixel x_s, we compute N_s, the number of pixels that have the same label with pixel x_s, and N_i, the number of the pixels belonged to the ith class, $i = 1, \ldots, k$. When $|N_s - N_i| \leq \beta$, for some selective threshold β, the pixel x_s should not be changed, otherwise $x_s = i$. An iterative is taken by scanning the image in this way, and then the threshold β is reduced.

V. Experiments Analysis

The proposed method is applied to real SAR images. Fig. 4(a) shows an original three-look X-SAR image (with the size of 1024 $\times$ 1024) of Matterhorn area in Switzerland, including urban zones, mountainous regions, and a part of lake. Fig. 4(b) is the result of urban zones extracted by the direct ffmax (Dffmax) algorithm. Fig. 4(c) is the extracted urban area result using ffmax algorithm and adaptive windows with significance level $t = 0.05$ (Affmax). Fig. 4(d) is the extraction result of the proposed AI ffmax algorithm (AIffmax).

According to the results, the Dffmax extraction algorithm represents robust performance but cannot provide precise borders, which just permits a low-level extraction result. Affmax extraction algorithm can detect every detail better and preserve the urban borders precisely, but it is not robust with plenty of bright ridges in the results. Finally, the proposed AIffmax extraction algorithm conquers the disadvantages of the two methods and balances the robust performance of the Dffmax extraction algorithm and the detail detection ability of the Affmax extraction algorithm, which provides a more precise extraction results of urban areas.

VI. Conclusion

In this letter, an AI method of urban area extraction from SAR images is proposed based on the ffmax algorithm. Owing to the different textures and local statistical characteristics of different kinds of scenes in SAR images, firstly, the method extracts urban areas using Dffmax algorithm with a fixed large-scale window (e.g., 60×60) to provide a low-level detection result. Then, an Affmax extraction algorithm based on the low-level detection result is adopted to get precise extraction results of urban areas iteratively. Experiments on real SAR images show that the proposed method can preserve the details of border information as well as have a robust performance. The extraction result of urban areas can be taken as a preclassification of a high-level processing such as image interpretation. But with the limitation of parametric statistical model of SAR images, in order to get more precise extraction results, other SAR image model with high precision must be employed.

References

[1] H. Maitre, *Synthetic Aperture Radar Image Processing (Chinese Edition, Translated by Hong Sun)*. Beijing, China: Publishing House of Electronics Industry, 2005, pp. 1–10.

[2] K. Weigl, G. Giraudon, and M. Berthod, *Application of Projection Learning to the Detection of Urban Areas in Spot Satellite Images*, 1993, Sophia Antipolis, France: INRIA. Contract report 2143.

[3] C. Gouinaud and F. Tupin, "Potential and use of radar images for characterization and detection of urban areas," in *Proc. IGARSS*, Lincoln, NE, May 1996, vol. 1, pp. 474–476.

[4] S. Yu, M. Berthod, and G. Giraudon, "Toward robust analysis of satellite images using map information-application to urban area detection," *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 4, pp. 1925–1939, Jul. 1999.

[5] C. Tison, J. M. Nicolas, F. Tupin *et al.*, "A new statistical model for Markovian classification of urban areas in high-resolution SAR images," *IEEE Trans. Geosci. Remote Sens.*, vol. 42, no. 10, pp. 2046–2057, Oct. 2004.

[6] I. Duskunovic, G. Heene, W. Philips, and I. Bruyland, "Urban area selection in SAR imagery using a new speckle reduction technique and Markov random field texture classification," in *Proc. IGARSS*, Jul. 2000, vol. 2, pp. 636–638.

[7] R. J. Dekker, "Texture analysis and classification of ERS SAR images for map updating of urban areas in the Netherlands," *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 9, pp. 1950–1958, Sep. 2003.

[8] F. Dell'Acqua and P. Gamba, "Texture-based characterization of urban environments on satellite SAR images," *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 1, pp. 153–159, Jan. 2003.

[9] M. Quartulli and M. Datcu, "Information fusion for scene understanding from interferometric SAR data in urban environments," *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 9, pp. 1976–1985, Sep. 2003.

[10] P. Lombardo, M. Sciotti, T. M. Pellizzeri, and M. Meloni, "Optimum model-based segmentation techniques for multifrequency polarimetric SAR images of urban areas," *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 9, pp. 1959–1975, Sep. 2003.

[11] T. Moriyama, S. Uratsuka, T. Umehara, and M. Satake, "A study on extraction of urban areas from polarimetric synthetic aperture radar image," in *Proc. IGARSS*, Jul. 2004, vol. 1, pp. 703–706.

[12] D. J. Weydhal, X. Becquey, and T. Tollefsen, "Combining ERS1 SAR with optical satellite data over urban areas," in *Proc. IGARSS*, 1995, vol. 3, pp. 2161–2163.

[13] J. W. Goodman, "Some fundamental properties of speckle," *J. Opt. Soc. Amer.*, vol. 66, no. 11, pp. 1145–1150, Nov. 1976.

[14] S. M. Kay, *Statistical Signal Processing-Estimation and Detection Theory (Chinese Edition, Translated by Peng-fei Luo)*. Beijing, China: Publishing House of Electronics Industry, 2003, pp. 14–20.

[15] I. M. Chakravarti, R. G. Laha, and J. Roy, *Handbook of Methods of Applied Statistics*, vol. 1. Hoboken, NJ: Wiley, 1967, pp. 392–394.

[16] G. Xia, "Study of SAR image segmentation methods based on MRF model," M.S. thesis, Wuhan Univ., Wuhan, China, 2005.