Non-parameter and Multiscale Classification of SAR Imagery

TIAN Zheng[1, 2, 3], WEN Xianbin[1, 2, 4], LIN Wei[1, 2]

[1] Department of Applied Mathematics, Northwestern Polytechnical University, Xi'an, China, 710072.

[2] Deparment of Computer Science, Northwestern Polytechnical University, Xi'an, China, 710072.

[3] National Key Laboratory of Pattern Recognition , Institute of Automation, Chinese Academy of Sciences, Postfach 100080,Beijing China.

[4] Shandong University of Technology, Zibo, Shandong,China, 255049.

Zhtian@nwpu.edu.cn

Abstract

This paper presents an efficient, non-parametric and multiscale approach to segmentation of natural clutter in synthetic aperture radar (SAR) imagery. The method we propose not only exploits the coherent nature of SAR sensor, and takes advantage of the characteristic statistical difference in imagery of different terrain types, but also does not require the distribution of pixels due to using Bootstrap method. Firstly, we employ multiscale autoregressive (MAR) model for describing random processes that evolve in scale. Secondly, the confidence interval of the parameters in MAR model for each category of terrain of interest are calculated using Bootstrap technique. Then, for each pixel, we generate a set of parameter estimation that characterizes the local evolution in scale. The pixel is classified by relation between the parameters estimation and the confidence internal of each type. Finally, test images are classified to demonstrate the method.

Keywords: non-parametric, confidence internal, SAR imagery, multiscale autoregressive (MAR) model.

1. Introduction

The speckle appearing on SAR imagery is a natural phenomenon generated by the coherent processing of radar echoes[1][2]. The presence of speckle not only reduces the interpreter's ability to resolve fine detail, but also makes automatic segmentation of such images difficult. Generally, segmentation of a SAR imagery falls into two categories: (i) segmentation based on grey levels and (ii) segmentation based on texture. To fully exploit and characterize the scale-to-scale statistical variations in SAR imagery due to radar speckle[3], recently, a class of MAR models was employed to SAR image for segmentation based on least square estimation of the parameters and the likelihood ratio classification[2][3]. These models provide a powerful framework for describing random fields that evolve in scale. However, the distribution of pixel grey must be known for the construction of

classifier in [4] and [5]. In general, the distribution is not known. The statistical distribution assumption of SAR imagery is only an approximation. The present paper deals with SAR imagery segmentation based on confidence intervals of parameters in MAR model, and uses computer-intensive resampling method in statistics, the Bootstrap, without knowing the distribution of grey.

The Bootstrap is a novel statistical tool with many possible applications in image understanding, which was first introduced by Efron[6][7]. It is a technique used for inferring distribution of statistics calculated from a sample of data. Indeed Efron's motivation for the Bootstrap was to produce a method for estimating confidence intervals[8] when standard tools were not valid. Such a situation may occur when we have few data points to work with. The Bootstrap method is an attractive tool as it replaces complex theoretical analysis with a computation based method suited to run on modern highly powered computers. It is also favorable over other methods as it requires little in the way of modeling, assumptions or analysis.

2 Bootstrap method

Let an estimated $\hat{\theta} = s(\mathbf{x})$ of θ, which denote an unknown characteristic of distribution F, be computed from the sample $\mathbf{x} = \{x_1, \ldots, x_n\}$. The data points x_i are independent and identically distributed random variables, and from the unknown distribution F. If F is known and $\hat{\theta} = s(\mathbf{x})$ has relative simple expression, the distribution of $\hat{\theta}$ could be precisely evaluated. However, the distribution F is, in general, not known, and, in the classical methods, it is replaced by a parametric (most often normal) distribution. The fundamental idea of the Bootstrap is to replace F by $\hat{F}$, the empirical distribution of the data. Since real data may not be normally distributed, Bootstrap can improve on the classical normal approximation. The Bootstrap is a nonparametric estimation technique of the statistical behavior of $\hat{\theta}$ from the available sample $\mathbf{x}$.

The Bootstrap paradigm dictates that the resampling of the data can come from a distribution chosen to be close to F if the actual distribution is not available. That is, we could resample with replacement from a distribution $\hat{F}$ provided that $\hat{F}$ approaches F as $n \to \infty$. The basic Bootstrap procedure is presented as follow:

(1) Obtain the data $\mathbf{x} = \{x_1, x_2, \ldots, x_n\}$ and calculate the estimated $\hat{\theta}$ from the data;

(2) Construct the distribution $\hat{F}$ by weighting each observation in $\mathbf{x}$ by $1/n$;

(3) Resample with replacement from the distribution $\hat{F}$ to obtain $\mathbf{x}^* = \{x_1^*, \cdots, x_m^*\} (m \le n)$ and calculate estimated $\hat{\theta}^*$ from $\mathbf{x}^*$;

(4) Repeat step 3 a large number of times M, to obtain $\hat{\theta}_1^*, \hat{\theta}_2^*, \ldots, \hat{\theta}_M^*$;

(5) Approximate the distribution of $\hat{\theta}$ by the distribution of $\hat{\theta}_i^*$, $i = 1, 2, \ldots, M$.

3 Quadtree Interpretation of SAR imagery

The starting point for our model development is a multiscale sequence X_L, $X_{L-1}, \ldots, X_0$ of SAR images, where X_L and X_0 correspond to the coarsest and finest resolution images, respectively. The resolution varies dyadically between images at successive scales. More precisely, we assume that the finest scale image X_0 has a resolution of $\delta \times \delta$ and consists of an $N \times N$ array of pixels (with $N = 2^M$ for some M). Hence, each coarser resolution image X_m has $2^{-m}N \times 2^{-m}N$ pixels and resolution $2^m\delta \times 2^m\delta$. Each pixel $X_m(k,l)$ is obtained by taking the coherent sum of complex fine-scale imagery over $2^m \times 2^m$ blocks, performing log-detection (computing 20 times the log-magnitude), and correcting for zero frequency gain variations by subtracting the mean value. Accordingly, each pixel in image X_m corresponds to four "child" pixels in image X_{m-1}. This indicates that quadtree is natural for the mapping. Each node s on the tree is associated with one of the pixels $X_m(k,l)$ corresponding to pixel (k,l) of SAR image X_m. As an example, Fig.1 illustrates a multiscale

sequence of three SAR images, together with the quadtree mapping. Here the finest-scale SAR imagery is mapped to the finest level of the tree, and each coarse scale representation is mapped to successively higher levels. We use the notation $X(s)$ to indicate the pixel mapped to node s. The scale of node s is denoted by $m(s)$, and the set of nodes in scale $m(s)$ by $S_{m(s)}$.

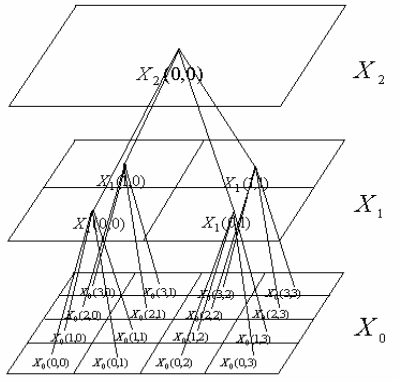

Fig. 1. Sequence of three multiresolution SAR images mapped onto a quadtree.

4 Parameters confidence interval estimation for MAR model

In this paper, we focus on a specific class of multiscale models, namely multiscale autoregressive models[2][3]

$$X_l(s) = a_{l,0}(s) + a_{l,1}(s)X_l(s\bar{\gamma}) + a_{l,2}(s)X_l(s\bar{\gamma}^2) + \cdots + a_{l,p}(s)X_l(s\bar{\gamma}^p) + \omega_l(s) \tag{1}$$

where $l = m(s)$, $a_{l,i}(s) \in R$, $\omega_l(s)$ is white noise, $\bar{\gamma}$ is defined to reference the parent of node s, p is order of the regression. For homogeneous regions of texture, the coefficients $a_{l,i}(s)$ are constant with respect to image location for any given scale l. That is, the coefficients $a_{l,i}(s)$ and the probability distribution for $\omega_l(s)$ depend only on the scale l. Thus, the set of MAR coefficients $a_{l,i}(s)$ for level l give the linear dependencies between the various scales of the representation. MAR model statistically captures the evolution in scale on the quadtree. For the application of segmenting different types of clutter in SAR imagery, a MAR model can be constructed for each clutter class. As a matter of convenience, we consider the problem of segmenting regions of forest and grass in SAR imagery. The parameters confidence interval estimation in (1) for a given classification are selected with the Bootstrap technique based on the least square estimation (LSE). The process is summarized as follows

(1) Select order p based on AIC;

(2) Calculate LSE $\hat{a}_l = (\hat{a}_{l,0}, \hat{a}_{l,1}, \ldots, \hat{a}_{l,p})$ of coefficients $a_l = (a_{l,0}, a_{l,1}, \ldots, a_{l,p})$ in (1) for any scale from pixel value. And, define the residuals

$$\hat{\omega}_l(s) = X_l(s) - \hat{a}_{l,0}(s) - \hat{a}_{l,1}(s)X_l(s\bar{\gamma}) - \cdots - \hat{a}_{l,p}(s)X_l(s\bar{\gamma}^p)$$

for all S_l and any scale l;

(3) Resample the residuals assuming iid, denoted by $\omega_l^*(s)$, and construct,

$$X_l^*(s) = \hat{a}_{l,0}(s) + \hat{a}_{l,1}(s)X_l(s\bar{\gamma}) + \cdots + \hat{a}_{l,p}(s)X_l(s\bar{\gamma}^p) + \omega_l^*(s);$$

(4) Estimate $\hat{a}_l^* = (\hat{a}_{l,0}^*, \hat{a}_{l,1}^*, \ldots, \hat{a}_{l,p}^*)$ from $X_l^*(s)$;

(5) Repeat step 3 and 4 M times to obtain $\hat{a}_l^*(1), \ldots, \hat{a}_l^*(M)$, where $\hat{a}_l^*(i) = (\hat{a}_{l,0}^*(i), \hat{a}_{l,1}^*(i), \ldots, \hat{a}_{l,p}^*(i))$;

(6) Sort the Bootstrap estimates $\hat{a}_{l,j}^*(1), \ldots, \hat{a}_{l,j}^*(M)$ into ascending order $\hat{a}_{l,j}^*[1], \ldots, \hat{a}_{l,j}^*[M]$ ($j = 1, \ldots, p$) where $\hat{a}_{l,j}^*[i]$ is the ith smallest of $\hat{a}_{l,j}^*(1), \ldots, \hat{a}_{l,j}^*(M)$;

(7) The upper and lower bounds of α % interval are selected as $\hat{a}^*_{l,j}[M(1-\alpha/100)/2]$ and $\hat{a}^*_{l,j}[M(1+\alpha/100)/2]$ respectively.

For forest, $(\hat{a}^*_{l,0}[M(1-\alpha/100)/2],\ldots,\hat{a}^*_{l,p}[M(1-\alpha/100)/2])$ and $(\hat{a}^*_{l,0}[M(1+\alpha/100)/2], \ldots,\hat{a}^*_{l,p}[M(1+\alpha/100)/2])$ are denoted by $\hat{a}^*_l[G_f,U]$ and $\hat{a}^*_l[G_f,L]$ respectively. For grass, by $\hat{a}^*_l[G_g,U]$ and $\hat{a}^*_l[G_g,L]$.

5 Segmentation of SAR Imagery

Using the multiscale representation and MAR models described above, in this section, we introduce a technique to classify pixel in the SAR imagery by statistically characterizing their evolution in scale. The segmentation technique proposed here is inspired by that in [4] and [5], and in contrast to that, utilizes the confidence intervals of model coefficients rather than the statistic distribution. For each $X_0(s)$, we select a $(2k+1)\times(2k+1)$ window centered at $X_0(s)$, denoted by $W_0(s)$. The window of pixels at level l corresponding to the ancestors of $W_0(s)$ will be denoted by $W_l(s)$. By applying LSE to $W_l(s)$ for $l\in\{1,2,\ldots,L-p\}$, we obtain the coefficient estimation of MAR model, that is,

$$\hat{a}_l = \arg\min_{a_l\in R^p}\left\{\sum_{t\in W_l(s)}\left[X(t)-a_{l,0}-a_{l,1}X(t\bar{\gamma})-\cdots-a_{l,p}X(t\bar{\gamma}^p)\right]^2\right\} \tag{2}$$

classification of $X(s)$, which is denoted as $S(s)$, is given by

$$S(s)=\begin{cases} G_g, if\ \ \hat{a}^s_l \in (\hat{a}_l[G_g,L],\hat{a}_l[G_g,U]) \text{ for any } l \\ G_f, if\ \ \hat{a}^s_l \in (\hat{a}_l[G_g,L],\hat{a}_l[G_g,U]) \text{ for any } l \\ \text{Defer decision,} \quad \text{other} \end{cases} \tag{3}$$

For pixels where the classification decision has been deferred, we select smaller size of window, and use a telescoping refinement procedure to repeat above process till completing segmentation.

6 Experimental Results

Although regression order can be chosen by AR model order's criterion, we found that by increasing the regression order to $R=3$ for both grass and forest, we could achieve a lower probability of misclassification in homogeneous regions of terrain. Hence, the results presented in this section were achieved using a third order regression for both the grass and the forest models.

To demonstrate the segmentation method proposed in this paper, we chose two homogeneous images, composed of grass and forest, respectively, which were used as training data, and let $\alpha=0.05$ and $M=1000$. The confidence intervals for each image were computed via above procedure. Experimental results of this technique using a 33×33 window are given in Fig. 2. The results show that this procedure gives better results than the approach in [4], and is extremely suited for homogeneous regions but tend to misclassify grass pixels as forest near the boundaries. This behavior is due to the fact that forest pixels have larger magnitude than grass pixels. They thus tend to dominate the LSE when the window contains both types of terrain. From experimentation, we found that the smaller window can reduces the number of errors associated with boundaries , but is more sensitive to the variability within the homogeneous regions. Although we illustrate the approach by focusing on distinguishing forest regions from grass. This methodology, however, can be generalized.

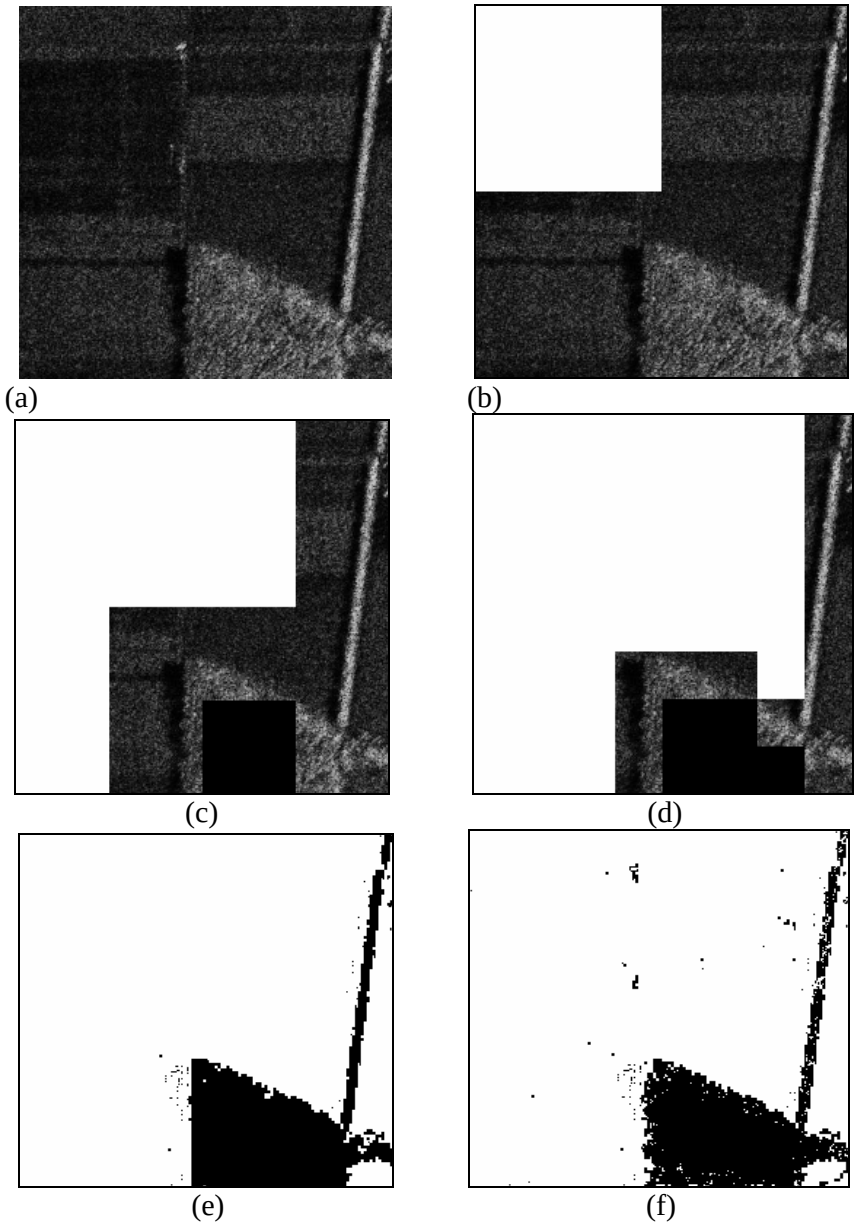

Fig. 2. (a) Original SAR image. (b) Segmented image of first step. (c) Segmented image of second step. (d) Segmented image of third step. (e) Final segmented image based on proposed method. (f) Segmented image based on parameter method.

7 Conclusion

We present the Bootstrap sampling techniques applied to the segmentation of SAR image based on the MAR model. Confidence internal rather than likelihood rate is used as classifier for segmentation. The approaches not only obtain segmentation of SAR imagery, but also give confidence level, and may be extended to include delineation of additional clutter types.

Acknowledgements

This work is supported by the National Natural Science Foundation of China (No. 60375003), the Aeronautics and Astronautics Basal Science Foundation of China (No. 03I53059), and the Doctorate Foundation of Northwestern Polytechnical University (No. 200201).

References

[1] Saad A., Assad S.E., and Barba D.: Speckle filtering in SAR images by contrast modification, comparison with a large class of filters. Ann Telecommun, 1996, 51, pp.233-244.
[2] Lee J.S.: Speckle suppression and analysis for SAR images. 1986, 25, (5), pp. 636-643.
[3] Irving W. W., Novak L. and Willsky A.: Multiresolution approach to discriminating targets from clutter in SAR imagery. IEEE Trans. On Aerospace and Electronic System, 1997, 33, (4), pp. 1157-1169.
[4] Fosgate C., Irving W., Karl W. and Willsky A.: Multiscale segmentation and anomaly enhancement of SAR imagery. IEEE Trans. On Image Processing, 1997, 6, (1), pp 7-20.
[5] Kim A. and Kim H.: Hierarchical stochastic modeling of SAR imagery for segmentation/compression. IEEE Trans. On Signal Processing, 1999, 47, (2), pp. 458-468.
[6] Efron B.: Bootstrap methods: another look at jackknife. The Annals of Statistics, 1979, 7, pp.1-26.
[7] Efron B. and Tibshirani R.: An Introduction to the Bootstrap. Chapman & Hall, 1993.
[8] Efron B.: Better Bootstrap Confidence intervals. Jour. of Amer. Statist. Assoc., 1987, 82, pp.171-185.
[9] Koch I. and Marshall G.: Bootstrap converge plots for image segmentation. IEEE ICPR, 1996, pp.447-451.
[10] Vijaya S., and Murty M.: Bootstrapping for Efficient Handwritten Digit Recognition. Pattern Recognition, 2001, 34, pp. 1047-1056.

Zheng Tian was born in 1948 in China. She is a professor at the Northwestern Polytechnical University, Xi'an, China. She has written numerous papers on image and signal processing. Her fields of interests include time series analysis, information processing and image processing.

Xian-bin Wen received his B.S. degree in mathematics from Huaibei Coal Industry Teachers College, China, in 1989, and his M.S. degree and Ph.D. degree from Northwestern Polytechnical University, China, in applied mathematics in 1992 and in Computer Application and Techniques in 2005, respectively. His research interests include image processing, computer vision, pattern recognition, statistical learning theory and mutiscale system theory.

Wei Lin received the B.S. and M.S. degrees from Northwestern Polytechnical University, Xian, China, in 1987 and 1990. Since 1997, she has been with the Department of Applied Mathematics, Northwestern Polytechnical University, where she is now an associate professor and director of the information processing and computer vision. Her main research interests include signal and image processing and pattern recognition.