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Research Article

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# Characterization of the Texture of Digital Images by Variography Approach: An Application to the Classification of SAR Images

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## Abstract

This paper presents a method of texture modelling using geostatistic theory. From variographics abacus and variogram proprieties, fractal and exponential models have been used to characterize Brodatz textures. In this approach, a texture is modelled by a vector called feature vector whose components are parameters characterizing the experimental variogram, notably the "Slope", the "Range", the "Landing" and the "Fractal Dimension (FD)". The parameters estimated by this approach help to promote an adequate method of quantitative analysis of the variogram of textured images. A comparative study of the proposed method for the evaluation of FD and the one proposed in the literature shows that the results obtained are identical to the nearest hundredth with the texture images of Brodatz used in this work for the experimentations. To demonstrate the applicability of the approach, a SAR image of ERS-1 from the Atlantic coast of Cameroon has been classified using an algorithm classification of type supervised. It is based on the methods of structural classification. The particularity of this approach lies in the fact that each pixel is fully characterized by its feature vector.

## Keywords

SAR image; Texture; Variogram; Feature vector; Supervised classification

## Introduction

Many approaches were developed for texture analysis. According to the processing algorithms, three major categories, namely, structural, spectral, and statistical methods are common ways for texture analysis. Grey Level Co-occurrence Matrix (GLCM), one of the most widely used methods, contains the relative frequencies of the two neighboring pixels separated by a distance in the image. Several statistical measures [1] such as homogeneity, contrast, and entropy can be computed from the matrix to describe specific textural characteristics. Each texture measure can create a new channel that can be incorporated with spectral features for classification purposes.

In this work, the structural method has been used to characterize texture. By using the structural method, the potential of the variogram in texture analysis applied for the characterization of digital images is proved, and used with success in a classification process. The experimental phase was conducted using Brodatz natural textures [2] and that because the textures are largely known and available by free gift to all researchers. Each texture is characterized by the parameters: Slope, Range, Sill, and the Fractal Dimension deduced on the variogram modelling the texture. The other objective of this work was to apply the methodology adopted for characterizing texture for the classification of satellite image.

Geospatial techniques utilize spatial information that considers the spectral dependence existing between a pixel and its neighbor. Radiometric data that are highly correlated within a range can be indicated through the variogram function [3]. The digital number (DN) value of each pixel can be interpreted as a regionalized variable. Meanwhile, a data driven variogram provides a method of measuring the spatial dependency of continuously varying phenomena. The approach of this paper intends to analyze the spatial dependence of radiometric data by geostatistical methods to obtain the suitable feature vector for the texture from data deriving of the variogram.

Various combinations of texture measures have been tested for different applications such as crop classification in agriculture [4] and forest species classification for management of nature resources. Results showed that incorporating texture features in classification was superior to the classification of the original image. Variogram derived texture has been recently proved to increase the accuracy. Recently, some techniques have involved geostatistical parameters deduced from the semivariogram function for image classification [5,6]. The approach of classification adopted in this work is one of the great families of supervised classification. It is based on the methods of structural classification. The particularity of this approach lies in the fact that each pixel is fully characterized by its feature vector. To demonstrate the applicability of the approach an ERS-1 SAR image from the Atlantic coast of Cameroon has been classified.

In the following of this work, the methodology will be firstly presented, the experimentation will follow and the result will be presented in the third part. The discussion and the conclusion will come to close the study.

## Methodology

### Texture analysis using variogram

**Definition of variogram:** The variogram is a two-point statistical function that describes the increasing differences, decreasing correlation, or continuity between sample values as separation between them increases. Traditionally, the variograms have been used for modelling spatial variability rather than the covariance although

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Krigeage systems are more easily solved with covariance matrices. In this study, we analyzed spatial distribution property of each image through variogram.

In many cases, the lag increase does not result in any more difference because the spatial autocorrelation between image values normally drops beyond a certain distance. The height of the "Sill" is however proportional to the global image variance while the lag $h$ at which the "Sill" is attained, called the "Range," is generally a very good indicator of the texture coarseness. The fractal dimension is used to characterize the fitting effects observed on the natural textures. This last parameter contains information on the geometric structure known as the most powerful indicator to measure the irregularity in the natural textures.

The variogram can be calculated along transects (Figure 1) but gives a better representation when calculated in more than one direction [7] because texture is in many cases anisotropic [8].

Two numerical values of image, $L(x,y)$ and $L(x+h,y+v)$ are considered, and established in two pixels distant by vector $(h,v)$. The variability between the two intensities is characterized by a variogram function $2\gamma(h,v)$ defined as variable expectancy.

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

Where $(N\text{-}h) \times (M\text{-}v)$ is the numbers of the experimental pairs of pixels for numerical image of size $N\times M$. The variogram can be estimated according to different directions (angle) notably East-West, South-North, South-West/North-East or South-East/North-West.

For the four directions, the following formulations are obtained:

For the horizontal direction (angle=0°)

$$2\gamma(h)=\frac{1}{N\times(M-h)}\sum_{i=1}^{N}\sum_{j=1}^{M-h}\left[I(i,j)-I(i,j+h)\right]^2 \quad (2)$$

Where $I(i,j)$ is the associated grey level of pixel in position $(i,j)$, $h$ is the lag, $N$ is the number of lines and $M$ is the number of columns.

- For the vertical direction (angle=90°)

$$2\gamma(h)=\frac{1}{(N-h)\times M}\sum_{i=1}^{N-h}\sum_{j=1}^{M}\left[I(i,j)-I(i+h,j)\right]^2 \quad (3)$$

- For the diagonal 1 direction (angle=45°)

$$2\gamma(h)=\frac{1}{(N-h)(M-h)}\sum_{i=1}^{N-h}\sum_{j=1}^{M-h}\left[I(i,j)-I(i+h,j+h)\right]^2 \quad (4)$$

- For the diagonal 2 direction (angle=135°)

$$2\gamma(h)=\frac{1}{(N-h)(M-h)}\sum_{i=1}^{N-h}\sum_{j=1}^{M-h}\left[I(i,j)-I(i-h,j+h)\right]^2 \quad (5)$$

**Algorithm of calculation of variogram:** Figure 2 illustrates the algorithm for calculating the variogram in the horizontal direction:

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.

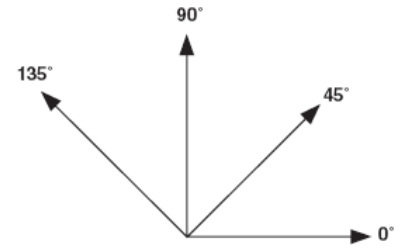



**Figure 1:** Variogram computation algorithm in the horizontal direction (angle 0°).

```
Start program
    To repeat for h=1 to M-1
        Sum=0
            To repeat for i=1 to N
                To repeat for j=1 to M-h
                    Sum=Sum+ (I (i, j) - I (i, j+h))²
                End for j
            End for i
        Y(h)=Sum / (2 x N x (M-h);
    End for
End program
```

**Figure 2:** Principal directions of variogram estimation.

## Modelling Functions

A theoretical variogram model is the function used to adjust the experimental variogram by least square fitting. In this work exponential and fractal model illustrated by equations below (6) and (7) are used. These two models are chosen because their graphics fit well to the experimental variogram and almost all image textures are classified into two main groups:

### Landing model

The graphic of variogram presents a horizontal asymptote. In general the adopted mathematical model is the exponential model (6).

$$\gamma(h)=C\left(1-e^{-h/H_p}\right) \quad (6)$$

Where $C$ and $H_p$ are positive constants.

### Fractal model

$$\gamma(h)=Kh^{\alpha} \quad (7)$$

where $K$ and α are positive constants.

For the phenomena which in all scale $h$ present a self-similarity, we know that the variogram verifies equation (8).

$$\gamma(h)=Kh^{2(3-DF)} \quad (8)$$

Where $DF$ is a fractal dimension of the phenomenon. Hence, for the models whose variogram is defined by equation (7), we can define the fractal dimension of the image texture by relation (9).

$$DF=3-\frac{\alpha}{2} \quad (9)$$

### Modelling parameters of texture using the variogram

Usually, variograms are characterized by three parameters:

Nugget effect, Range and Sill [9]. Nugget effect described the behavior of the variogram at the origin. Variogram Range ($H_p$) measures texture coarseness and it has been proven that Range is an important discriminator of forest stands, vegetation types and land cover classes. Range is also directly related to the size of objects: for small patches (in dispersed landscapes) the Range is shorter. Hence it is inappropriate to measure all the classes and objects with the same dimension. On the contrary, Sill ($C$) results from a complete absence of spatial structuring. The Sill is also known as the association of Nugget effect and structured variability [10].

Berberoglu et al. [11] pointed out that variograms for short lag measure of field edges, rather than within-field variability. In fact, semi-variance for the first lag is a strong edge detector, and semi-variance at consecutive lags is a gradually smoother edge detector. Thus, to give an account of this phenomenon we introduce a new parameter call "Slope" ($k$).

Fotsing et al. [12] have shown that variogram can be better known by adding Slope and Fractal Dimension (deduced of the coefficient α) and in the same work the authors show that the Nugget Effect is null for the cases of natural textures. Thus, modeling parameters in this study are Slope, Range, Sill and Fractal Dimension (FD).

Those parameters are obtained by using interpolation between experimental variogram with theoretical models such as exponential model (equation 6) and fractal model (equation 7).

### Automatic calculation of model parameters

Generally in literature, variogram parameters, that are Nugget effect, Range and Sill, are obtained in a qualitative manner. In this study, these parameters are calculated quantitatively by using simple mathematical models. Therefore, the parameters which are presented above, are estimated by theoretical adjustment of variograms defined by equations (6) and (7) with the experimental variogram given by equations (2) to (5).

The methodology used to estimate the models parameters of equations 6 and 7 is based on the interpolation of the theoretical and experimental variograms. The optimal interpolation technique called Krigeage has been used to achieve the expected results. This method is original in that it allows the combination of the least squares method to the method of Krigeage interpolation to achieve two variograms with output tracking automatic modelling parameters.

To obtain the results, many procedures in programming language C++ have been developed. Thus when the model given by equation (6) is selected, the parameters Range «$H_p$» and a Sill «$C$» are deduced. The model given by equation (7) helps to deduce the Slope «$K$» and the exponent «α» and with the value of α the parameter DF is calculated using equation (9).

## Feature Vector

The four parameters previously estimated are arranged by a vector called feature vector. Then every texture will be modelled by a feature vector shown by equation (10).

$$V_{CC}\big|_{Texture}\big|_{Direction} = (V_{c1}, V_{c2}, V_{c3}, V_{c4}) \tag{10}$$

Where $V_{ci}$ is the component of a feature vector in position $i$ deduced from the variogram. In this work for example, the first component is Slope, second is Range, third is Sill and the fourth is Fractal Dimension.

### Algorithm classification

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.

1. Extraction of an image window W entirely enclosed in the class X;
2. Select the direction of calculation of texture parameters;
3. Calculation and representation of the experimental variogram and fitting it with the two functions model by using the least square criterion;
4. 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 (6)) and Slope and Fractal Dimension (deduced on the fractal model (7));
5. Construction of a feature vector $V_{CC}$ with the various parameters previously extracted;
6. For each pixel of the image, do the following instructions:

**a.** Extraction of an image window $F$, with size $W$ and centered on the pixel $i$;

**b.** Do the steps 2 to 4 described above;

**c.** Construction of a feature vector $V_i$ with the various parameters previously extracted;

**d.** Evaluation of the distance between $V_{CC}$ and $V_i$ by the formula given below;

$$d_i = \sqrt{\sum_{k=1}^{4} \left(V_{CC}(k) - V_i(k)\right)^2} \tag{11}$$

If the threshold $T = \frac{d_i}{d_{\max}} \times 100$ 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.

## Experimentation

### Data used

To demonstrate the contribution of the variogram for texture analysis, variography modelling is applied for the characterization of Brodatz natural textures [2]. As an illustration, a structural macro texture namely the texture D94 "wall" and a random micro texture namely the texture D09 "grass" are both represented on the Figure 3 and have been chosen for the experimentations. The choice of textures was conducted by taking into account the distinctive feature of natural textures that are often as directional or random. In addition, the work of [13] was used to select the two textures. These two textures (D09 and D94) are used for testing and the author used the Hurst distance to estimate the fractal dimension. His work is therefore emerged as a basis for validation of the results obtained in this study.

## Experimental Results

The experimental variograms of textures D09 and D94 with the adjusted regression model (6) are respectively illustrated on the Figure 4 and 5, in the direction East-West (angle 0°). Parameters Sill and Range correspond to positive constants $C$ and $H_p$ of model (6). They are obtained when the experimental and the theoretical variogram coincides than in the steady growth and when there is coincidence of abrupt change during the experimental and the theoretical variogram. The projection from the point of abrupt change on the horizontal axis indicates the Range in number of pixels and illustrated by the parameter "$H_p$" of model (6). Locating the point of abrupt change and its coincidence with the Sill of the theoretical model allows by projection on the y-axis to deduce the value of Sill which is also illustrated by the parameter "$C$" of model (6).

The characteristics of the experimental variograms and fractal model tend to be linear at the origin; we operate for estimating the fractal dimension "DF". For this, an interpolation of the experimental variogram of textures D09 and D94 with the fractal model (equation 7) to estimate the Slope and the exponent of "α" on the basis of which the DF is deduced from the relation (7). Figure 6 and 7 illustrate this case.

To validate this approach for estimating the DF, results are compared with those obtained by DG Papi (2004) [13] or DF is estimated on the basis of the Hurst exponent in the single East-West direction. For texture D09 "grass", he gets the DF equal to 2.6571 and

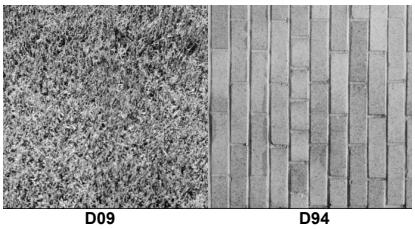



**Figure 3:** Image of natural textures of size 512 x 512 pixels: D09 "grass" and D94 "wall".

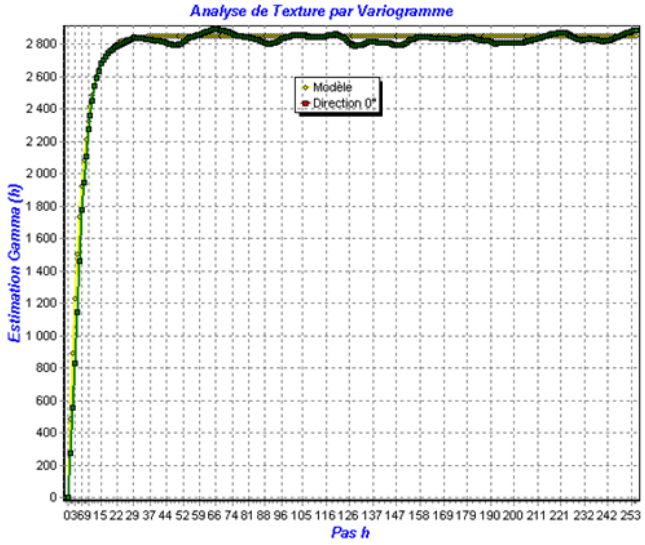



**Figure 4:** Interpolation between experimental variogram and exponential model for the texture D09.

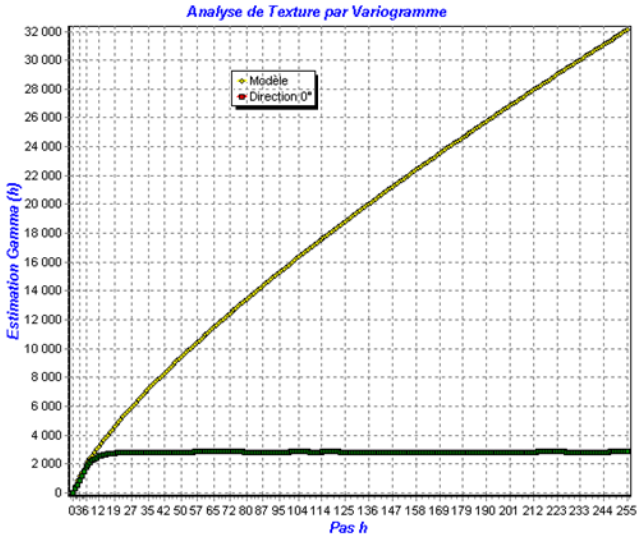



**Figure 5:** Interpolation between experimental variogram and fractal model for the texture D09.

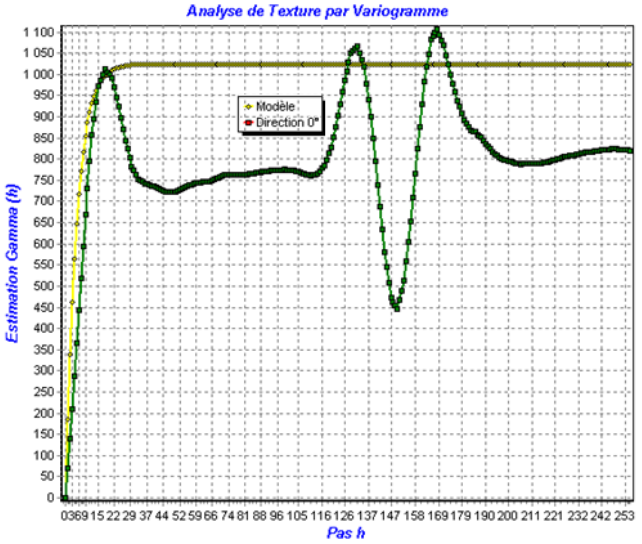



**Figure 6:** Interpolation between experimental variogram and exponential model for the texture D94.

DF equal to 2.7039 for the texture D94 "wall". With our approach, we find for the texture D09, DF equal to 2.6544 and DF equal to 2.7025 for the texture D94. Results obtained here by authors are therefore identical to the nearest hundredth. Besides these two textures, the approach has been experimented on several other textures and conclusions are identical. The results show that it is possible to model the texture by a characteristic directional vector.

Characterizing parameters for the two textures D09 and D94 obtained by this method are conciliated on the Table 1. As an illustration, texture D09 will be identified for example by the feature vector:

$$V_{CC|D09}\,|_{0^\circ} = (500; 16; 2850; 2,6544) \qquad (12)$$

## Application

### Satellite data used

This approach has been experimented on an ERS-2 SAR image (Figure 8) of the Atlantic coast of Cameroon, registered in band C (5.66 cm of wave length) and in VV (vertical-transmit, vertical-receive) polarization with a resolution of 12.5m. The SAR image with the size of 3778 columns and 8165 lines was taken on October, 1994. This data was received in the Libreville's (Gabon) station of the European Space Agency (ESA).

### Characterization of the training zones

Numerically, the various training zones A, B and C illustrated from the original image are respectively characterized by the following feature vectors: VA= (2; 347.44; 268; 2.87), VB= (5; 405.91; 151.13; 2.69) and VC= (24; 2096.37; 227.21; 2.66). These training zones A, B and C were chosen because well known on the study site [14].

## Result of the Classification

The result of the classification is illustrated on the Figure 9. These result highlights three main classes of information of the coastal strip: the Atlantic Ocean (dark blue), the emerged part (brown) and flooded areas and /or rivers (sky blue).

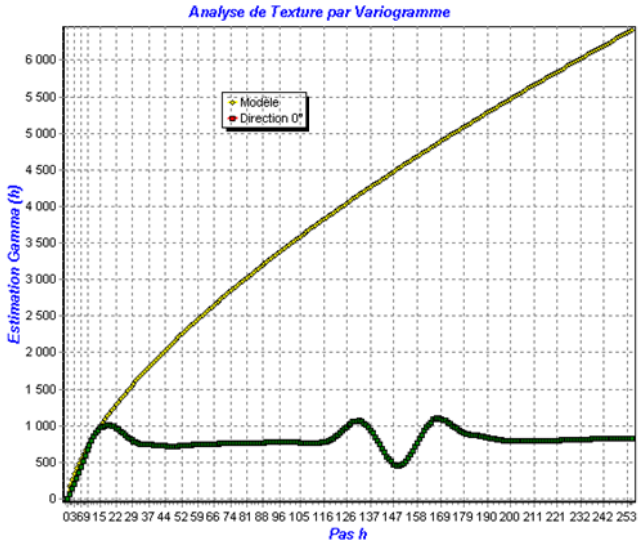



**Figure 7:** Interpolation between experimental variogram and fractal model for the texture D94.

**Table 1:** Summary result of the two textures D09 and D94 following all directions.

| | Direction | Slope | Range | Sill | DF |
|---|---|---|---|---|---|
| **Texture D09 « Grass »** | 0° | 500 | 16 | 2850 | 2,6544 |
| | 45° | 750 | 7 | 2865 | 2,5668 |
| | 90° | 650 | 8 | 2900 | 2,5668 |
| | 135° | 775 | 7 | 2950 | 2,5788 |
| **Texture D94 « Wall »** | 0° | 170 | 15 | 1025 | 2,7025 |
| | 45° | 200 | 16 | 1085 | 2,6769 |
| | 90° | 150 | 6 | 700 | 2,6777 |
| | 135° | 230 | 16 | 1100 | 2,6977 |

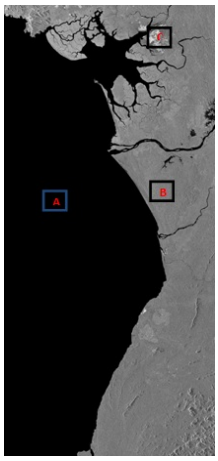



**Figure 8:** SAR Image and training zones.

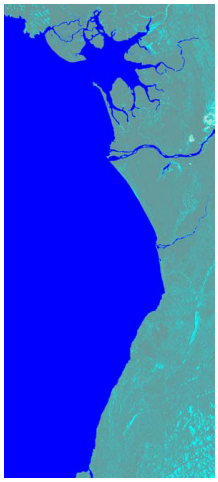


**Figure 9:** Result of the classification using texture analysis by variogram.

## Discussion of the Classification

The method of characterization of natural textures described here shows that, it is possible to use quantitatively the structural approach by using variogram for the textures analysis. The importance of the texture analysis is largely known today for the processing of digital images obtained by the satellites. But several works have been done using statistic approaches and very small works using structural approaches by variogram analysis. In addition, the method saves memory space while significantly reducing the processing time and the calculation of texture parameters. The proof here is the processing of an image of big size of all the Atlantic Coast of Cameroon.

By comparing the results obtained here with the results obtained by the approach under the statistical methods of texture analysis and based on the same classification procedure, the approach tested in this paper provides further details on the spatial occupation of the different classes of information. Readers interested in this comparative study can read the article [14].

The results obtained here are in concordance with other studies on the same site by other researchers [15,16] and using other methods

of classification. Also, the calculation of the classification accuracy using the Kappa coefficient shows that the average precision of the approach proposed here is around 94% whereas with the statistical approach the average accuracy is around 90%. The tests were made by varying several window sizes of the images with a sample of 500 points for each window size chosen.

## Conclusion

The aim of this study was to propose a modelling method of image texture by means of the geostatistical approach. To do so, a model of texture characterization has been proposed. This model is based on variographical analysis and on the proprieties of the variograms using the exponential and power (fractal) functions. Besides the classical parameters (nugget effect, sill and range), others parameters have been associate such as Slope and Fractal Dimension (FD). A texture is then characterized by a feature vector which has four components named Slope, Range, Sill and FD. To estimate these parameters, the new approach based on the interpolation with experimental variogram and appropriate functions is proposed. The approach used to calculate the parameters of texture helps us to board quantitative analysis with variogram.

The method has been applied to classify a large area SAR image. The supervised classification was used. In the future of this work, the method will be applied to process multisource data and these in view to make cartography of precision using satellite images.

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### References

1. Haralick RM, Shanmugan KS (1974) Combined spectral and spatial processing of ERTS imagery data. Remote Sens Environ. 3: 3-13.
2. Brodatz P (1966) Textures: A photographic Album for Artists and Designers Dover Publications, New York, USA.
3. Curran P (1988) The semivariogram in remote sensing: an introduction. Remote Sens Environ. 24: 493-507.
4. Treitz PM, Howarth PJ, Filho OR, Soulis ED (2000) Agricultural crop classification using, SAR tone and texture statistics. Can. J. Remote Sens. 26: 18–29.
5. Wen-Ya C, Couloigner I (2004) Evaluation of incorporating texture into wetland mapping from multispectral images. EARSel eProceedings 3: 363-371.
6. Chica-Olmo M, Abarca-Hernandez F (2000) Computing geostatistical image texture for remotely sensed data classification. Comput. Geosci. 26: 373-383.
7. Cohen WB, Spies TA, Bradshaw A (1990) Semivariograms of digital imagery for analysis of conifer canopy structure. Remote Sens Environ. 34: 167–178.
8. Kourgli A, Belhadj Aissa A (2003) Segmentation texturale des images urbaines par le biais de l'analyse variographique. Teledetection 3: 337–348.
9. HeeYoung Y, Kiwon L, Byung Doo K (2006) Spatial Pattern Analysis of High Resolution Satellite Imagery: Level Index Approach using Variogram. Korean Journal of Remote Sensing, 22: 357-366.
10. Zawadzki J, Cieszewski CJ, Zasada M, Lowe RC (2005) Applying geostatistics for investigations of forest ecosystems using remote sensing imagery. Silva Fennica 39: 599-618.
11. Berberoglu S, Alphan H, Yilmaz KT (2003) A remote sensing approach for detecting agricultural encroachment on the eastern Mediterranean coastal dunes of Turkey. Turk J Agric 27: 135-144.
12. Fotsing J, Tony eE, Talla Tankam N, Rudant JP (2009) Modélisation de la Texture des Images par le Biais de l'Analyse Variographique. SETIT09 5th International Conference Sciences of Electronic, Technologies of Information and Telecommunications March 22-26, 2009-TUNISIA
13. Papi DG (2004) An artificial intelligence application for architectural texture analysis The International Archives of the Photogrammetry. Remote Sensing and Spatial Information Sciences 34: 250-254.
14. Tonye E, Fotsing, J Essimbi Zobo B, Talla Tankam N, Kanaa TFN, Rudant JP (2011) Contribution of Variogram and Feature Vector of Texture for the Classification of Big Size SAR Images Seventh International Conference on Signal-Image Technology and Internet-Based Systems (SITIS) 382 – 389.
15. Tony eE, Akono A, Rudant JP, Dzepa C, Talla Tankam N (2005) Utilisation des signatures de texture d'ordre elev epour une meilleure discrimination des classes d'occupation du sol sur une image radar a synthese d'ouverture, Revue française de photogrammetrie et de Teledetection (RFPT), ISSN 1768-9791, n°179, : 3-17.
16. Akono A, Tony E, Nanci Yossi R (2002) Etude comparative de quatre techniques de multiresolution par ondelettes pour la classification des images radar a synthese d'ouverture. Teledetection. 2 : 267-277.

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