Synthetic Aperture Radar (SAR) Images Classification Using Speckle Filtering and Texture Information

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***Abstract*–Synthetic aperture radar (SAR) is very efficient instrument for obtaining remotely sensed images of the earth's surface. However, SAR image is degraded by a form of multiplicative noise known as speckle, which is a result of the illumination, by the coherent radar. Hence speckle reduction is a necessary procedure before automatic image classification can be performed.**

This paper deals with the supervised classification of SAR images. Our approach consists in the speckle filtering before the clustering. But the only knowing of the filtered intensity image is not sufficient because of the high noise level. The other possible information to help the clustering is the texture, thus our approach is based on these two criteria.

I. INTRODUCTION

The supervised classification of SAR images involves sophisticate algorithms because of the high multiplicative noise level known as speckle[1-3]. The well-known methods for SAR image classification consists of speckle filtering before the clustering but the only knowing of the filtered intensity images is not sufficient because of the high noise. The other possible information to help the clustering is the texture, but it is usually difficult to isolate it in a noise image.

In a first part we briefly explain the algorithm for speckle reduction, the assumptions, the models and edge preserving processing. Next we develop the classification criteria, the definition of classes and the definition of neighborhood. In The second part we explain how to isolate the texture in a SAR images and how to use this information to help the classification. Finally we present the results of our supervised classification on real SAR image.

II. FILTERED IMAGE CLASSIFICATION

Since the multiplicative aspect of noise in SAR modulus images makes classification difficult, therefor we classify the result of speckle filtering.

A. Speckle Filtering

Let us state the following multiplicative model:

$$Y = BX \tag{1}$$

Y represents the magnitude of the observed image, X the unknown data and B the multiplicative noise.

In image processing, the knowledge of the measured data and the model is not sufficient to determine a satisfying solution. It is necessary to impose constraints on the solution. Then we assume that X is piece–wise constant and the noise intensity B follows a Gamma pdf, is independent and identically distributed over all the image[4, 5].

The algorithm estimates three images :

- The filtered image $\hat{X}$.
- The estimation of noise $\hat{B}$.
- The edge map d (Edge preserving while smoothing) d.

d is a coefficient between 0 and 1 which value tends toward 1 for flat areas and toward 0 on strong gradient areas.

B. Criterion

We define an auxiliary variable Xc, $Xc \in \Re$. This variable represents a compromise between the values of the filtered image $\hat{X}$ and the values of the neighborhood classes Cl_k for each pixel. For clustering we minimize the criterion:

$$J(Xc) = \left\| Xc - \hat{X} \right\|^2 + \lambda \sum_{i,j} \Big(\sum_{k \in s} d_k (Xc_{i,j} - Cl_k)^2 \Big) \tag{2}$$

S represents the neighborhood of the pixel $Xc_{i,j}$. λ is a regularization parameter which weighs the influence between the two terms. This criterion takes into account the value of the filtered image $\hat{X}$ and the neighboring classes weighted by the edge map d.

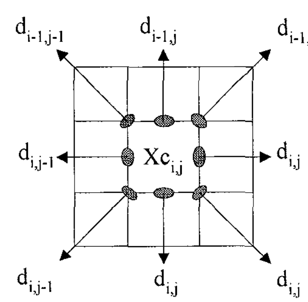

Fig. 1. The neighborhood of a pixel weighted by the discontinuities.

The minimum of the criterion of classification, satisfies the following equation:

$$\frac{\partial J(Xc)}{\partial Xc}|_{i,j} = 0 ,$$

$$Xc_{i,j} = \frac{\hat{X}_{i,j} + \lambda \begin{pmatrix} d_{i-1,j}Cl_{i-1,j} + d_{i-1,j}Cl_{i-1,j+1} + d_{i,j}Cl_{i,j+1} \\ + d_{i,j}Cl_{i+1,j+1} + d_{i,j}Cl_{i+1,j} + d_{i,j-1}Cl_{i+1,j-1} \\ + d_{i,j-1}Cl_{i,j-1} + d_{i-1,j-1}Cl_{i-1,j-1} + Cl_{i,j} \end{pmatrix}}{1 + \lambda(2d_{i-1,j} + 3d_{i,j} + 2d_{i,j-1} + d_{i-1,j-1} + 1)} \tag{3}$$

C. Projection

We define a class by its mean μ and its standard deviation σ. In order to obtain the classified image C, we defined the membership of a pixel to a class A as shown below.

$$Xc_{i,j} \in \text{class A} \ \text{ if } \ Xc_{i,j} \in [\mu_A - \beta\sigma_A, \mu_A + \beta\sigma_A] \tag{4}$$

And then $Cl_{i,j} = \mu_A$, β is a constant.

III. Texture Information

For SAR image, the high level of noise involves numerous classification errors. Thus we try to find more information to help classification. The main idea is to use, and to isolate the texture in the SAR image. One more time we use the results of the speckle filtering to isolate the texture. We calculate the noise $\tilde{B} = \frac{Y}{\hat{X}}$ and define $T = f\left(\left|\tilde{B} - \hat{B}\right|\right)$

The image T represents the absolute value of the texture and the modeling errors, on which a low pass filter f is applied.

A. Criterion

We define an auxiliary variable Tc, Tc $\in \Re$. This variable represents a compromise between the values of the texture image T and the values of the neighborhood classes Cl_{Tk} for each pixel. We define the classification criteria as:

$$J(Tc) = \|Tc - T\|^2 + \lambda \sum_{i,j} \left(\sum_{k \in s} d_k (Tc_{i,j} - Cl_{Tk})^2 \right) \tag{5}$$

Our second criterion takes into account the texture and the modeling errors (image T) as well as the neighborhood classes weighted by the edge map d.

The minimum of the criteria J(Tc) in order to obtain Tc image, satisfies the following equation:

$$\frac{\partial J(Tc)}{\partial Tc}|_{i,j} = 0 ,$$

$$Tc_{i,j} = \frac{T_{i,j} + \lambda \begin{pmatrix} d_{i-1,j}Cl_{i-1,j} + d_{i-1,j}Cl_{i-1,j+1} + d_{i,j}Cl_{i,j+1} \\ + d_{i,j}Cl_{i+1,j+1} + d_{i,j}Cl_{i+1,j} + d_{i,j-1}Cl_{i+1,j-1} \\ + d_{i,j-1}Cl_{i,j-1} + d_{i-1,j-1}Cl_{i-1,j-1} + Cl_{i,j} \end{pmatrix}}{1 + \lambda(2d_{i-1,j} + 3d_{i,j} + 2d_{i,j-1} + d_{i-1,j-1} + 1)} \tag{6}$$

B. Projection

We define a class by its mean μ_T and its standard deviation σ_T. In order to obtain the classified image C, we defined the membership of a pixel to a class A as shown below.

$$Tc_{i,j} \in \text{class A} \ \text{ if } \ Tc_{i,j} \in [\mu_{AT} - \beta\sigma_{AT}, \mu_{AT} + \beta\sigma_{AT}] \tag{7}$$

And then $Cl_{Ti,j} = \mu_{AT}$, β is a constant.

IV. Classification

A class is defined by 2 couples of values, the means (μ, μ_T) of the class and its standard deviations (σ, σ_T)

In order to take into account the information of texture to classify the filtered image, we define the distance to a class A as following:

$$\text{Dist}\left(\hat{X}, \text{classA}\right)_{i,j} = \alpha \frac{|Xc_{i,j} - \mu_A|}{\sigma_A} + (1-\alpha)\frac{|Tc_{i,j} - \mu_{AT}|}{\sigma_{AT}} \tag{8}$$

α is a parameter, which weighs the influence between the two terms. Thus the new definition of the membership of a pixel to a class A is:

$$\begin{aligned} &\hat{X}_{i,j} \in \text{ClassA} \\ &\text{if } \left\{\min \text{ classes is obtained for Class A}\left(\text{Dist}\left(\hat{X}, \text{Classes}\right)_{i,j}\right)\right\} \\ &\text{and } \left\{\text{Dist}\left(\hat{X}, \text{Class A}\right)_{i,j} \le \text{Distance max}\right\} \end{aligned} \tag{9}$$

Thus $Cl_{i,j} = \mu_A$ and $Cl_{Ti,j} = \mu_{AT}$

V. The Proposed Algorithm

In this paper, the proposed algorithm for supervised classification of SAR image can be shown below:

Repeat
- Compute Xc
- Compute Tc
- Compute Cl and Cl_T

Until convergence

The classified image C is composed by the $Cl_{i,j}$.

VI. The Experimental Results

In this paper we have used the SAR image which was acquired by JERS-1 over Chantraburi Province (Thailand). The original image consists of 256 x 256 pixels as shown in the Fig. 2, Fig. 3 shows the Xc image, Fig. 4 shows the Tc image and Fig. 5 shows the result of the supervised classification. On the last image, the most of classified areas have continuous boundaries and no much too small size, which can be a sign of little error. This little error due to the high noise level in the original SAR image and makes filtering difficult. The categories classified are water, vegetation, and urban.

VII. Conclution

A new supervised classification in this paper by using speckle filtering and texture information was successfully applied to JERS-1 SAR image. The results indicate high classification accuracy for all classes; classified areas have continuous boundaries. A little error occurs because of the high noise level in the original SAR image, especially water area. In the future we will also seek to find a method to tune automatically the program parameters.

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Fig. 2. The original SAR image.

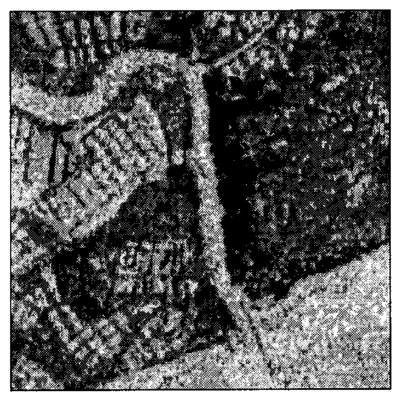

Fig. 4. The Tc image.

Fig. 3. The Xc image.

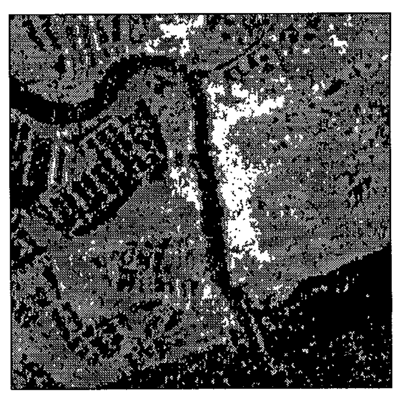

Fig. 5. The classified image.