Adaptive Speckle Filters and Scene Heterogeneity

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Abstract—**The presence of speckle in radar images makes the radiometric and textural aspects less efficient for class discrimination. Many adaptive filters have been developed for speckle reduction. In this paper, the most well-known filters are analyzed. It is shown that they are based on a test related to the local coefficient of variation of the observed image, which describes the scene heterogeneity. Some practical criteria are then introduced to modify the filters in order to make them more efficient. The filters are tested on a simulated SAR image and a SAR-580 image. As was expected, the new filters perform better, i.e., they average the homogeneous areas better and preserve texture information, edges, linear features, and point target responses better at the same time. Moreover, they can be adapted to features other than the coefficient of variation to reduce the speckle and at the same time preserve the corresponding information.**

I. Introduction

An extended area can be characterized by the radar backscattering coefficient $\sigma°$ and by its intrinsic spatial variability (called texture). Both the radiometric and textural aspects are less efficient for area discrimination in the presence of speckle. Reducing the speckle would improve the discrimination among different land use types, and would make the usual per-pixel or textural classifiers more efficient in radar images. This supposes that the filters reduce speckle without loss of information.

In the case of homogeneous areas (agricultural areas, for example), the filters should preserve the backscattering coefficient value (the radiometric information) and edges between the different areas. For textured areas (forest, for example), the filters should preserve, in addition, the spatial variability (textural information).

Adaptive filters seem to be suitable for preserving radiometric and textural information. Many adaptive filters have been developed for speckle reduction. The most often used are the Frost *et al.*, Lee, and Kuan *et al.* filters [1]-[3]. These filters are analyzed theoretically in Section II. It is shown that they all originate from simplified theoretical studies and are based on a test related to the local image coefficient of variation which measures the scene heterogeneity. Some practical criteria are then introduced in the test to let the filter be more efficient for both speckle smoothing and texture preservation (Section III). Finally, the filters are tested on a real and a simulated SAR image (Section IV).

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II. Analysis of Adaptive Speckle Filtering

A. Frost et al. Filter

A simplified model for the recorded image is used:

$$I(t) = [R(t) \cdot u(t)] * h(t) \quad (1)$$

where $t = (x, y)$ is the spatial coordinate, $R(t)$ is a stationary random process which describes the terrain reflectivity at each point within a homogeneous area, $u(t)$ is the multiplicative noise due to the fading and modeled by a real stationary white non-Gaussian random process with a χ^2 probability density function, and $h(t)$ is the system impulse response. In order to estimate the reflectivity $R(t)$ in the ideal image, an MMSE filter (Minimum Mean Square Error), under the assumption of stationary image data, is applied. The system transfer function $H(f)$ is also assumed to be constant over some finite bandwidth. This leads to the uncorrelated multiplicative speckle model:

$$I(t) = R(t) \cdot u(t) \quad (2)$$

where $u(t)$ is a pseudowhite noise (with a χ^2 probability density function) used by many authors [2], [4]. In addition, it is assumed that the scene reflectivity R is an autoregressive process with an autocorrelation function $R_R(\tau) = \sigma_R^2 \exp(-a|\tau|) + \overline{R}^2$, where $\overline{R}$ is the signal local mean, σ_R^2 is its local variance, and "a" is the autocorrelation parameter. The three parameters have different values for different terrain categories. This model is not necessarily the suitable model for the different textured scenes, and so other models should also be used. Under these assumptions, the MMSE filter impulse response $m(t)$ is given by

$$m(t) = K_2 \alpha \exp(-\alpha|t|) \quad (3)$$

where $\alpha^2 = a^2 + 2a \cdot (\overline{u}/\sigma_u)^2/(1 + (\overline{R}/\sigma_R)^2)$, and K_2 is a normalizing constant. This variable should be given as a function of the observed local statistics. After many simplifications which lead to the loss of the "a" parameter, the simple expression $\alpha^2 = K \cdot C_I^2$ is used, where $C_I = \sigma_I/\overline{I}$ is the observed coefficient of variation. Hence the Frost *et al.* filter is given by the following adaptive impulse response:

$$m(t) = K_1 \exp[-K C_I^2(t_o)|t|] \quad (4)$$

where K is the filter parameter, $C_I(t_o)$ is computed over a uniform moving window centered at t_o, and K_1 is a normalizing constant which includes the "α" parameter and allows preservation of the mean signal absolute level.

B. Kuan et al. Filter

First of all, a filter for additive noise is developed. The observed image brightness I (which can represent intensity as well as amplitude image) is given as a function of the ideal image $R(t)$ and a zero mean uncorrelated noise by: $I(t) = R(t) + N(t)$. A nonstationary mean, nonstationary variance image model is assumed. The image covariance matrix can then be considered diagonal. Given the observation $I(t)$, the original signal $R(t)$ is estimated so that the mean square error is minimum. In addition, a linear constraint on the estimator structure is imposed. The linear MMSE filter estimate is then given by $\hat{R}(t) = \bar{I}(t) + [I(t) - \bar{I}(t)]\,[\sigma_R^2(t)/(\sigma_R^2(t) + \sigma_N^2(t))]$. In the case where the signal is independent of noise, the local statistics of the ideal image can be replaced as a function of the observed local statistics. This leads to the same linear filter as the Lee additive noise filter [2].

The multiplicative noise model for radar image is then considered from which the linear filter (for uncorrelated speckle) is deduced. It can be written in the following form as a weighted sum of the observed and mean values:

$$\hat{R}(t) = I(t) \cdot W(t) + \bar{I}(t) \cdot (1 - W(t)) \tag{5}$$

where the weighting function W is given by

$$W(t) = [1 - C_u^2/C_I^2(t)]/[1 + C_u^2] \tag{6}$$

and where $C_u = \sigma_u/\bar{u}$ is the noise variation coefficient.

C. Lee Filter

Lee adapted the additive noise algorithm filter to the multiplicative noise by introducing, in addition, a linear approximation to transform (2) to the sum of the signal and an additive noise independent of the signal. The Lee filter can be described by (5) with,

$$W(t) = 1 - C_u^2/C_I^2(t). \tag{7}$$

D. Homomorphic Filters

Arsenault *et al.* [5] and Yan and Chen [6] also assumed the multiplicative speckle model. A logarithmic transformation is performed before filtering to make the noise additive with a mean value equal to zero. The Lee additive noise filter is applied on the logarithm of the observed image. Contrary to Arsenault *et al.*, who estimated all the local statistics on the logarithm of the observed image, Yan and Chen used directly the observed image to compute the local statistics. In addition, the original image R pdf is assumed to be a Gaussian pdf approximated by a bounded triangular distribution.

E. Conclusion

From this brief study, the following points can be mentioned.

- All the considered adaptive filters are equivalent to a test based on the local coefficient of variation, which is known to be an efficient and robust index of textural information which measures the image homogeneity [7], [8].
- The filters are based on the multiplicative speckle model. This model supposes the speckle to be fully developed: Within each resolution cell there must be a large number of scatterers whose phase and amplitude are statistically independent; the different scatterer amplitudes must belong to the same statistical distribution; their phases are $[0, 2\pi]$ uniformly distributed. This is not generally the case for built-up areas, for example, and the above filter estimates are then not valid. In addition, the filters are no longer reliable when the speckle is not multiplicative. This is the case within a scene which has smaller or comparable details than the resolution cell, such as edges and some very textured areas [9].
- As the multiplicative speckle model is valid for the amplitude representation ($A = r \cdot u$, where r and u are the scene and speckle amplitudes), these filters can easily be adapted to amplitude images by replacing the local intensity statistics by the amplitude ones. In the following, the amplitude A representation which is currently used will be considered. As seen above and noted by Lee [10], the filters are originated from simplified theoretical studies. Hence, for a better efficiency, the filters can be reconsidered and their practical implementation modified under the multiplicative, fully developed speckle model.

III. Filter Enhancement

A. General Considerations

The "ideal" filter should eliminate the speckle so that the original signal r is retrieved. In practice, its behavior depends on the heterogeneity of the considered area.

First, two classes can be considered: 1) the homogeneous class corresponding to the areas where $r(t)$ is constant; and 2) the heterogeneous class corresponding to the areas where $r(t)$ varies and includes textured areas, edges, and point targets. The filter should have the following behavior.

1) Within the Homogeneous Class: The filter should restore $r(t)$. As the minimum variance unbiased estimator is the mean pixels value, the filter should assign to each pixel C the average of the pixels in a moving window centered at C for an image: this filter is currently called the Box filter.

2) Within the Heterogeneous Class: The filter should smooth the speckle and, at the same time, preserve edges and textural information (r variations). This supposes that: i) The filter is based on good discriminators which allow a perfect separation between speckle and textural information; and ii) the conditions assumed for the filter establishment (for example, the multiplicative fully developed speckle noise) are satisfied.

In practice, these two conditions are not always satisfied. A third class is then pointed out where the filter is no longer reliable, and original pixel values are then preserved. In the case of an isolated point target, the filter should conserve the observed value $A(t)$. This is also the case when there are a few scatterers within the resolution cells; i.e., when speckle is no longer fully developed.

B. Filters Based on the Coefficient of Variation

According to the previous consideration, the following classes are pointed out as a function of the coefficient of variation value.

1) Class to be Averaged: If $C_A(t_o) \leq C_u$, then $\hat{r}(t_o) = \bar{A}(t_o)$.

2) Class to be Filtered: If $C_u < C_A(t_o) < C_{\max}$, then the filter should operate so that the more heterogeneous the area [the larger $C_A(t_o)$], the less it has to be smoothed.

3) Class to be Preserved: If $C_A(t_o) \geq C_{\max} \Rightarrow \hat{r}(t_o) = A(t_o)$, the threshold determination is given by the following considerations. For an L-look amplitude image, an area is considered homogeneous if its observed coefficient of variation value is equal to $C_u \simeq 0.523/\sqrt{L}$. In practice, the coefficient of variation within a homogeneous area is computed over a moving window and is then distributed along a bounded quasi-Gaussian function. Fig. 1 presents the distribution of the coefficient of variation computed over a 5×5 window within a homogeneous area of a simulated amplitude SAR image of look number $L \simeq 4$. The central pixel of the window can be assigned without any doubt to the homogeneous class if $C_A(t_o) \leq C_u$.

The threshold $C_{\max}$ value is more difficult to determine. It is obviously larger than $C_{u\max}$, which is defined as the maximum coefficient of variation value over the moving window within a homogeneous area (0.34 for the simulated image Fig. 1). It is also limited by the coefficient of variation value of a target where the multiplicative fully developed speckle condition is not satisfied. A theoretical and experimental study should be developed to determine exactly the $C_{\max}$ value as a function of the image parameters (scene properties, look number, spatial resolution, etc.). For example, such an upper threshold equal to $\sqrt{1 + 2/L}$ for an intensity image has been obtained for likelihood ratio edge detection [12]. However, satisfying results are obtained with a $C_{\max}$ value fixed over built-up areas. The user can also take $C_{\max} = C_{u\max}$ if he does not want to lose any textural information. The pixels belonging to the heterogeneous class then have their value preserved, and other textural features which are more efficient than the coefficient of variation, like the ones based on the spatial correlation between pixels, can then be applied for area discrimination [7]. The use of a threshold $C_{\max}$ may present a problem concerning the pixels within homogeneous class, which corresponds to high coefficient of variation value (near $C_{u\max}$). In fact, the speckle is less averaged in this case. This leads to the occurrence of some heterogeneous patches within homogeneous areas in the filtered image. In the case of homogeneous areas, the highest values of the coefficient of variation are obtained over neighborhoods including an isolated pixel (pixel of very high or very low value). The problem can be solved if these points have their values flattened out. Unfortunately, some point targets can be smeared at the same time. As the point target response is spreaded over several pixels, the filter should then operate as explained in the following:

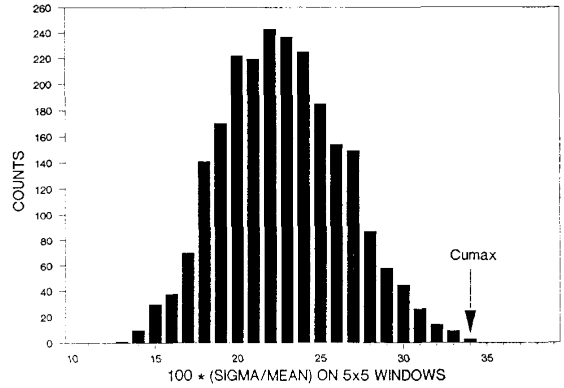


Fig. 1. Distribution of the coefficient of variation within a homogeneous area (2501 pixels) of a simulated 4-look image.

i) Make an intermediary image where isolated points are flattened out: The central pixel C of the neighborhood V is replaced by max [C, min ($V - C$)] or min [C, max ($V - C$)].

ii) Compute the coefficient of variation over a given moving neighborhood in the intermediary image.

iii) Compute the estimate filter by using the original image and the observed coefficient of variation file.

Hence even if the isolated points are flattened out in the coefficient of variation file, high coefficient of variation values are obtained around a point target (as its response is spreaded over several pixel), and the corresponding original value is preserved. This is not the case within a homogeneous area, where the coefficient of variation value around an isolated point becomes much lower than $C_{\max}$, and the isolated point is consequently filtered.

In the following, these considerations will be applied to the adaptive filters.

C. Frost et al. Filter

1) Filter Analysis: The filter behavior is a function of the observed local coefficient of variation. The limit cases are

$$C_A(t_o) = 0 \Leftrightarrow \sigma_A(t_o) = 0 \Rightarrow \hat{r}(t_o) = \bar{A}(t_o)$$
$$C_A(t_o) \rightarrow +\infty \Leftrightarrow \sigma_A(t_o) \rightarrow +\infty \Rightarrow \hat{r}(t_o) = A(t_o).$$

In the other case, the filter operates so that the larger the coefficient of variation of the central pixel, the narrower the subwindow over which the average is calculated.

Once the previous considerations concerning the optimal filter are taken into account, the filter should at the same time: 1) Average within the homogeneous class (the K filter parameter must satisfy the following condition for $C_A(t_o) \leq C_u$, then $r(t_o) = \bar{A} \Leftrightarrow K\, C_A(t_o) \rightarrow 0 \Rightarrow \underline{K \rightarrow 0}$), and 2) preserve the observed value within the non-multiplicative fully developed speckle class (for bounded $C_A(t_o)$ so that $C_A(t_o) \geq C_{\max}$, then $r(t_o) = A(t_o) \Leftrightarrow K\, C_A(t_o) \rightarrow +\infty \Rightarrow \underline{K \rightarrow +\infty}$).

Hence the two conditions cannot be satisfied simultaneously. Fig. 2 presents, for a 4-look image, the normal-

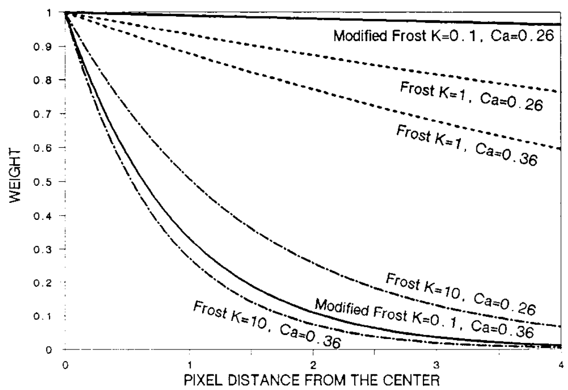


Fig. 2. Normalized adaptive impulse responses of the Frost filter ($K = 1$, $K = 10$) and of the modified filter ($K = 0.1$) within a homogeneous area ($C_u = 0.26$) and within a heterogeneous area ($C_u = 0.36$) for a 4-look amplitude image. Modified Frost filter: $C_u = 0.25$, $C_{\max} = 0.37$.

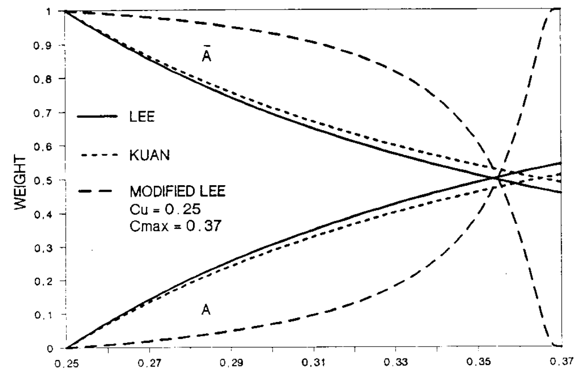


Fig. 3. Weighting function of the Lee and Kuan *et al.* filter and modified Lee filter ($K = 0.1$) for a 4-look amplitude image.

ized impulse response $m(t)$ given by (4) for different C_A and K values. It can be noted that with a large K value ($K = 10$), the averaging window is narrow even within the homogeneous class ($C_A \approx 0.26$). The heterogeneous class is then well preserved, but speckle is not sufficiently smoothed within homogeneous areas. With a small K value ($K = 1$), the homogeneous areas are well averaged, but the heterogeneous class is too smoothed. Hence the filter cannot adequately average homogeneous areas and preserve heterogeneous areas at the same time. The same conclusions can be drawn by using a simulated image [11].

2) Enhanced Frost Filter: The filter impulse response should be replaced by

$$m(t) = K_1 \exp\left[-K \operatorname{fonc}\left(C_A(t_o), C_{\max}, C_u\right) |t|\right] \quad (8)$$

where fonc is a decreasing function such as fonc $= 0$ for $C_A(t_o) \leq C_u$ and fonc $\rightarrow +\infty$ for $C_A(t_o) \rightarrow C_{\max}$. Hence the filter estimated value is

$$\hat{r}(t_o) = A(t_o), \qquad \text{for } C_A(t_o) \geq C_{\max}$$
$$\hat{r}(t_o) = \bar{A}(t_o), \qquad \text{for } C_A(t_o) \leq C_u. \quad (9)$$

The hyperbolic function is a simple function which satisfies the previous conditions, yielding to

$$\begin{aligned}\operatorname{func}(C_A) &= [C_A(t_o) - C_u]/[C_{\max} - C_A(t_o)], \\ &\qquad \text{for } C_u \leq C_A(t_o) \leq C_{\max} \\ &= 0, \quad \text{for } C_A(t_o) \leq C_u \\ \operatorname{func}(C_A) &= \operatorname{func}(C_{\max}), \quad \text{for } C_A(t_o) > C_{\max}. \quad (10)\end{aligned}$$

As can be noted on Fig. 2, the modified filter adequately averages the homogeneous class, filters the intermediary class, and preserves, at the same time, the third class where the filter is no longer reliable.

D. Lee and Kuan et al. Filter

1) Filter Analysis: An examination of (5)–(7) leads to the conclusion that the more heterogeneous the neighborhood, the larger the weight on the observed value, with the following limit cases for $C_A(t_o) \geq C_u$:

$$C_A(t_o) \rightarrow +\infty \Rightarrow \hat{r}(t_o) = A(t_o)$$
$$C_A(t_o) = C_u \Rightarrow \hat{r}(t_o) = \bar{A}(t_o).$$

However, when $C_A(t_o) \leq C_u$, there is still a weight on the observed value even if the weight on the average value is larger. This should lead to an amplification of the noise [5]. This is due to the replacement of the statistics of the ideal image r by the observed image statistics, which are related by the following relation established under the multiplicative noise model [1], [2]:

$$C_r^2 = (C_A^2 - C_u^2)/(1 + C_A^2). \quad (11)$$

As C_r^2 is a positive quantity, this leads to the relation $C_A(t_o) \geq C_u$, which unfortunately is not always satisfied when the local statistics are computed over a neighborhood of limited size. Hence the filter equations given as a function of the observed local statistics are only valid when $C_A(t_o) \leq C_u$. Fig. 3 presents the weights on $A(t_o)$ and $\bar{A}(t_o)$ of the two filters for a 4-look image. It can be noted that they have a similar performance.

2) Filter Enhancement: Modified Lee Filter: If the previous considerations are taken into account, the filters should then be modified so that

$$\begin{aligned}\hat{r}(t_o) &= \bar{A}(t_o), \qquad \text{for } C_A(t_o) \leq C_u \\ \hat{r}(t_o) &= \bar{A}(t_o)W(t_o) + A(t_o)(1 - W(t_o)), \\ &\qquad \text{for } C_u < C_A(t_o) < C_{\max} \\ \hat{r}(t_o) &= A(t_o), \qquad \text{for } C_A(t_o) \geq C_{\max}. \quad (12)\end{aligned}$$

This filter presents a discontinuity at $C_{\max}$. This problem can be solved if $W(t_o)$ is replaced by

$$W(t_o) = \exp\left[-K(C_A(t_o) - C_u)/(C_{\max} - C_A(t_o))\right] \quad (13)$$

which is similar to the weight of the modified Frost filter for a constant distance $|t|$. Fig. 3 presents the behavior of the modified Lee filter ($K = 0.1$) for $C_u < C_A(t_o) \leq C_{\max}$.

E. Homomorphic Filters

The best estimator of the mean reflectivity of the ideal image $[E(\log(r)]$ is theoretically the average computed on the logarithm of the observed image $E(\log(r)) = E(\log(A))$. The Arsenault filter should then have better performance than the Yan and Chen filter. However, this is not confirmed in practice. In fact, the assumed Gaussian distribution for the original image intensity approximated by a bounded triangular distribution should take only positive values. Its lower limit must then be positive. This leads to the following condition:

$$C_A^2(t_o) \leq C_u^2 + C_u^2 \frac{1}{(2.5)^2} + \frac{1}{(2.5)^2} = C_{\text{sup}}^2. \tag{14}$$

Consequently, the better performance of the Yan and Chen filter is not due to the method used for local statistics estimation, but is due to the implicitly introduced threshold C_{sup}. The same corresponding modifications reported on the Arsenault filter would give the same performance.

F. Filter Extension

The optimized Frost filter and the modified Lee filter are based on a test on the observed local coefficient of variation which is a feature of heterogeneity. The same filters can be adapted to other indexes to reduce the speckle and preserve the information related to the considered index. In a previous paper, it has been shown that the ratio edge operator detects better edges than the coefficient of variation [12]. The filters based on this operator, such as the Ratio Frost filter, should then preserve edges better in spite of a loss of some textural information [13]. Such filters can then be applied in textureless areas.

IV. Test of the Filters

Fig. 4 presents a 4-look SAR-580 image consisting of some homogeneous fields, forest areas, and urban areas; three filtered image examples (the Lee, Frost filter with $K = 10$, and the modified Frost with $K = 0.1$); and an aerial photograph. The Lee filter does not smooth enough speckle. The Frost filter with $K = 10$ smooths it better, but not as well as the Box filter (or the Frost filter with $K = 1$) for which all details are blurred. The sharpness of edges and linear features or subtle details (hedges, point target responses) are enhanced in the modified Frost filtered image, whereas speckle is well smoothed within the homogeneous areas. Moreover, the modified Lee and Kuan filters give similar visual results. For the other filters, the remarks given in Section III can also be verified.

However, such a visual comparison is not sufficient to evaluate accurately all filters. Hence some quantitative criteria must be used to evaluate speckle reduction and, at the same time, radiometric and texture information integrity.

A. Principle of the Test

The filter performance is tested by evaluating the following points: 1) Equivalent number of looks within homogeneous areas (speckle reduction); 2) point target response preservation; and 3) texture and edge preservation.

A 4-look SAR-580 image consisting of homogeneous areas and textured areas is used for these tests. However, the first point is difficult to evaluate because it requests a perfect homogeneous area. A radar image consisting only of homogeneous fields is then simulated.

B. SAR Image Simulation

A more suitable model than the simplified model given by (1) for fully developed speckle is given by

$$I(t) = \left|\left[R^{1/2}(t) \cdot u^c(t)\right] * h^c(t)\right|^2 \tag{15}$$

where $u^c(t)$ is a circular complex Gaussian process, and $h^c(t)$ is the complex system impulse response. Extended homogeneous areas (stationary Gaussian scene) are simulated by a constant R. The phase term of the system impulse response can be joined to the phase of u^c. The fully coherent speckle model is then equivalent to the following one:

$$I(t) = \left|R^{1/2}(t) \cdot u^c(t) * \left|h^c(t)\right|\right|^2. \tag{16}$$

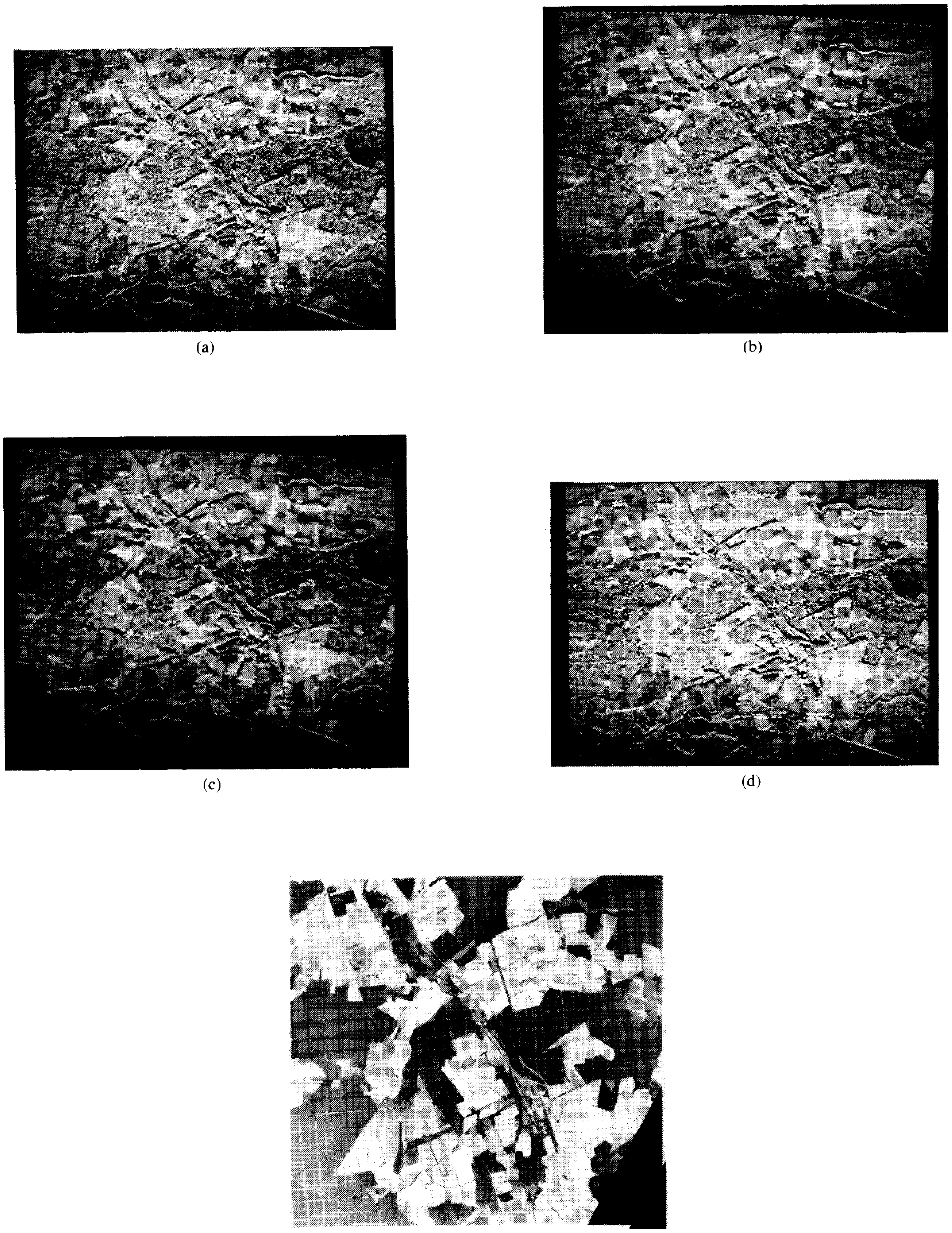
The software has two input files: 1) The reflectivity map file $R(t)$; and 2) a complex Gaussian pseudorandom file whose adjacent samples are statistically independent (white noise). The pixel size is then taken equal to the half of the -3 dB resolution cell size, and the sinc function is chosen as impulse response. The module of the complex image obtained in this way is then computed to give an intensity 1-look image. The amplitude L-look image is obtained by the square root of the sum of L 1-look intensity images obtained from L independent complex Gaussian random files.

C. Test and Results

1) Mean Tonal Value Preservation: All previous filters preserve the mean backscattering coefficient value of homogeneous areas within 0.1 dB, except for the homomorphic ones which underestimate up to 0.25 dB. Hence all filters give satisfactory results for the radiometric information preservation.

2) Equivalent Number of Looks (ENL)—Speckle Reduction: The filters are applied over a 5×5 window on the simulated agricultural scene image with $C_u = 0.25$ and $C_{\max} = 0.37$. The equivalent number of looks (ENL) is then evaluated over homogeneous samples of the filtered images.

The following points concerning the original filters can be concluded for the first time: The Frost filter with $K = 10$ does not adequately average homogeneous areas as well as the Box filter or the Frost filter with $K = 1$; the Kuan and Lee filters have bad performance within homogeneous areas; the Arsenault filter (homomorphic additive Lee filter) averages homogeneous areas better than



(a) (b) (c) (d) (e)

Fig. 4. SAR 580 X-band amplitude image: (a) Original 4-look image; (b) Lee filtered image; (c) Frost ($K = 10$); (d) modified Frost ($K = 0.1$, $C_u = 0.25$, $C_{max} = 0.37$) filtered image; and (e) aerial photograph.

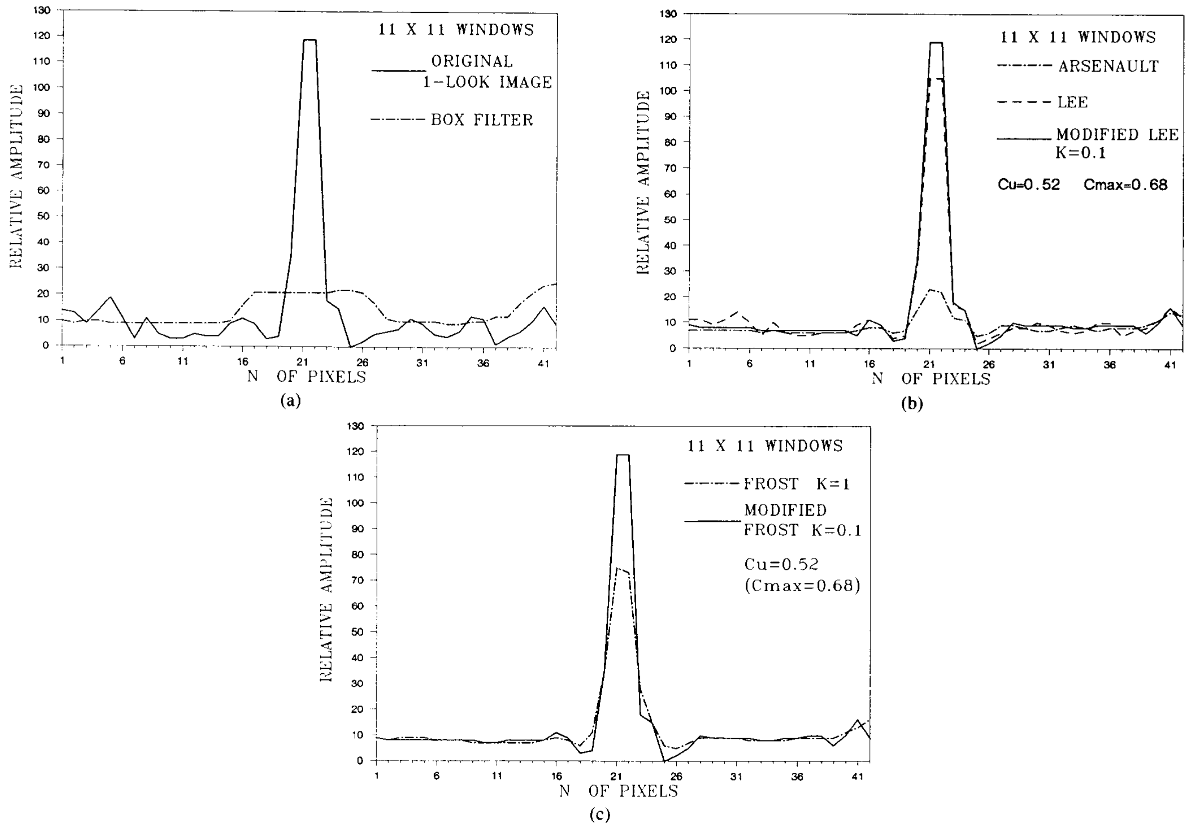


Fig. 5. Range Luneberg response in a 1-look amplitude image: (a) Original and Box filtered images; (b) Arsenault, Lee, and modified Lee filtered images; and (c) Frost and modified Frost filtered images.

TABLE I

Image	Coefficient of Variation Amplitude	Coefficient of Variation Intensity	ENL	CPU Time
Simulated 4-Look Image	0.2557	0.5075	3.88	
Box Filter	0.0639	0.1283	60.78	3 s
Multiplicative Lee	0.1387	0.2815	12.62	4 s
Additive Lee (Arsenault)	0.1070	0.2191	20.83	4 s
Yan and Chen	0.0792	0.1589	39.63	6 s
Frost ($K = 10$)	0.0737	0.1481	45.59	32 s
Frost ($K = 1$)	0.0640	0.1286	60.50	32 s
Modified Multiplicative Lee	0.0732	0.1451	47.48	4 s
Modified Multiplicative Lee ($K = 0.1$) + Isolated Points Elimination	0.0667	0.1336	56.07	7 s
Modified Frost ($K = 0.1$)	0.0642	0.1289	60.21	32 s
Modified Frost ($K = 0.1$) + Isolated Points Elimination	0.0639	0.1284	60.70	35 s
Ratio Frost Filter ($K = 0.1$)	0.0640	0.1284	60.65	32 s

the Lee filter, and this is due to the homomorphic logarithm transformation which contracts the scale of pixel values and hence reduces the class of pixels whose the coefficient of variation is lower than C_u, and where the filter is not reliable.

Now comparing the original filters to the modified ones, it can be noted that the modified Frost filter ($K = 0.1$) is as efficient as the Box filter. The modified Lee filter ($K = 0.1$) with isolated point elimination (cf. Section III-C) is slightly less efficient but needs much less computing time.

Hence the introduction of the lower threshold C_u im-

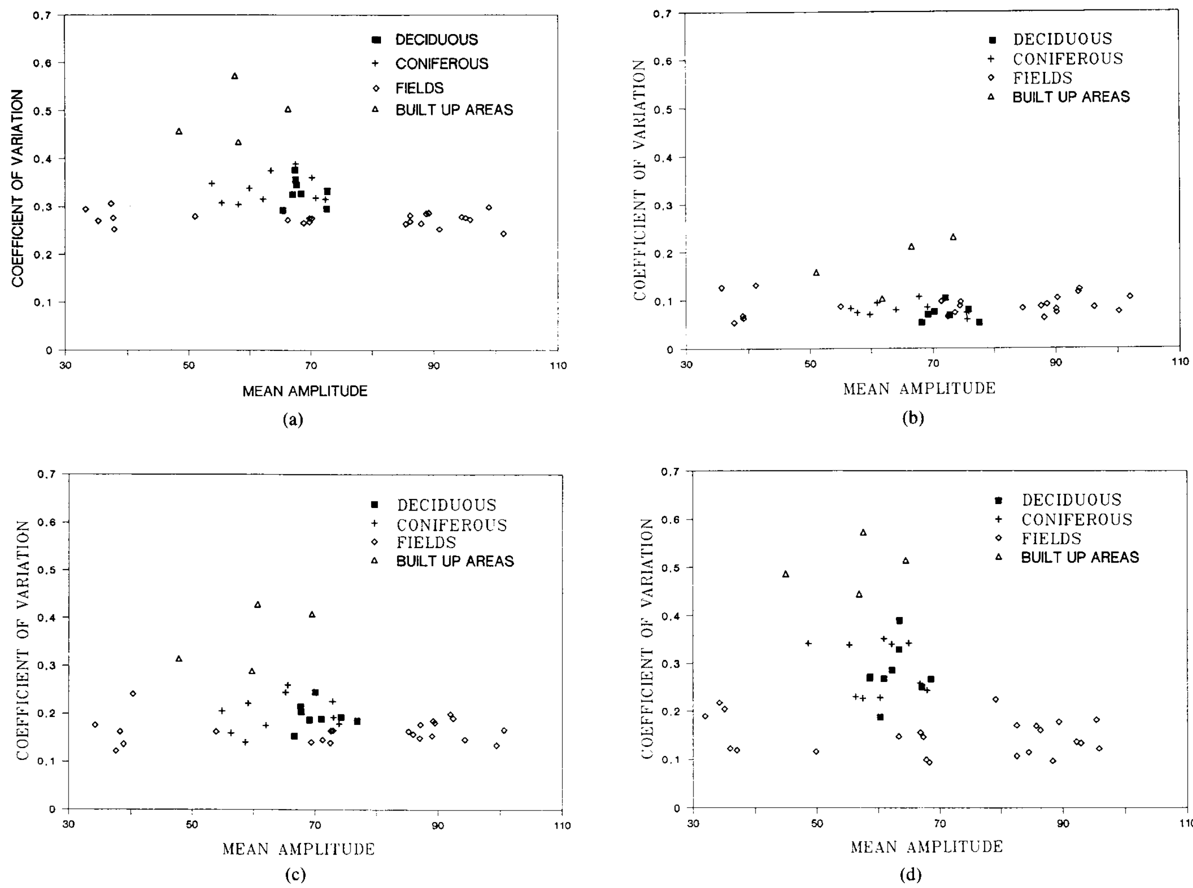


Fig. 6. Coefficient of variation spread in a 4-look SAR-580 amplitude image for: (a) Original image; (b) Box filter (5 × 5 windows); (c) Lee filter (5 × 5 windows, $C_u = 0.25$); and (d) modified Lee filter (5 × 5 windows, $K = 0.1$, $C_u = 0.25$, $C_{\max} = 0.33$).

proves the filter performances and makes them practically as efficient as the Box filter for speckle smoothing.

3) Preservation of Point Target: The filters are applied on a 1-look SAR-580 image including a Lüneberg lens located in a calm lake. The point target range responses are presented in Fig. 5. It can be noted that the Box filter is the poorest with the Arsenault filter. The Frost filter with $K = 1$ and the Lee filter truncate the profile, but the modified versions preserve it.

The introduction of the high threshold $C_{\max}$ allows then the modified filters to adequately preserve point target responses without any efficiency loss within homogeneous areas. For speckle smoothing and subtle image details preservation, the modified Frost, Lee, and Kuan filters give the best compromise. The modified Lee and Kuan are very similar and need less computing time than the modified Frost filter.

4) Texture and Edge Preservation: The filters are applied on an SAR-580 image. Fig. 6 presents the coefficient of variation value for different textured areas as a function of the mean value computed over some samples. It can be noted that the coefficient of variation value spread is larger for the modified Lee filter than for the Lee filter; i.e., the different textured classes are better separated from each other. The modified Frost and Kuan filters have the same performance within textured areas as the modified Lee filter.

For edge preservation, the ratio edge detector, which is less sensitive to the multiplicative noise than the usual gradient edge detector, is applied on the modified Frost, modified Lee, and the ratio Frost filtered images. The modified Frost and modified Lee filters have similar performance and adequately preserve edges. The filter based on the ratio edge detector preserves edges better than the ones based on the coefficient of variation in spite of a loss of textural information.

The application of some iteration of edge-retaining filters based on edge detection [14] over small window and above C_u may give similar results without introduction of $C_{\max}$. The C_u value must be gradually reduced according to the remaining speckle level [15]. This process would be achieved at the expense of more computation time and the loss of some small details, which are entirely preserved by the modified filters above $C_{\max}$. For a better local statistics estimation, gradient or ratio edge detectors could also be introduced in the modified filters for $C_u < C_A$.

V. Conclusion

The most well-known adaptive filters for SAR images are analyzed. It is shown that they are only reliable in a bounded field. Their behavior is then modified by introducing two thresholds on the coefficient of variation. The lower one is easily established as a function of the image parameters. The second upper threshold is fixed approximately, but a study should be done to determine it more precisely in conjunction with the function of C_a, C_u, $C_{\max}$. When tested on real or simulated SAR images, the proposed modified filters adequately average homogeneous areas and better preserve, at the same time, edges and textural information. The modified Frost and Lee filters have similar performances over small windows (5×5 window) in spite of the larger computing time of the Frost filter (twice as much time when the Frost filter implementation is optimized). However, this last one is recommended for larger windows, which is the case when the use of many averaging subwindows becomes worthwhile. In addition, these filters can be improved by applying the isolated points elimination, which appears very efficient in reducing more speckle without loss of textural information. Furthermore, the modified filters, based originally on the coefficient of variation, can be adapted to other features of information, allowing a better separation between speckle and textural information.

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