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The Effect of Speckle Filtering On Sar Texture Discrimination

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Abstract. In tropical ecology studies, forest classification is a key issue.Although there is no widely accepted forest classification criterion, it is recognized that texture is an important factor to discriminate forest types and other land cover, particularly when using radar images. Synthetic Aperture Radar (SARA) images, however, are contaminated by a multiplicative noise, known as speckle, wich disturbs the texture identification. Several filters have been proposed to atenuate this kind of noise, but the effect of these filters on texture is not well known. In this paper, textures are modelled by two-dimensional autorregressive (AR-2D) models. These models are estimated for each one of the samples of SAR textures before and after speckle filtering. Eight samples of primary forest and seven samples of non-forest (pasture and agricultural crops) were collect from SAREX data (C-band, HH polarization, 6m resolution, 6 looks) in the Tapajós National Forest (Flona) region in Pará state, Brazil. All these samples were filtered by a 3 x 3 Box filter and a 3 x 3 Frost filter. Euclidean distances were computed between the model coefficient vector of the samples and the average coefficient vector for the two classes (defined here as the class vectors) for the unfiltered and filtered cases separately. For all cases the coefficient vectors formed two separated clusters, corresponding to each one of the classes, in a non-linear mapping of the coefficient space. The conclusions are: AR modelling is an effective method to idendify and discriminate radar texture. The discriminatory power, however, is higher using the unfiltered channels than when the simple Box and the Frost filter are used.

Key words: AR models, SAR texture, speckle filtering

1 Introduction

One of main concerns of using spatial filtering either for reducing noise or enhancing image features is the effect that the filtering operation has on the image texture. It is usually desired to preserve as much image texture as possible, while reducing the deleterious effect that the noise imposes on the visual or automatic remote sensing interpretability.

Texture is an important factor to discriminate land cover using remote sensing imagery, particularly forest types, when using radar images. However there is no widely accepted mathematical definition which comprises all types of texture thar can be found in nature. Traditional texture measures, like concurrence matrix, derived features and structural approaches have failed to give an adequate characterization of texture in Synthetic Aperture Radar (SAR) images because of the strong influence of the speckle noise. Other commonly used features, like the coefficient of variation, although well fitted for the SAR theory, can not gather all the texture information, and is considered a simple roughness measure.

Sant'Anna and Dutra (1995) developed a new method, based on two-dimensional ARMA models (ARMA-2D) that was found to provide a good characterization of a class of random textures. In this paper the effect that speckle noise reduction methods has on SAR image textures is studied. Special attention is given to texture discrimination before and after noise filtering by using this method as a tool for assessment and comparison.

In the following sections a brief review of ARMA models is given, the speckle filters are presented and the results of determining the texture models before and after filtering are also presented and compared.

2 One and Two Dimensional ARMA Models

One dimensional time series is described by a sequence of random variables y_1, y_2,...y_N.These series are modelled as being generated by a sequence of independent shocks w_1, sample values of a white noise process with zero mean and variance σ^2_w, which is the input of a linear filter that characterizes the process, This filter is defined by the equation:

$$y_i = \sum_{k=0}^{q} \alpha_k w_{i-k} + \sum_{j=1}^{p} \beta_j y_{i-j} + \mu \qquad (1)$$

where μ is the expected value of y_i.

This is called an autoregressive-moving average model of order *p* and *q* (ARMA(*p,q*); α_0 is normally set to one. Specialized models are derived from eq. (1); for $q = 0$ an autoregressive model of order *p* (AR(*p*)) is obtained and for $p = 0$ (no regressive terms), a moving average model of order *q* (MA(*q*)) is defined. Note that these models are causal, because the output, given certain initial conditions, depends only on the past values of the random process and on the past shocks.

Preliminary estimation of model parameters are obtained, from existing training data, by examing the plots of the autocorrelation function (ACF) and the partial autocorrelation function (PAF) to help decide the model orders. A non-interative method is used (Box and Jenkins, 1970) to determine a first set of model coefficients which is used as initial guess to an iterative maximum likelihood approach.

An extension to univariate one dimensional ARMA models can be defined to generate two-dimensional random fields (two dimensional ARMA models), by considering proper support regions on the plane. The most used support regions are the so-called non symmetrical half plane support (NSHP) (Dudgeon and Mersereau, 1984) and the quarter plane (QP) support. The estimation of two-dimensional ARMA models, either using NSHP support, also known as unilateral ARMA models (UARMA), or using QP support (QARMA) are not trivial however, being available (Marple, 1987) only the least squares method or the so called Yule-Walker estimated solution for the QAR models (Therrien, 1989).

Trying to overcome the problems found for estimating true two-dimensional models, it is possible to assume that images are two-dimensional separable processes, or an image can be linearized through the concatenation of rows or columns. In these cases unidimensional methods can be readily applied, in spite of the inaccuracies implied by the aforementioned hypothesis. In this paper, SAR images are linearized by the concatenation of stacked portions of image rows. A non-zero coefficient at lag multiple of the size of the row (or column) would correspond to a pixel contiguous to the pixel being generated (Dutra, 1990).

Sant'Anna and Dutra (1995) give a more detailed description of the estimation method used.

3 Speckle Filtering

Several speckle reduction filters have been developed in the literature. See Lee et al (1994) for a compreensive review. The Frost filter, (Frost et al, 1982) which was found in Sant'Anna (1995) to have the best performance among the speckle reduction filters tested, in terms of a specially developed criterion based on resolution preserving behaviour, was used to filter all test sites considered in this experiment.

The Frost filter is an adaptative linear convolutional proposal, derived from the minimization of the mean quadratic error over a multiplicative noise model. Dependence among observations is incorporated through an exponential spatial correlation function. Also for comparison a simple Box (average) filter was employed in the tests. Box filtering was found in Sant'Anna (1995) as one of the best in terms of increasing the signal to noise ratio.

4 Estimation and Classification of Forest Texture Models

To test the methodology eight test sites were selected from Tapajós National Forest (Flona) in Brazilian Amazônia and seven test sites were selected from regrowth areas beside Flona. Tapajós National Forest is a forest reserve under the administration of the Brazilian Institute of the Environment (IBAMA). Its geographic coordinates are: S 02^0 40' to S 04^0 10' and W 54^0 45' to W 55^0 00'. The forest localization is shown in Figure 1. All these test areas were also filtered by a 3 x 3 Frost filter with number of looks equal to 6 and 3 x 3 Box filter, given a total of 45 sample areas with 1000 pixels each. See Figure 2 for a sample image of forest and non-forest and corresponding filtered versions.

The estimations were initially restricted to Univariate Autoregressive (UAR) models that were estimated for all 45 training sites, using the methodology given in the previous section. Figure 3 presents the average models for the forest and non-forest classes for all filtering cases.

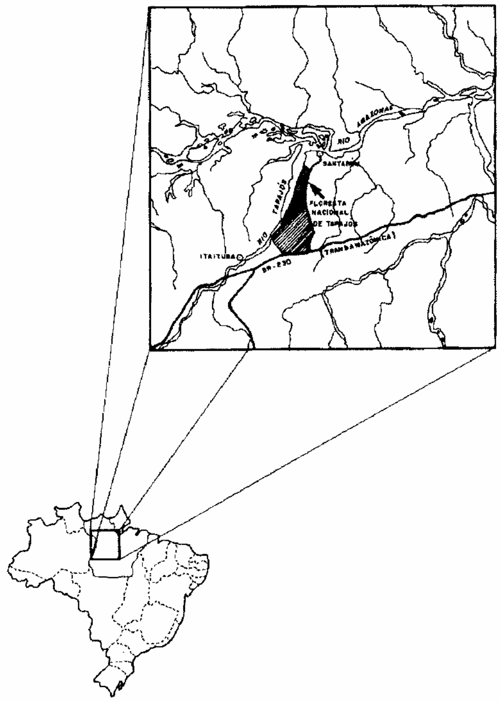

Figure 1: Tapajós National Forest localization.

Figure 4 represents the distances of the model vectors to the two average model vectors for the unfiltered and Box filtered cases. In this graphic "+" represents the primary forest, "x" the non-forest, as estimated from unfiltered channel and "o", forest, and "*", non-forest as estimated from the Box filtered channel. It is noticeable that the separation between the clusters of the vectors for the unfiltered case is perfect in both axis, while the separation for the Box filtered case is not so good. Figure 5 represents the distances of models vectors for the unfiltered and Frost filtered cases. Again a higher separation is noticeable for the unfiltered case. Table 1 presents the average distances between the model vectors and the average model vectors for each filtering case. From this table it is possible to note that, for all filtering cases, the average distances between the class model vectors and the like average models are smaller than the distances between class model vectors and the dissimilar average models. From this fact, and from the examination of Figure 4 and 5 is possible to conclude that the discriminatory power is preserved for these cases, although no information about the modification of discriminatory power is given.

A separation coefficient for the class Ω_i defined by

$$\partial(\Omega_i) = \frac{\min(\text{averagedist. between } \omega_{j,i} \text{ and } \Omega_{k \neq i})}{(\text{averagedist. between } \omega_{j,i} \text{ and } \Omega_i)}$$

is used to evaluate the discriminatory power, where $\omega_{j,i}$ are the model vectors belonging to class Ω_i. Table 2 presents the separation coefficient for each class (forest and non-forest) and the total separation index which is defined by $\Delta = \sum_i \partial(\Omega_i)$ for each filtering case. From the table, one sees that the filtering process degrades the texture definition, which is visually perceived when low pass filtering is applied. The effect of the filters, however are diverse: the Frost filter has a better performance when filtering high roughness texture (forest), problably because, being adaptative, its effect is more pronounced in relatively plane regions. As the Box filter is fixed, rougher regions will be more affected because of the larger amount of high frequencies damped.

From/To	Class	Forest	Non-Forest
Original	Forest	143.1	415.3
	Non-Forest	385.4	169.0
Box	Forest	376.1	640.2
	Non-Forest	684.3	275.0
Frost	Forest	213.5	733.3
	Non-Forest	594.3	521.4

Table 1: Average distance ($x10^{-3}$) between the model vectors.

Image	Unfiltered	Box	Frost
Forest	2.69	1.82	2.78
Non-forest	2.46	2.33	1.41
Total	5.15	4.15	4.19

Table 2: Separation index for each class.

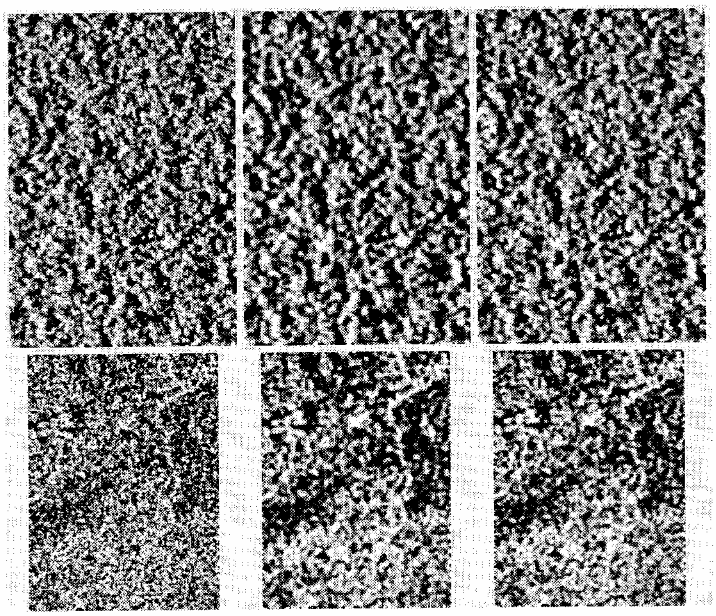

Figure 2: Texture samples of Forest (top) and Non-Forest (bottom), from left to right: Original, Box filtered and Frost filtered

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5 Conclusions and Future Work

An experience was done to assess the effect of filtering on SARA texture. A separation index was defined to measure the discriminatory power of each filtering case.

Two main conclusions can be drawn from the presented results:

- ARMA modelling is shown to be a potencially good tool for characterizing and discriminating SAR textures.
- Linear and non-linear low pass filtering process can degrade the texture definition and discriminatory power.

(a)

–	–	•	0.488	-0.107
0.108	0.526	0.137	-0.180	0.044
-0.146	-0.160	0.141	-0.023	

(b)

			•	0.393	-0.107	0.011
	0.012	0.507	-0.043		–	
-0.018	-0.097		–	–		–

(c)

	–	–	–	•	0.593	-0.080	-0.060	0.021
-0.011	0.095	0.102	0.455	0.657	-0.667	0.136	0.090	-0.047
-0.016	-0.112	-0.083	-0.330	0.031	0.202	-0.079	-0.036	0.018
0.036			–		–		–	–

(d)

				•	0.463	-0.010	-0.023	0.016
	0.018	0.160	0.548	0.319	-0.332	0.014	0.028	-0.026
-0.012	-0.082	-0.128	-0.262	0.126	0.020		–	0.010
0.014	–	–	–		–		–	

(e)

–	–	•	0.573	-0.147
0.169	0.474	0.411	-0.442	0.156
-0.152	-0.272	0.138	0.050	-0.055

(f)

–	–		–	•	0.547	-0.198	0.026		-0.036
0.034	-0.045	0.058	0.168	0.302	-0.238	0.092	-0.023	-0.012	–
	–	-0.040	-0.034	0.232	-0.155	0.044	0.018	0.010	0.014

Figure 3: Average UAR models for (a) Forest, (b) Non-Forest, (c) Box filter (Forest), (d) Box filter (Non-Forest), (e) Frost filter (Forest) and (f) Frost filter (Non-Forest).

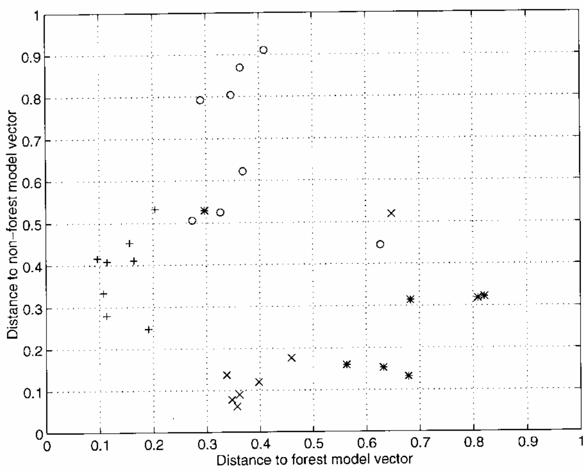

Figure 4: Distances between the model vectors and average model vectors from Box filter.

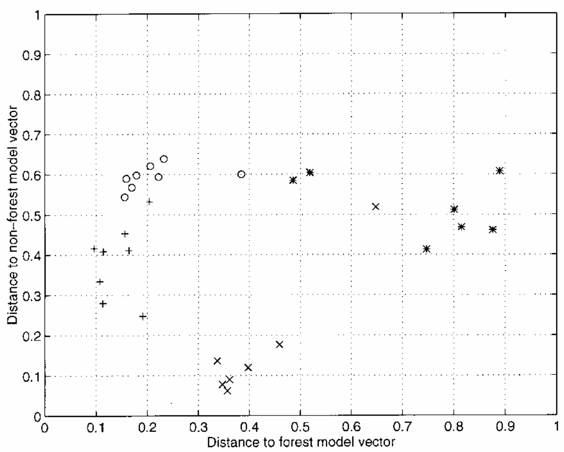

Figure 5: Distances between the model vectors and average model vectors from Frost filter.

Future work will be focused on testing other SAR textures and types of models for modelling and discrimination. Separable ARMA estimation will be used to asssess its performance was a texture descriptor and its discriminatory properties. Also ARMA modelling provides a good theorectical framework to develop statistical texture descriptors.

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7 References

Box, G.E.P.; G.M. Jenkins *Times series analysis: forecasting and control.* Holden Day, San Francisco, 1970.

Dudgeon, D.E.; R.M. Mersereau Multidimensional digital signal processing. Englewood Cliffs, NJ, Prentice Hall, 1984.

Dutra, L.V. Classificação de texturas usando modelos ARMA e distâncias da função de autocorrelação. (Tese de Doutorado em Computação Aplicada) - INPE, São José dos Campos, SP, Brazil, 1990.

Frost, V.S.; Stiles, J.A.; Shanmugan, K.S.; Holtzman, J.C. A Model for Radar Images and its Application to Adaptive Digital Filtering of Multiplicative Noise. IEEE Transactions on Patern Analysis and Machine Intelligence, v.4, n.4, pp. 157-166, Mar. 1982.

Lee, J.S., Jurkevich, I.; Dewaele, P.; Wambacq, P.; Oosterlinck, A. Speckle Filtering of Synthetic Aperture Images: A Review. Remote Sensing Reviews., v.8, pp.313-340, 1994.

Marple, S.L. Digital spectral analysis. Englewood Cliffs, NJ, Prentice Hall, 1987.

Sant'Anna, S.J.S. Avaliação do Desempenho dos Filtros redutores de "speckle" em Imagens de Radar de Abertura Sintética. (Dissertação de Mestrado) - INPE, São José dos Campos, SP, Brazil, 1995.

Sant'Anna, S.J.S.; Dutra, L.V. Sar Texture Discrimination Using AR-2D Models for Amazonian Land Use Classification In: Simpósio de Especialistas Latinoamericanos em Percepcion Remota, (SELPER) VII, Puerto Valarta, México, October 1995. Memorias, pp. 516-523.

Therrien, C.W. Decision estimation and classification: an introduction to pattern recognition and related topics. Jonh Wiley and Sons, 1989.