Analyse Radiométrique Multirésolution et son Application au Filtrage du Chatoiement

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Abstract — A new concept, radiometric multiresolution analysis (RMA) is proposed by applying multiresolution analysis to statistical mechanics. A measure issued from RMA decomposition is taken as a measure of homogeneity for speckled signal. This measure is speckle-model free. Some results of speckle filter for both synthetically generated image and SAR image by the RMA are shown.

1. INTRODUCTION

In radar image analysis, it is necessary to reduce multiplicative correlated noise, also called speckle noise. Two global types of speckle analysis have been developed: statistical analysis and wavelet-based space-frequency analysis. The former has been developed for more than 20 years, and the latter was proposed in the 1990's.

Speckle in a single image is generally treated as a multiplicative process[1]: I= σ n where I is the intensity of the image, σ the reflectivity and n the speckle contribution. In homogeneous areas (where the reflectivity σ is constant) the observed intensity I obeys a Gamma distribution.

The use of wavelets to filter images with additive noise is well documented in the literature. Wavelet transform is directly applied to speckled Radar images in some methods [2][3]. It is shown that the wavelet coefficients are modulated by the multiplicative character of the speckle, and that they are also sensitive to a local linear transformation of data.

We know that the wavelet analysis is a linear transform and techniques of singularity detection and de-noising based on wavelet transform are developed for additive noise. However, speckle is not additive noise. An easy way to turn a multiplicative process into an additive one is to apply a logarithmic transformation[4]. In this case, a bias is introduced in the estimation.

Some experiments[5] have reported that the results of the wavelet-based speckle filters are not better than those of traditional statistical speckle filters.

Most adaptive statistical filters, such as Kuan[6], Wu-Kuan[7] and EPOS[8] speckle filters, take the local normalized variance as a measure of the speckle level. However, this criterion is very sensitive to the spatial arrangement of neighboring pixels. It is hard to find a threshold between the measure of speckle variance and the variance caused by edges. In addition, this measure is estimated under a speckle model (a Gamma distribution), but the probability density function (PDF) of speckle may noticeably differ from it[9].

Therefore we propose a model-free, more robust method to analyze speckle and explore a new way for speckle filtering.

2. RADIOMETRIC MULTIRESOLUTION ANALYSIS (RMA)

2.1 Concept of the RMA

We propose to apply wavelet-based multiresolution analysis to local statistics of data instead to data itself. The reason for wavelet-based multiresolution statistical analysis derives from the fact that the probability distribution of Radar images has, like wavelets kernels, the property to be invariant under expansion (ref.: Fig.1a). Another important fact is that in a heterogeneous zone a combination of probability distributions exists. Within an analysis window, including m different zones, the PDF $p_{r(n)}(R)$ of the signal r(n) in the window behaves like the linear combination of every PDF in these zones, that is: $p_{r(n)}(R) = \sum_m c_m p_{r(n)}(R)$ where c_m are the ratio of the area m to the analysis window area. These distributions may well be detected and separated using multiscale analysis.

We define RMA as the wavelet transform of the local probability density $p_{r(n)}(R)$ of the signal r(n). The components of the function $p_{r(n)}(R)$ on the wavelet basis functions are described by

$$D_a p(b) = \left\langle p_{r(n)}(R), \psi_{a,b}(R) \right\rangle \tag{1}$$

where < , > is the inner product defined in the space of measurable, square integrable functions $p_{r(n)}(R)$, a>0 is the scale parameter, $r \in \Re$ is the translation parameter, ψ is a fixed function called the "mother wavelet", which is well localized in space and scale and has a compact support and $\psi_{a,b}(n) = a^{-1}\psi\left(\frac{n-b}{a}\right)$. Equation (1) can also be interpreted as a process of correlation with radiometry R as variable of integration, which is why we call it radiometric multiresolution analysis. Comparatively, conventional wavelet transform $c_{a,b} = \langle r(n), \psi_{a,b}(n)\rangle$ with space n as variable of integration is a spatial multiresolution analysis.

Mallat proposes[10] a multiresolution signal decomposition based on an orthogonal wavelet representation, which is particularly powerful to analyze the information content of signals. Mallat's approach is taken as the underlying core of our research on the RMA.

In RMA, the approximation of the probability density function $p_{r(n)}(R)$ at the resolution a, is thus denoted by $A_a p(b) = \langle p_{r(n)}(R), \phi_{a,b}(R)\rangle$ where ϕ is a scaling function and $\phi_{a,b}(n) = a^{-1}\phi\left(\frac{n-b}{a}\right)$.

2.1 Algorithm to estimate the RMA

We define RMA as the wavelet transform of the local probability density as estimated using local normalized histogram. We present now an efficient algorithm to estimate the RMA directly from image data.

Assuming that the time average of a set member, over the infinite past and future is equal to the set average, which can be written as:

$$\int_{-\infty}^{\infty} R p_{r(n)}(R)dR = \lim_{N\to\infty}\frac{1}{2N}\int_{-N}^{N} r(n)dn \qquad (2)$$

We can expand (2) into a more general form by considering an arbitrary function of r(n), $\psi[r(n)]$, instead of r(n) itself, which gives:

$$\int_{-\infty}^{\infty} \psi(R) p_{r(n)}(R)dR = \lim_{N\to\infty}\frac{1}{2N}\int_{-N}^{N} \psi[r(n)]dn \qquad (3)$$

and in the case of finite pixels in an analysis window, the right hand side of (3) can be approximated by

$$\lim_{N\to\infty}\frac{1}{2N}\int_{-N}^{N} \psi[r(n)]dn \approx \frac{1}{N}\sum_{n=1}^{N}\psi[r(n)] \qquad (4)$$

Since equation (1) can be rewritten as:

$$D_a p(b) = \int_{-\infty}^{\infty} \psi_{a,b}(R) p_{r(n)}(R)dR \qquad (5)$$

replacing (3) with (4) and (5), an estimate of the wavelet decomposition on scale a of the PDF can be found directly from the image r(n):

$$D_a p(b) = \lim_{N\to\infty}\frac{1}{2N}\int_{-N}^{N} \psi[r(n)]dn \approx \frac{1}{N}\sum_{n=1}^{N}\psi_{a,b}[r(n)] \qquad (6)$$

For the same reason, the estimate of the PDF approximation on scale a is given by

$$A_a p(b) = \lim_{N\to\infty}\frac{1}{2N}\int_{-N}^{N} \phi[r(n)]dn \approx \frac{1}{N}\sum_{n=1}^{N}\phi_{a,b}[r(n)] \qquad (7)$$

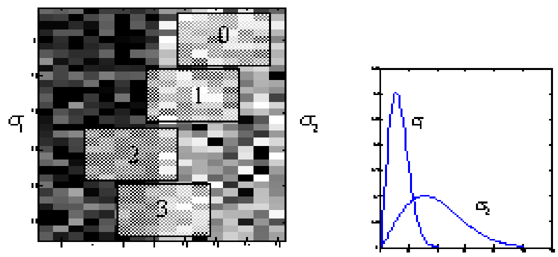
Now we may define exactly the radiometric multiresolution analysis (RMA) by radiometric wavelet decomposition (6) and the PDF approximation (7) of a random signal r(n).

3. RMA For Speckle Filter

3.1 Measurement of homogeneity

It is well known that an important speckle reduction can be obtained if a homogeneous zone around the pixel to be filtered is considered as an analysis window for the estimation. Generally, local relative standard deviation is taken as a measure of homogeneity [6,7,8]. However, local relative standard deviation is rather random, exactly, the probability density function of squared that approximates the chi-squared function.

Based on the RMA, properties at larger scales and relationship between those at different scales are taken as a measure of homogeneity. Let us consider a speckled image (Fig.1a) with a vertical edge in the middle, the left half part has lower mean reflectivity σ_1 and the right half part has higher mean reflectivity σ_2. The ideal PDFs of the two parts should be as shown in Fig.1b. We take a scanning window with size of 7×7 pixels.



(a) (b)

FIG. 1: (a) A speckled image with a vertical edge in the middle (scanning widow 7×7); (b) The ideal PDFs of the two homogeneous areas.

Hypotheses: In a scanning window,

Case 0: homogeneous signal (as at position 0 of Fig.1a).

Case 1: a small number of pixels belongs to the area with lower reflectivity (as at position 1).

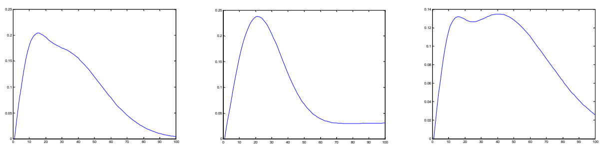
Case 2: a small number of pixels belongs to the area with higher reflectivity (as at position 2).

Case 3: a boundary between the two stationary areas (as at position 3). ■

Case 1 or Case 2 are equivalent to a line crossing a homogeneous area. The ideal PDFs corresponding to the case 1, 2 and 3 should be as in Fig.2.

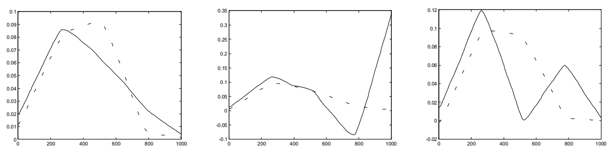
Practically, the PDF curves will probably not be exposed to such a noisy signal in so small analysis windows as in Figure 1(a). Using second-order Coiflet function, we present an approximation of PDF on scale 2^{-2} in Fig.3 where the ideal PDF curves do not appear clearly. However, an important fact is exposed: higher-order statistics should be used to measure the homogeneity. Exactly, a lower skewness (associated with third-order moment) and a higher kurtosis (associated with fourth-order moment) of PDF in Fig.3 means a higher homogeneity, whereas relative standard deviation using only second-order statistics to a non-Gaussian signal is insufficient to be a measure of the homogeneity. Especially, for Case 1, it is difficult to tell homogeneous signal from heterogeneous one by relative standard deviation, while the skewness is very different (ref.: Fig.3a) in this case.

Note that, in another hand, an estimate of a higher-order statistics with a small number of samples has a high variance [11]. The usefulness on the proposed method is better demonstrated when looking at the wavelet coefficients computed by (6). Figure 4 present the wavelet decomposition of the RMA on scales 1, 2^{-1} and 2^{-2} corresponding to case 1, 2 and 3 compared with those of a homogeneous signal Case 0.



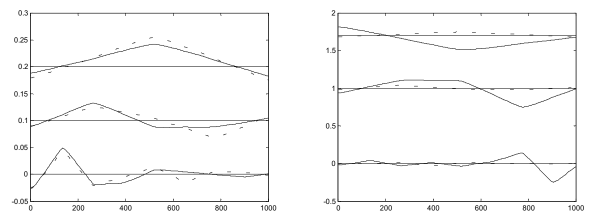
(a) (b) (c)

FIG. 2: The ideal PDFs corresponding to (a) Case 1, (b) Case 2 and (c) Case 3 of Figure 1(a)

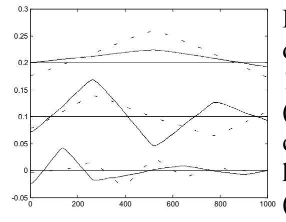


(a) (b) (c)

FIG 3: Approximation of PDF by the RMA on scale 2^{-2} for (a) Case 1, (b) Case 2 and (c) Case 3 compared with that for homogeneous signal (dash line) with scanning window 7×7



(a) (b)



(c)

FIG.4: The RMA decomposition on scale $1, 2^{-1}$ and 2^{-2} for (a) Case 1, (b) Case 2 and (c) Case 3 compared with those for homogeneous signal (shown by dash line) with scanning window 7×7

[12], [13] give us some principles to detect singularity and characterize signal based on multiresolution representation computed using dyadic orthogonal wavelets. Accordingly, the local extrema and the zero-crossings of the RMA composition can well characterize the high-order statistics of the PDF behind in the signal samples. Accordingly, following are some important properties of heterogeneity on radiometric wavelet transform, where the translation parameter r is normalized by 400 over the local mean-reflectivity.

[HP1] The maximum of D_1p in the middle range $H_1=Max[D_1p(300:600)]$ is lower.

[HP2] The number of zero-crossings between 200 and 600 will be more than 1: $H_2=Num[D2\text{-}1(200:600)=0]<1$.

[HP3] If $H_2=1$, then $H_4=Arg[D_1p(500:1000)=0]-Arg[D_1p(0:500)=0]$ is larger.

For Case 2 and 3,[HP1] and [HP2] or [HP3] are evident, but they are not for Case 1. The following properties expose well the skewness especially for Case 1.

[HP4.1] $H_{41}=\left|Max[D_{2^{-1}}p]-Min[D_{2^{-1}}p]\right|$ is larger.

[HP4.2] $H_{42}=\left|ArgMax[D_1p]-ArgZero[D_{2^{-1}}p]\right|$ is larger.

[HP4.3] $H_{43}=\left|\begin{matrix}ArgMax[D_{2^{-1}}p]+ArgMin[D_{2^{-1}}p]- \\ -2ArgZero[D_{2^{-1}}p]\end{matrix}\right|$ is larger.

We take [HP2] and $\alpha=\dfrac{H_3H_{42}}{H_1}<260$ as the measure of homogeneity in our implementation.

This measurement is speckle-model free.

3.2 The RMA in EPOS speckle filter

In [8], an efficient statistical filter of speckle called EPOS algorithm is proposed. The process of the algorithm contains the following steps.

Step 1: Estimation of the relative standard deviation from the image.

Step 2: Calculation of the relative standard deviation for all degrees of freedom from the chi-squared distribution.

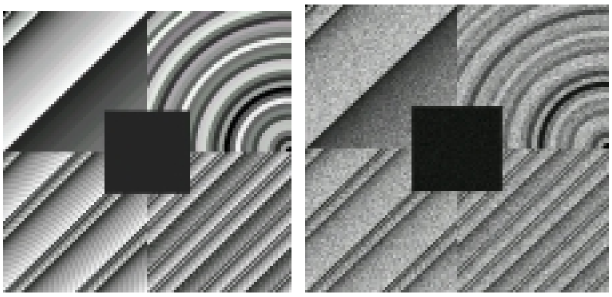
Step 3: Searching for the largest homogeneous area around each pixel.

Step4: The area found is used for calculating the new gray-value by averaging.

Now we apply the RMA to EPOS filter. Step 1 above is omitted and, in Step 2, the criteria of homogeneity described in section 3.1 are taken as the measure of homogeneity instead of relative standard deviation.

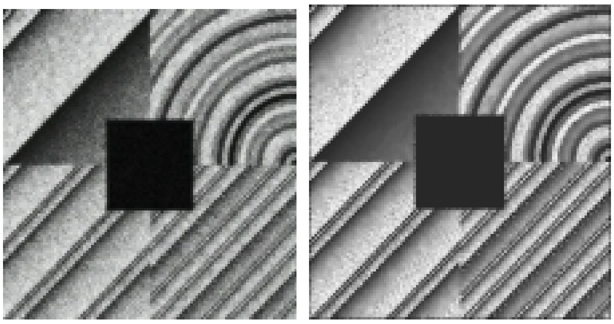
Fig.5 shows a synthetically generated image without and with multiplicative Rayleigh noise added. The results of the filtering are shown in Fig.6 for the Kuan filter [6] on the left and for the RMA-EPOS filter on the right side. With the RMA-EPOS filter the texture in the image is better restored and the speckle within the homogeneous areas is higher reduced.

Fig.7 shows an original SAR image from the ERS-1 satellite and filtered result. The legibility of the image is considerably improved, mainly in the textured parts in the filtered image.



(a) (b)

FIG 5: Synthetically generated image (a) without and (b) with Rayleigh speckle



(a) (b)

FIG 6: Filtered image with (a) Kuan and (b) RMA-EPOS filter

4. RMA FOR SPECKLE FILTER

A new type of speckle analysis, radiometric multiresolution analysis (RMA), is proposed and the potential of using it for speckle filter is shown.

REFERENCES

[1] H. Maître ed., Le traitement des Images de radar RSO, Hermès, Paris, 2001

[2] A. Bijaoui, Y. Nonichon, Y. Fang, "Méthodes multiéchelles appliquées au filtarge des images SAR", Quinzième Colloque Gretsi-Juan-les-Pins, pp.475-478, 1995

[3] M. Simard, G. DeGrandi, K. P. B. Thomson, et al., "Analysis of speckle noise contribution on wavelet decomposition of SAR images", IEEE Trans on Geoscience and Remote Sensing, 36(6), pp.1953-1962, 1998

[4] H. Guo, J. E. Odegard, M. Lang, et al., "Wavelet based speckle reduction with applications to SAR based ard/r", IEEE Proc. ICIP, pp.75-79, 1994

[5] E. Hervet, R. Fjortoft, P. Marthon and A. Lopes, "Comparison of wavelet-based and statistical speckle filters", European Symposium on Remote Sending, SAR Image Analysis, Modelling, and Techniques, Proc conference, pp.21~25, 1998

[6] D. T. Kuan, A. A. Sawchuk, T. C. Strand and P. Chavel, "Adaptive noise smoothing filter for images with singnal-dependent noise", IEEE Trans. Patt. Anal. Machine Intell. 7(2), pp.165-177, 1985

[7] Y. Wu and H. Maître, "Smoothing speckled synthetic aperture radar images by using maximum homogeneous region filters", Optical Engineering 31(8), pp.1785-1792, 1992

[8] W. Hagg and M. Sties, "Efficient speckle filtering of SAR images", Proc. of IEEE Inter. Geoscience and Remote Sensing Symposium (IGARSS'94), Pasadena, California, S.2140, 1994

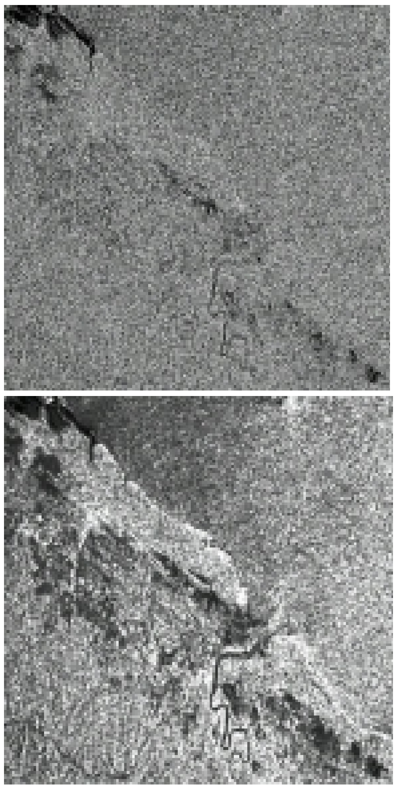
[9] J. Bruniquel and A. Lopès, "On the true multilook intensity distribution in sar imagery," Proc. Inter, Geoscience and Remote Sensing Symposium (IGARSS'98), Seattle, Washington, 1998

[10] S. Mallat, "A theory for multi-resolution signal decomposition: The wavelet representation," IEEE Trans. Pattern Anal, Machine Intell., vol.11, pp.674-683, July 1989

[11] B. Friedlander and B. Porat, "Asymptotically optimal estimation of MA and ARMA parameters of non-Gaussian processes from high-order moments," IEEE Trans. Automat. Contri., Vol.35, pp.27-35, 1990

[12] S. Mallat, et al., "Sigularity detection and processing with wavelets," IEEE Trans. vol. IT-38(2), pp.617-643, 1992

[13] S. Mallat, et al., "Characterization of signals from multiscale edges," IEEE Trans. Vol.PAMI-14(7), pp.710-732, 1992



(a)

(b)

FIG 7: SAR image from the ERS-1 (a) original and (b) RMA-EPOS filtered