A NEW IMAGERY CLASSIFICATION METHOD USING SPATIAL COVARIANCE INFORMATION: AN APPLICATION TO THE SAR IMAGE OF THE COASTLINE OF CAMEROON

[1]Emmanuel TONYE, [1]Janvier FOTSING[*], [2]Bernard ESSIMBI ZOBO, [1]Narcisse TALLA TANKAM, [1]Thomas F. N. KANAA, [3]Jean Paul RUDANT

[1]Laboratoire d'Electronique et de Traitement du Signal (LETS), Ecole Nationale Supérieure Polytechnique, Université de Yaoundé I, Cameroun.
jfotsing@gmail.com, tonyee@hotmail.com, t_kanaa@yahoo.fr, ntalla@gmail.com
[2]Département de Physique, Faculté des Sciences, Université de Yaoundé I, Cameroun
bessimb@yahoo.fr
[3]Laboratoire des Géomatériaux, Institut Francilien des Géosciences, 5 Boulevard Descartes, Champs-Sur-Marne, Université de Marne-La-Vallée, France
rudant@univ-mlv.fr

Key words: Classification, SAR image, variogram, texture, feature vector.

Abstract: Classical and modern statistical methods offer wide variety approaches of data classification in general and image classification in particular. Among these approaches none of them explicitly use spatial information. Structures with spatial covariance have been used for predicting data, but are not directly use for classifying. This paper deals with a supervised classification method based on spatial covariance information obtained by image texture analysis. An experimental variogram is plotted for each training zone, and fitted with empirical variogram models. The parameters deduced from these models are stored in a feature vector of texture. This method has been applied for the classification of a SAR image of the Atlantic coast of Cameroon.

1. INTRODUCTION

Classification in general involves choosing the correct value of y when there are k finite choices, given a number of observations x, where x is p-dimensional variable. Classification of imagery in particular involves choosing the correct category for a given square pixel, given the input from one or more bands and information from neighboring pixels. Accurate classification of remotely sensed imagery and other spatial data is important for cartographic support and other efforts to protect Cameroon's security coastline.

There are many different existing methods for classification. Some of these include discriminant analysis, clustering, neural networks, support vector machines, decision trees, nearest neighbors, and various ensemble approaches such as bagging and boosting. In general, these approaches do not use spatial information in the classification process. Even inherently spatial processes such as PRISM [1] and linear kriging are prediction procedures rather than classification procedures. Recently, some techniques have involved geostatistical parameters deduced from the semi-variogram function for image classification ([2]; [3]), but none in quantitative approach. Four approaches use

spatial information in the overall classification process ([4], [5], [6], [7]), but no known classification method to directly classify data.

The objective of this study is to assess the potential of spatial covariance derived from texture pattern measures applied to classify SAR image of big size. The aim of this study is also to show the potential of quantitative analysis using geostatistical approach in classification of SAR image.

This approach in the classification of SAR images is original in that it allows a more faithful characterization of each pixel of the image classification.

This paper is organized as follows. In the next section, we present an overview of variograms in numerical image. The second section gives the methodology with schemes and algorithm applied in this study. The third section presents the experimental results. Finally, we conclude with the summary and future prospects.

2. VARIOGRAM AND NUMERICAL IMAGE

2.1. Variogram Formulation

Traditionally, variograms have been used for modelling spatial variability rather than the covariance although kriging systems are more easily solved with covariance matrices. In this study, we analyzed the spatial distribution property of each image through variogram.

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The variogram must be checked for changes in values based on different directional orientation, known as anisotropy [8]; however, anisotropy is rarely significant in imagery variograms.

To estimate a variogram, we consider two numerical values of image, $L(x, y)$ and $L(x + h, y + v)$, established in two pixels distant by a vector (h, v). We characterize the variability between the two intensities by variogram function $2\gamma(h, v)$ defined as variable expectancy.

$$[L(x, y) - L(x + h, y + v)]^2 \quad , \qquad \text{whether}$$

$$2\gamma(x, y, h, v) = E[L(x, y) - L(x + h, y + v)]^2 \quad (1)$$

Then, the estimator $2\gamma(h, v)$ is equal to the mathematical average of the gap quadratics between two intensities $[L(x_i, y_i), L(x_i + h, y_i + v)]$:

$$2\gamma(h,v) = \frac{1}{(N-h) \times (M-v)} \sum_{i=1}^{N-h} \sum_{j=1}^{M-v} [L(x_i, y_j) - L(x_i + h, y_j + v)]^2 \quad (2)$$

where $(N - h) \times (M - v)$ is the number of the experimental pairs. For one numerical image, we can estimate the duplex variogram according to different directions (angles).

2.2. Modeling Functions

Once a variogram is obtained, the spatial covariance structure can be quantified by choosing a variogram model. Usually a model is chosen to minimize a fitting criterion such as the sum of least square. The equations for these models are:
– Exponential model

$$\gamma(h) = C\left(1 - e^{-h/H_p}\right) \quad (3)$$

where C is a constant that denotes the highest values of γ (the "Sill"), and H_p denotes the distance where the variogram effectively becomes level (the "Range").
– Fractal model

$$\gamma(h) = Kh^{\alpha} \quad (4)$$

where K is a constant that denotes continuity crossing of γ (the "Slope") and α denotes the exponent of variability.

For the phenomena which in a scale h present a self-similarity, we know that the variogram verifies the equation given below.

$$\gamma(h) = Kh^{2(3-D)} \quad (5)$$

where D is a fractal dimension of the phenomenon [9]. Hence, for the models whose variograms are defined by equation (4), we can define the fractal dimension of the texture image by the equation given below.

$$D = 3 - \frac{\alpha}{2} \quad (6)$$

3. METHODOLOGY

The new approach described in this paper is a supervised approach. This approach use the variogram for texture measures in the field of remote sensing. The variogram was modeled by mathematical functions ((3) and (4)) and the coefficients of the functions were used as texture measure.

3.1. Characterization of the training zones

At this stage, one is expected to evaluate, for each of the n training sites, the spatial covariance information that is quantified using texture information from spatial pattern. In the previous work [10], we showed that, texture can be characterized by four parameters: Range, Sill, Slope and Fractal Dimension deduced on spatial covariance from information of a texture pattern.

The four parameters are calculated in various directions such as East-West, South-North, South-West / North-East and South-East / North-West. The method of calculation is also investigated in Fotsing et al. [10].

The weakness of this approach is that the modeled coefficients may not have sufficient discriminatory power for identifying different land-uses. To overcome the problem, we suggest using simultaneously two functions of modeling experimental variogram. The two functions (exponential (3) and fractal (4) models) are chosen with as criterion the aptitude of function to fit an experimental variogram.

$$V_{CC}\big|_{Site}\big|_{Direction} = (V_{c1}, V_{c2}, V_{c3}, V_{c4}) \quad (7)$$

where V_{ci} represents in order the (Range, Sill, Slope and Fractal Dimension) for the ith component of the feature vector deduced on the variogram

3.2. Classification Algorithm using Spatial Covariance Information from Texture Pattern

In the classification phase, the adopted approach consists in the extraction of a single layer at a time. A fusion is then made to the various extracted classes and the global classification with the various classes of soil occupation is obtained. To extract a given class X, the following operations are carried out after the order.

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- Extraction of an image window W entirely enclosed in the class X;
- Select the direction of calculation of texture parameters;
- Calculation and representation of the experimental variogram and fitting it with the two functions model by using the least square criterion;
- Deduction of texture parameters. In this step, the fitted model is quantified through its coefficients such as Range and Sill (deduced on the exponential model (3)) and Slope and Fractal Dimension (deduced on the fractal model (4));
- Construction of a feature vector V_{CC} with the various parameters previously extracted;
- For each pixel of the image, do the following instructions:
    - Extraction of an image window F, with size W and centered on the pixel i;
    - Do the steps 2 to 4 described above;
    - Construction of a feature vector V_i with the various parameters previously extracted;
    - Evaluation of the distance between V_{CC} and V_i by the formula given below;

$$d_i = \sqrt{\sum_{k=1}^{4}\left(V_{CC}(k)-V_i(k)\right)^2} \qquad (8)$$

    - If the threshold $T = \dfrac{d_i}{d_{max}} \times 100$ is less than a

certain value (less than 5% in general), then the pixel i belongs to the class X. If not, the pixel i does not belong to the class X.

d_{max} is the maximum distance between the feature vectors of two image windows with the same size as W on the image.

4. EXPERIMENTATION

4.1. Experimental Zone and Data Used

This approach has been experimented on an ERS-2 SAR image, registered in band C (5.66 cm of wave length) and in VV (vertical-transmit, vertical-receive) polarization with a resolution of 12.5m. Using topographical and lithographical charts at a scale 1:200 000, we identified three main classes of soil occupation on the image of the site of study (Figure 1). The first class, identified by the training zone A represents the

aquatic zone. The second class identified by the training zone B represents the mangrove 1 zone. The third class identified by the training zone C represents the mangrove 2 zone.
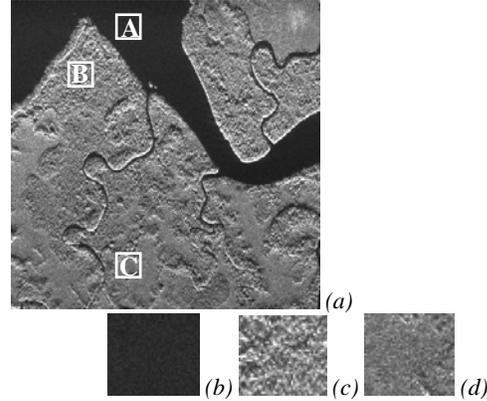

Figure 1. (a) Global view of the site of study; (b) Zone A; (c) Zone B; (d) Zone C

4.2. Characterization of Training Site

Figure 2 presents the example of characterization of structural information deduced from a textural pattern of the two first training zones (Zone A and Zone B). To practice, we show on the graphs (Figure 2a and 2b) the interpolation of the experimental variogram (green color) with empirical variogram (yellow color). Figure 2a (a) helps to deduce the parameters (Sill) C_A= 347.44 and (Range) Hp_A= 2 given by the exponential model (3) and the figure 2a (b) the two others parameters (Slope) K_A=268 and (Fractal Dimension) DF_A=2.87 given by the fractal model (4). Figure 2b (a) gives by using exponential model the following parameters: (Sill) C_B=405.91 and (Range) Hp_B=5 and the figure 2b (b) with fractal model (Slope) K_B=151.13 and (Fractal Dimension) DF_B=2.69.

Numerically, the various training zones A, B and C are respectively characterized by the following feature vectors: V_A= (2; 347.44; 268; 2.87), V_B= (5; 405.91; 151.13; 2.69) and V_C= (24; 2096.37; 227.21; 2.66).

4.3. Experimental Results

Figure 3 presents the various results obtained during the various stages of our classification methodology. Figure 3a presents the extraction of the class A "sea" (white color) on the study site. Figure 3b presents the extraction of the class B "mangrove 1" (white color) and Figure 3c presents the extraction of the class C "mangrove 2" (white color). The fusion of the various classes extracted is represented on the figure 3d. This figure 3d constitute the classified image witch in our case has three classes.
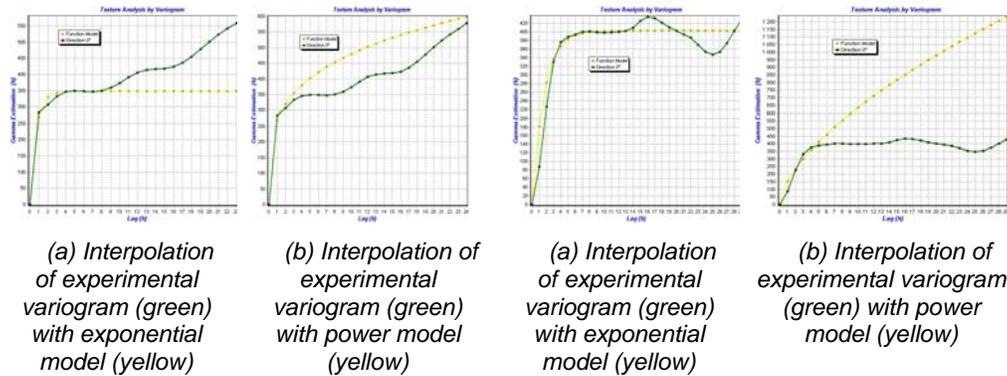
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(a) Interpolation of experimental variogram (green) with exponential model (yellow)

(b) Interpolation of experimental variogram (green) with power model (yellow)

(a) Interpolation of experimental variogram (green) with exponential model (yellow)

(b) Interpolation of experimental variogram (green) with power model (yellow)

Figure 2a. Zone A
Figure 2b. Zone B

Figure 2. Using semi-variance and functions for the characterization of spatial texture information

(a) Class "sea"(white color)

(b Class "Mangrove 1" (white color)

(Class) "Magrove 2" (white color)

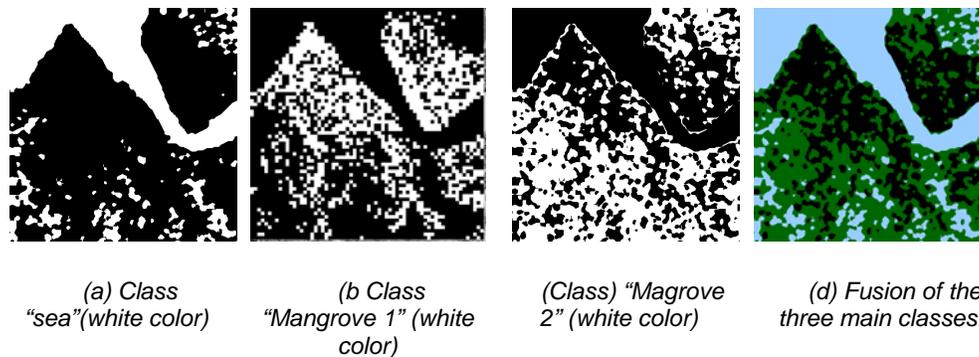*(d) Fusion of the three main classes.*

Figure 3. Result of classification using spatial covariance information

5. CONCLUSION

This study tested the effectiveness of semi-variance information of a texture analysis in the classification of SAR image. Modelling texture using combination of variogram and fitted functions, algorithm, feature vectors are also investigated. The best classification result was considered satisfactory.

Land-use classification for the SAR image gets more difficult when knowledge of the site study is not available. The quantitative and qualitative analysis of the proposed approach help to conclude that structural information using covariance information can be powerfully recommender to study SAR image.

Future research needs to use this new approach to extract coastline of the study site. The methodology presented in this paper doesn't take in to consideration the variation of the inter-pixels direction. We used the West-East inter-pixels direction for the experimentation. Other future prospect of this work may consist to combine the various inter-pixels directions to accurate the rate of classification.

6. ACKNOWLEDGMENT

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