

SUPERVISED CLASSIFICATION FOR SYNTHETIC APERTURE RADAR IMAGE

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ABSTRACT

This paper deals with the supervised classification of synthetic aperture radar (SAR) images. Our approach is based on two criteria, which explicitly take into account the intensity of the SAR image and the neighborhood classes, similarly to the Pots model, but weighted by a discontinuity map. The high level of noise involves numerous classification errors, then we classify a restored image filtered with a well-adapted algorithm to clustering. Moreover, we isolate the texture of SAR images in order to help the classification. Finally, we present results on real SAR images.

1. INTRODUCTION

The supervised classification of SAR images involves sophisticated algorithms because of the high noise level. Well known methods are based on growing regions algorithms [1], or on detection of areas followed by the merging of these areas [2]. Most of these algorithms chain different methods as edge detection, watershed and region merging.

Our approach consists in the speckle filtering before the clustering. The only knowing of the filtered intensity image is not sufficient because of the high noise level. An other possible information to help the clustering is the texture, but it is difficult to isolate it in a noisy image.

Thus in a first part we briefly explain our algorithm for speckle reduction, the assumptions, the models and the edge preserving processing.

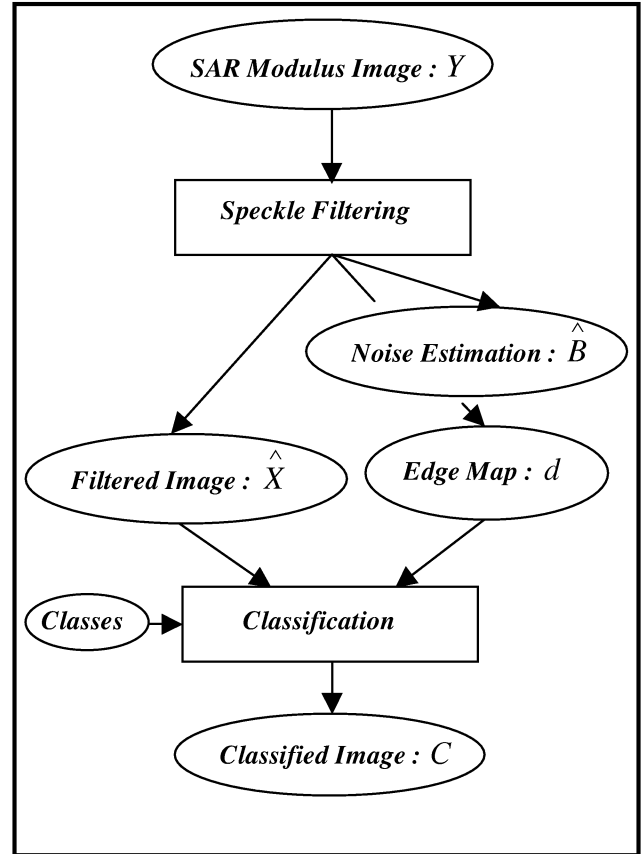
Next we develop our classification criteria, the definition of our classes and the definition of the neighborhood.

Then, we explain how we isolate the texture in a SAR images and how we use this information to help the classification.

Finally, we present results on a real single look SAR image.

2. CLASSIFICATION

The multiplicative aspect of noise in SAR modulus images makes classification difficult, therefore, we classify the result of speckle filtering. The used classification scheme is :



2.1 Speckle Filtering

To filter the speckle, we use the algorithm developed in [3].

Let consider the multiplicative model :

$$Y = BX \quad (1)$$

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

To filter we made the hypothesis :

- X is piece-wise constant.
- The noise intensity B follows a Gamma pdf, is independent and identically distributed over the image.

Our algorithm estimates three images :

- The filtered image \hat{X} .
- The estimation of noise \hat{B} .
- The edge map (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 [3].

Notice that the piece-wise constant assumption is closed to the classification aim.

2.2 Criterion

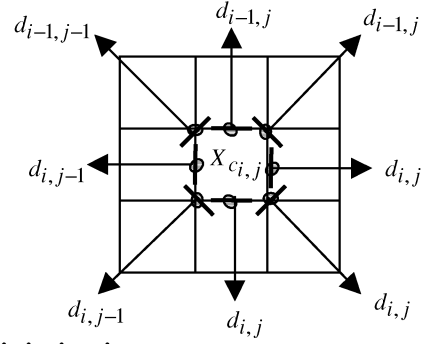
We define an auxiliary variable X_c , $X_c \in \mathfrak{X}$. This variable represents a compromise between the values of the filtered image \hat{X} and the values of the neighborhood classes Cl_k for each pixel.

For clustering we minimize the criterion :

$$J(X_c) = \left\| X_c - \hat{X} \right\|^2 + \lambda \sum_{i,j} \left(\sum_{k \in S} d_k (X_{c_{i,j}} - Cl_k)^2 \right) \quad (2)$$

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

According to the definition of the edge map, we define the neighborhood of a pixel weighted by the discontinuities as follows :



2.3 Minimization

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

$$\frac{\partial J(X_c)}{\partial X_c} \bigg|_{i,j} = 0 \Leftrightarrow \hat{X}_{i,j} + \lambda \left(\begin{aligned} & d_{i-1,j} Cl_{i-1,j} + d_{i-1,j} Cl_{i-1,j+1} + d_{i,j} Cl_{i,j+1} \\ & + d_{i,j} Cl_{i+1,j+1} + d_{i,j} Cl_{i+1,j} + d_{i,j-1} Cl_{i+1,j-1} \\ & + d_{i,j-1} Cl_{i,j-1} + d_{i-1,j-1} Cl_{i-1,j-1} + Cl_{i,j} \end{aligned} \right) X_{c_{i,j}} = \frac{1 + \lambda (2d_{i-1,j} + 3d_{i,j} + 2d_{i,j-1} + d_{i-1,j-1} + 1)}{\quad} \quad (4)$$

2.4 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 :

$$X_{c_{i,j}} \in \text{Class } A \quad \text{if} \quad X_{c_{i,j}} \in [\mu_A - \beta \sigma_A, \mu_A + \beta \sigma_A]$$

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

3. MORE INFORMATION

For a single look 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 then to isolate the texture in the SAR images. One more time we use the results of the speckle filtering to isolate the texture :

- We calculate the noise : $\tilde{B} = \frac{Y}{\hat{X}}$
- We 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.

3.1 Criteria

We define an auxiliary variable T_c , $T_c \in \mathbb{R}$. 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 :

$$\begin{aligned} J(X_c) &= \left\| X_c - \hat{X} \right\|^2 + \lambda \sum_{i,j} \left(\sum_{k \in S} d_k \left(X_{ci,j} - Cl_{Tk} \right)^2 \right) \\ J(T_c) &= \left\| T_c - T \right\|^2 + \lambda \sum_{i,j} \left(\sum_{k \in S} d_k \left(T_{ci,j} - Cl_{Tk} \right)^2 \right) \end{aligned} \quad (5)$$

S represents the neighborhood of the pixel $X_{ci,j}$.

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 .

We minimize the criteria $J(X_c)$ and $J(T_c)$ in order to obtain X_c and T_c .

Notice that we have an analytic expression of X_c and T_c , then to cluster the image we just have to define a distance and a projection.

4. DISTANCE

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:

$$Dist \left(\hat{X}, Class A \right)_{i,j} = \alpha \frac{|X_{ci,j} - \mu_A|}{\sigma_A} + (1 - \alpha) \frac{|T_{ci,j} - \mu_{AT}|}{\sigma_{AT}} \quad (6)$$

α is a parameter which weighs the influence between the two terms.

The new definition of the membership of a pixel to a class A is:

$$\begin{aligned} \hat{X}_{i,j} \in Class A \text{ if } & \left\{ \begin{array}{l} \min_{Classes} \left(Dist \left(\hat{X}, Classes \right)_{i,j} \right) \\ \text{is obtained for } Class A \end{array} \right\} \\ \text{AND } & \left\{ Dist \left(\hat{X}, Class A \right)_{i,j} \leq Distance \max \right\}. \end{aligned}$$

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

5. ALGORITHM

Repeat

- Compute X_c .
- Compute T_c .
- Compute Cl , and Cl_T .

Until convergence

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

6. EXPERIMENTAL RESULTS

Experiments on our algorithm were conducted for real ERS1 data. Fig 1 represents a single looks SAR image of various maturates rice fields, Fig 2 the filtered image, Fig 3 the absolute value of the texture image and Fig 4 the result of the supervised classification. On this last image, the classified areas have continuous boundaries and no too small size which can be a sign of errors. This qualitative criterion is enforced by the knowledge of the cultivating distribution on a map (Fig. 5).

7. CONCLUSION

In this paper, we propose a new supervised classification algorithm for SAR images. This algorithm is very fast and efficient but we also seek to find a method to tune automatically the program parameters.

8. REFERENCES

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- [2] R. Cook, I. M Connell, C. Oliver, *MUM (Merge Using Moments) Segmentation For SAR Images*, Satellite Remote Sensing I EUROPTO (Rome), 2316 (1994), pp : 92-103.
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Fig. 1 : Original Single Look SAR Image

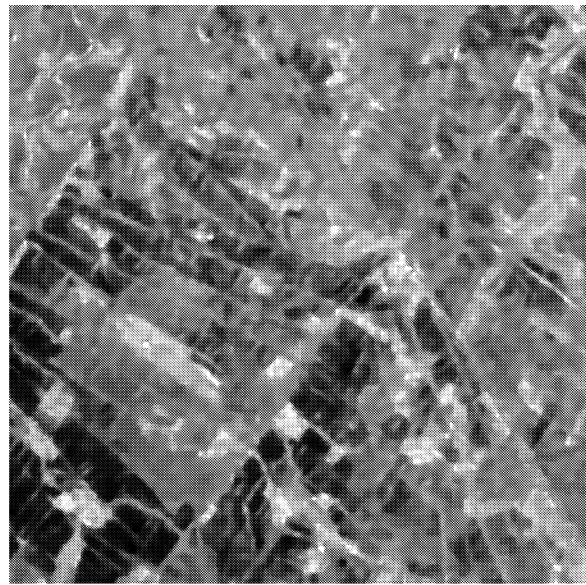


Fig. 2 : Filtered image

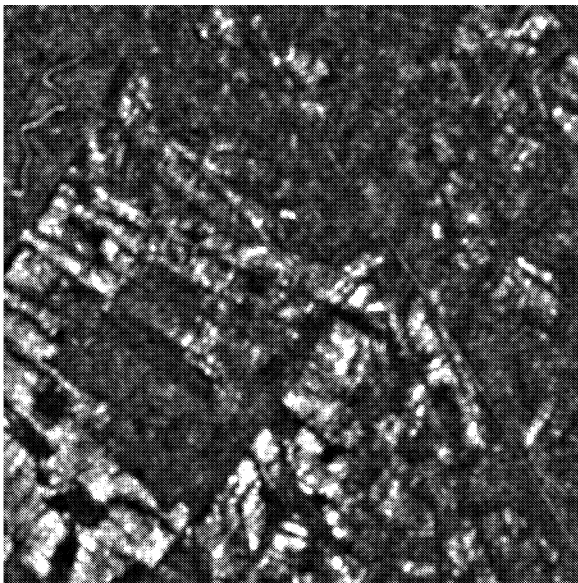


Fig. 3 : Image of Texture and Modeling Errors.

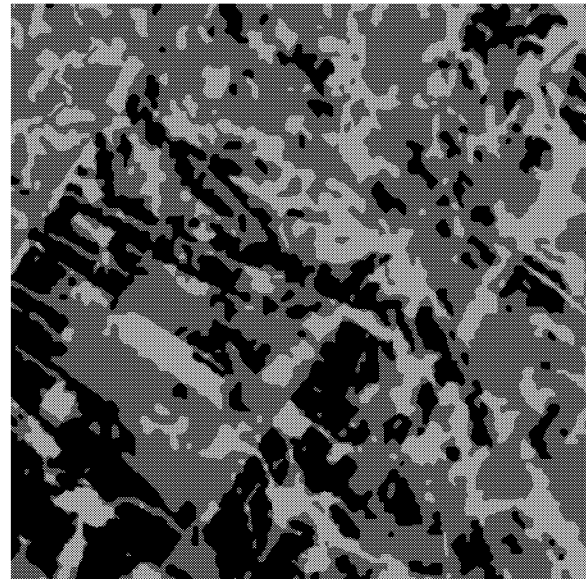


Fig. 4 : Classified Image



Fig. 5 : Fields Map

- Mature rice
- Non mature rice
- Other