A Hybrid Scaling Factor for Speckle Reducing Anisotropic Diffusion

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***Abstract*—Classical Speckle Reducing Anisotropic Diffusion (SRAD) is a noise filtering method tailored to speckle reduction in digital images. It is well known that SRAD has a tendency to produce dislocated and un-sharp edges. This property of SRAD is highly attributed to its reliance on a homogeneous image region, selected initially, for a scaling factor calculation. Moreover, this scaling factor calculation strategy requires the interaction of an experienced user. To reduce the reliance on an initially selected perfect/near-perfect homogeneous region, we propose a hybrid scaling factor that reduces edge dislocation and preserves the sharpness of edges. The proposed scaling factor selection strategy uses a ratio-based edge detection technique for an estimation of the homogeneity of the initially selected region.**

Keywords*— Speckle, multiplicative noise reduction, scaling factor, SRAD

I. INTRODUCTION

NOISE in digital images can be defined as random variation of brightness or color information. It reduces image quality and makes object recognition, segmentation, and classification difficult. The principal sources of noise in digital images arise during image acquisition and/or transmission. According to the noise-model, noise created in image acquisition and/or transmission process can be grouped into two major categories— additive and multiplicative noise.

A good number of recent image de-noising research-works focus on the reduction of a special form of multiplicative noise named speckle. Speckle commonly occurs in *Synthetic Aperture Radar* (SAR), *Synthetic Aperture Sonar* (SAS) and *ultrasound* images. The ultimate goal of speckle reducing filters is to reduce the speckle noise level with minimal distortion of image details. But, this form of multiplicative noise is locally correlated which makes speckle reduction quite challenging.

Local correlation property of the speckled images demands special treatment. Some classical filters like Lee [1], Kuan [2] and Frost [3] exploited local statistics to deal with the local correlation in SAR images. Successful additive noise filtering techniques like Perona-Malik Diffusion filter [4] are not efficient in speckle reduction since they do not account for the local correlation property of the speckled images.

Being inspired by the filtering technique of Lee and Kuan, Yu and Acton [5] came up with *Speckle Reducing Anisotropic Diffusion* (SRAD) where they incorporated local statistics based adaptive technique in the diffusion model of Perona-Malik. Though SRAD shows impressive speckle reduction performance, it has a tendency to produce dislocated and un-sharp edges. The *scaling factor* selection strategy is largely responsible for this unwanted behavior of SRAD. The scaling factor selection strategy of SRAD also demands the interaction of an experienced user who needs to select a perfect/near-perfect homogeneous region before starting the core diffusion process.

To overcome the above mentioned shortcomings of SRAD, we propose a hybrid scaling factor selection strategy. We use ratio-based edge detection technique to estimate the homogeneity of the initially selected region and based on the estimation we select an appropriate scaling factor in the run time. This hybrid scaling factor ensures sharp edges as well as reduces edge dislocation. Moreover, since we do not rely blindly on the initially selected region, human interaction can be easily skipped. For example, a small region in the top-left corner of an input image can be considered as the initial region.

II. BACKGROUND

A. Local correlation in speckle

The reason behind the local correlation in speckle pattern can be explained by the image acquisition processes of SAR, SAS and ultrasound images. For example, speckle noise in SAR system results from random fluctuations in the electromagnetic return signals (radio/microwave, specifically) from the underlying objects. Reflected signals returned from different objects have different fluctuation patterns. The speckles in a sub-region of the SAR image representing a specific object exhibit local correlation since they resulted from the same fluctuation pattern. Similarly, in case of SAS and ultrasound images, the local brightness of the speckle pattern, reflects the local echogenicity (the extent to which a structure/object gives rise to reflections of ultrasonic waves) of the underlying backscatter.

B. Speckle reducing filters

Several filters have been proposed to reduce speckle noise. Roughly, they can be grouped into two families: homomorphic and adaptive. Homomorphic filtering refers to a technique of preprocessing the observed image to transform non-additive noise into additive noise using some nonlinear memoryless operator. Then standard additive noise filtering is applied for noise reduction. The enhanced image is formed by applying the inverse nonlinear operator. For speckle-like multiplicative noise, logarithmic and exponential operators are required for forward and inverse transformation, respectively. But, a speckled image represents the observed data as being multiplicative noise operated on by a linear system. A logarithmic operator cannot separate the signal from the noise in this case. As a result, homomorphic filters are not efficient in speckle reduction.

Adaptive filters account for the local correlation of speckle model and exploit local statistics. Among the earlier speckle reducing adaptive filters, Lee [1] and Kuan [2] filters were quite successful. Both Lee and Kuan filters have the same formation though the signal model assumptions and derivations are different. They are based on a linear speckle noise model and the *minimum mean square error* (MMSE) design approach. These filters are designed to reduce speckle noise while preserving edges and point features in radar imagery. Both Lee and Kuan filters produce the enhanced data by

$$\hat{I}_s = I_s * W + \bar{I}_s(1-W) \tag{1}$$

where $\hat{I}_s$ is the filtered intensity data, $\bar{I}_s$ is the mean value of the intensity within the filter window η_s and W is a weighting function representing the adaptive filter coefficient. In Lee filter, the weighting function is given by

$$W = 1 - \frac{C_u^2}{C_s^2} \tag{2}$$

Here, C_s is the coefficient of variation and is the core component of Lee filter which accounts for the local statistics of input image data. The coefficient of variation C_s is defined as

$$C_s^2 = \left(\frac{1}{|\eta_s|}\right) \sum_{p \in \eta_s} \left(I_p - \bar{I}_s\right)^2 / (\bar{I}_s)^2 \tag{3}$$

where $|\eta_s|$ is the size of filter window, p denotes a pixel in the window η_s , I_p is the image intensity of pixel p. C_u is an image specific constant which is determined by

$$C_u^2 = \frac{var(z')}{\left(\bar{z'}\right)^2} \tag{4}$$

where $var(z')$ and $\bar{z}'$ are the intensity variance and mean over a small homogeneous area z' of the image, respectively.

The coefficient of variation C_s plays the most crucial role in controlling the filter. If $C_s \to C_u$, then $W_s \to 0$ and if $C_s \gg C_u$, then $W_s \to 1$. In the homogeneous regions, the value of C_s should take a lower value as the variance goes low there and ideally, we expect $C_s \to C_u$ in a perfectly homogeneous region. So, in the homogeneous region the W_s is expected to take the value 0 which leads to a mean filter. On the contrary, in the heterogeneous regions the value of C_s should be higher than C_u. Ideally, it is expected that at the center of an edge $C_s \gg C_u$ and W_s approaches unity. That makes the Lee filter to act like an identity filter. As a result, edges are kept in the heterogeneous regions.

Unlike Lee, Kuan defined the weighting function W by

$$W = \frac{1 - \frac{C_u^2}{C_s^2}}{1 + C_u^2} \tag{5}$$

Both C_s and C_u are similarly defined as in Lee filter. However, in Kuan filter, C_u plays a more important role as W_s is more directly scaled by C_u in (5). Frost [3] filter employs similar strategy as Lee and Kuan.

Perona and Malik [4] introduced a diffusion based filter to reduce additive noise. In their method, a gradient based diffusion function controls the level of smoothing. The diffusion function is chosen to vary spatially in such a way that it encourages intra-region smoothing in preference to inter-region smoothing.

Yu and Acton [5] modified the diffusion filter of Perona and Malik using the local statistics based coefficient of variation concept of Lee and Kuan. They proposed *Speckle Reducing Anisotropic Diffusion*, SRAD, which uses both gradient magnitude and Laplacian for edge detection unlike Perona-Malik filter. The discrete form of the update function of SRAD is given by

$$I_{i,j}^{t+\Delta t} = I_{i,j}^{t} + \frac{\Delta t}{|\eta_s|} div[c(C_{i,j}^{t})\nabla I_{i,j}^{t}] \tag{6}$$

where $c(.)$ is the diffusion function of anisotropic diffusion model. $C_{i,j}^t$ is the local statistics based coefficient of variation in time t. To create a fusion of PDE based classical anisotropic diffusion with the local statistics based Lee and Kuan filters, Yu and Acton used the coefficient of variation parameter as the edge detector instead of gradient and then the diffusion function has been defined in terms of the coefficient of variation.

Yu and Acton provided a discretized version of the coefficient of variation which is applicable to the classical PDE evolution. Considering a window of four neighboring pixels, they came up with the following discretized version of coefficient of variation.

$$(C_{i,j}^t)^2 = \frac{\frac{1}{2}\left|\nabla I_{i,j}^t\right|^2 - \frac{1}{4^2}\left(\nabla^2 I_{i,j}^t\right)^2}{\left(I_{i,j}^t + \frac{1}{4}\nabla^2 I_{i,j}^t\right)^2} \tag{7}$$

where (i,j) represents the position in 2D image matrix, $C_{i,j}^t$ is the coefficient of variation at (i,j) in time t, ∇ denotes the gradient and ∇^2 denotes the Laplacian. This coefficient of variation is the inherent edge detector of SRAD which is apparently a combination of the gradient magnitude and Laplacian. High relative gradient magnitude and low relative Laplacian tend to indicate an edge. At the center of the edge, the relative value of $C_{i,j}^t$ is maximum as the Laplacian goes to zero and gradient reaches its peak. Assuming that the image intensity function has no zero point over its support, Yu and Action defined an *Instantaneous Coefficient of Variation*, ICOV, which is given by

$$q_{i,j}^t = \sqrt{\frac{\frac{1}{2}\left(\frac{|\nabla I_{i,j}^t|}{I_{i,j}^t}\right)^2 - \frac{1}{4^2}\left(\frac{\nabla^2 I_{i,j}^t}{I_{i,j}^t}\right)^2}{\left(1+\frac{1}{4}\left(\frac{\nabla^2 I_{i,j}^t}{I_{i,j}^t}\right)\right)^2}} \qquad (8)$$

where $q_{i,j}^t$ and $I_{i,j}^t$ are the ICOV and image intensity of pixel (i,j) in 2D image grid in time *t*, respectively. Finally, the update function of SRAD takes the form

$$I_{i,j}^{t+\Delta t} = I_{i,j}^t + \frac{\Delta t}{|\eta_s|} div[c(q_{i,j}^t)\nabla I_{i,j}^t] \qquad (9)$$

Being inspired by Lee and, Yu and Acton used a scaling factor while defining the diffusion function. The diffusion function, $c(q_{i,j}^t)$, is given by

$$c(q_{i,j}^t) = \frac{1}{1+\frac{(q_{i,j}^t)^2-(q_0^t)^2}{(q_0^t)^2[1+(q_0^t)^2]}} \qquad (10)$$

where q_0^t is the speckle scaling factor. q_0^t is equivalent to the constant term C_u of Lee and Kuan filters and determined by the (4).

The ICOV exhibits high values at edges or on high-contrast features and produces low values in homogeneous regions. As a result, according to (10), $c(q_{i,j}^t)$ takes small values at edges and larger values at homogeneous regions. That ensures less smoothing on edge or detail containing regions and more smoothing on homogeneous areas. The diffusion becomes isotropic when $q_{i,j}^t \approx q_0^t$. In a sense, the scaling factor, q_0^t, controls the amount of smoothing applied to the image by SRAD.

SRAD avoids the use of threshold of the norm of gradient in the diffusion function. This independent threshold parameter of Perona-Malik's diffusion has been replaced by an estimation of the standard deviation of the noise (q_0^t), at each iteration. This scheme introduces less dependence on the norm of the gradient which can vary across a speckled image. At the same time, SRAD is benefited by the natural decrease of diffusion as the estimated standard deviation of the noise decreases with time which leads to a convergence without smoothing out interesting features of the image.

Like Lee and Kuan filters, the scaling factor q_0^t is computed over an initially selected homogeneous region z' by taking the ratio of stand deviation and mean over z'. If z' is a perfect or near-perfect homogeneous region then it gives a good idea about how good or bad we are doing in speckle reduction and thereby, enables us to adjust the amount of smoothing accordingly. However, if an inappropriate initial region is selected, this diffusion adjustment does not work properly.

In lieu of the original speckle scaling factor calculation strategy of SRAD, Aja-Fernández et al. [6] proposed some alternatives. First, they propose to take the minimum value of all CVs (i.e., *coefficient of variations*) in the input image as the value of scaling factor q_0^t, i.e.,

$$(q_0^t)^2 = \min_{i,j}((C_{i,j}^t)^2) \qquad (11)$$

where $C_{i,j}$ is the coefficient of variation of pixel (i,j) in 2D image grid. But the presence of outliers makes the minimum to be biased towards zero [7]. So, the minimum should be considered as the lower bound for q_0^t. Another alternative estimator of the speckle scaling factor is the average

$$(q_0^t)^2 = \frac{1}{N}\sum_{i,j}(C_{i,j}^t)^2 \qquad (12)$$

where N is the total number of pixels in the image. Then the authors marked it as an over-estimator of q_0^t and claimed that it should be the upper bound of the speckle scaling factor. Finally, due to the robustness to outliers, they proposed the median of CVs as the speckle scaling factor. That is,

$$(q_0^t)^2 = Median_{i,j}((C_{i,j}^t)^2) \qquad (13)$$

In practice, the median based estimation of the scaling factor helps to preserve edge details.

C. *Ratio-based edge detection*

The most common approaches to edge detection are based on gradient and Laplacian. However, in speckled environment, ratio-based edge detection techniques are more effective. Ratio-based edge detectors estimate edge strength on any pixel of interest in an image by calculating the ratio between neighboring pixel values. The estimated ratio may be improved by calculating averages of pixel values in two adjacent and non-overlapping regions, selected on opposite sides of pixel of interest. These two regions, P and Q, may be selected from any orientation around the pixel of interest.

Zaman and Moloney proposed *Modified Ratio of Averages* [8], MRoA, method that uses four orientations (horizontal, vertical, left-slanted, and right-slanted) for P and Q. P_i is calculated as the average of pixels in the region P of orientation i and Q_i the average in the region Q in the orientation i, for $i = 1,2,3,4$. The ratio edge strength for orientation i is taken to be $R_i = Min(P_i/Q_i, Q_i/P_i)$ and the overall edge strength is taken as $R = Min(R_1, R_2, R_3, R_4)$. MRoA determines an edge location if $R \leq T_R$, where T_R is a user selected threshold. MRoA has been extended by combining gradient edge information with ratio measure to improve the performance [8]. Edge is detected if either $R \leq T_R$ OR $G \geq T_G$, where $G = Max(G_1, G_2, G_3, G_4)$ and $G_i = |P_i - Q_i|$ for $i = 1, \ldots, 4$. Zhengyao et al. [9] changed the condition to $R \leq T_R$ AND $G \geq T_G$. They also calculated the threshold dynamically by taking the average of maximum and minimum R values over the entire image.

Maximum Strength-edge Pruned Ratio of Averages, MSP-RoA, method [10] of Moloney et al. performs pruning after ratio comparison stage. For each pixel, this method stores both the minimal ratio value and the direction producing the value. If $R \leq T_R$, for a pixel, it is considered as a candidate edge pixel and pruning process is started which runs on a small window along the direction perpendicular to the minimal ratio producing direction. If the ratio value of the candidate pixel is the smallest one in the pruning window, the pixel is accepted as edge. Otherwise, it is rejected and pruning process continues with other candidate edge pixels. This method produces thinner edge compared to the others.

III. THE PROPOSED HYBRID SCALING FACTOR

The homogeneity of the initially selected region is crucial for the optimal performance of the SRAD filter. This necessity implies that SRAD requires an experienced user to select this homogeneous region. Moreover, in some cases of SAR images, it is not easy to detect a homogeneous region due to the existence of extensive details. If the region is not homogeneous enough, q_0^t may take a large value due to high intensity-variance over the region. The diffusion function of SRAD given by (5) makes it clear that high value of q_0^t produces high value of diffusion function. As a result, SRAD ends up producing a over-smoothed image where the edges are dislocated and un-sharp.

To deal with this issue, we employ a hybrid strategy. We do not take the ratio of standard deviation and mean as the scaling function by default. First, we perform MSP-RoA [10] ratio-based edge detection with dynamic threshold [9] on the initially selected region. Let, the dimension of the initially selected region z is $u \times v$ (in pixel) and e is the number of edge pixels in z detected by MSP-RoA. We calculate the percentage of edge pixels in z by

$$p_e = \frac{e}{u \times v} \times 100 \tag{14}$$

Then the scaling function, $(q_0^t)_{hybrid}$, is given by

$$(q_0^t)_{hybrid} = \begin{cases} \dfrac{stdDev(z)}{mean(z)}, & if\ p_e < T_e \\ median_{i,j}(q_{i,j}^t), & otherwise \end{cases} \tag{15}$$

where T_e is a positive threshold. If p_e is less than T_e, then we take the conventional ratio between standard deviation and mean over z as the scaling function $(q_0^t)_{hybrid}$. If not, the median of all instantaneous coefficients of variation (ICOV) values throughout the image is taken as the scaling function. We suggest $T_e \leq 3$ for effective implementation. We calculate p_e over the initially selected region as an indicator of homogeneity. It is compared against a pre-defined threshold (T_e) to determine if it is homogeneous enough or not. We can also substantially eliminate the risk of losing finer edge details by using the median based scaling function when the region is not a homogeneous one.

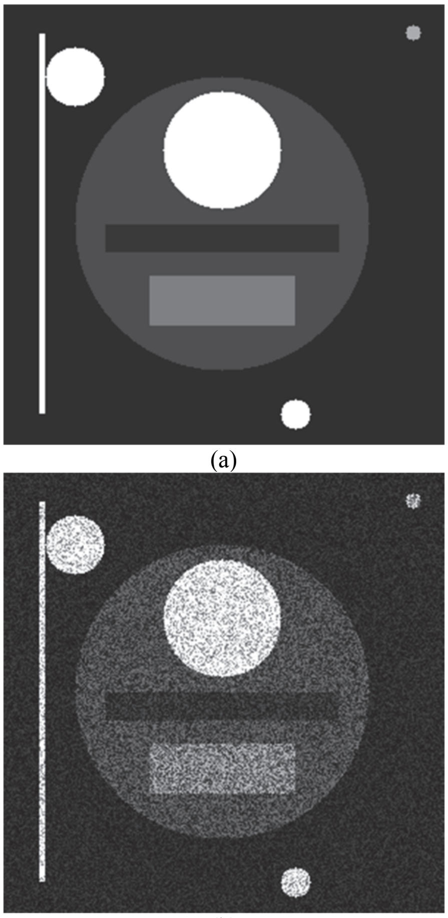
Unlike DPAD [6], our scaling factor selection strategy sticks with the original scaling factor of Yu and Acton [5], if the initially selected region is homogeneous enough. The median based ICOV sacrifices de-noising performance to prevent edge dislocation and over-smoothing of edges. So, as long as we have a perfect or near-perfect homogeneous region we want to stick with the original scaling factor to ensure higher level of de-noising and edge preservation, at the same time. Whenever we detect considerable amount of variance in the initial region, the median of ICOV values is used since dislocated and un-sharp edges are not acceptable.

IV. EXPERIMENTAL RESULTS

To evaluate the performance of our proposed scaling factor selection strategy, we used a synthetic image containing some geometrical shapes. Fig. 1(a) shows the noise-free original image of size 300×300. Later, that image was corrupted by Guassian multiplicative noise with zero mean and standard deviation of 0.35. Fig. 1(b) shows this corrupted version of the original image.

We de-noised the image of Fig. 1(b) using SRAD with original scaling factor and a modified version of SRAD that uses the proposed hybrid scaling factor. For both filters, the number of iterations and step size were set to 300 and 0.05, respectively. For the proposed hybrid scaling factor, T_e value was set to 3. A 75×80 rectangular area at the top-left corner of the input image was chosen as the initial region for both methods. In Fig. 2, we showed this initial region by a gray rectangle at the top-left corner. For MSP-RoA, we selected a 3×3 window for ratio calculation and a 2×1 vector sub-window for the pruning process.

Fig 3. shows the outputs of both filters for subjective evaluation. The SRAD with original scaling factor produced an output image (shown in Fig. 3(a)) where edges are highly dislocated and noticeably un-sharp (or smoothed). On the contrary, SRAD with the proposed hybrid scaling factor succeeded to avoid unacceptable edge dislocation and at the same time, keep the edges sharp. The $p_e$value was 4.01% which surpassed the threshold T_e. So, the median of ICOV values was chosen as the scaling factor in the run time. As expected, it sacrificed the de-noising performance for the sake of preventing edge dislocation and over-smoothing of edges.



(a)

(b)

Fig. 1 Synthetic image used in our experiment. (a) The original noise-free image containing some geometrical shapes, (b) Synthetically corrupted by Gaussian multiplicative noise with zero mean and standard deviation of 0.35.

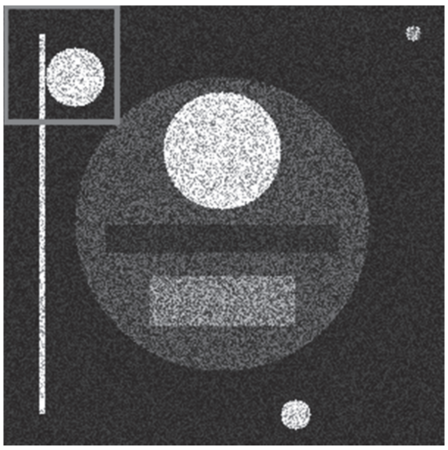
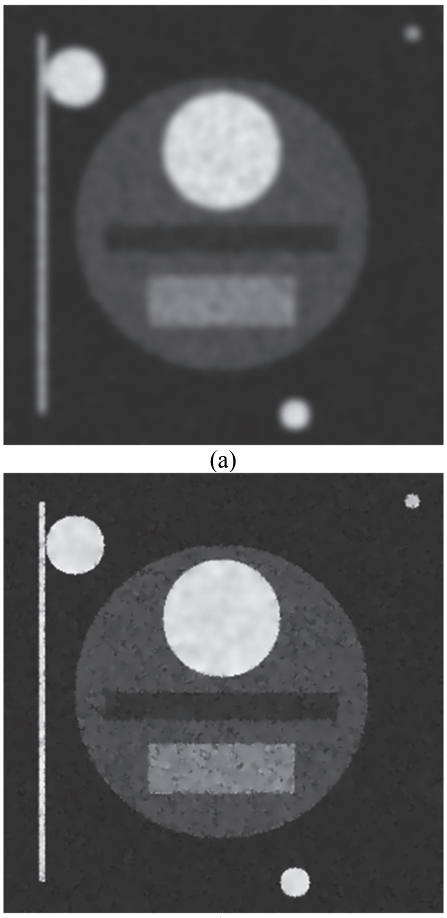


Fig. 2 The 75×80 rectangular region at the top-left corner (shown by a gray rectangle) was selected as the initial region.

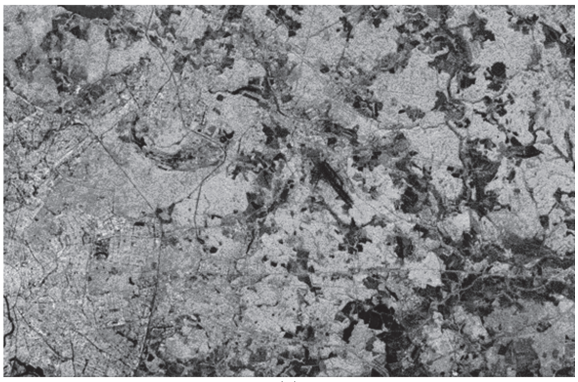


(a)

(b)

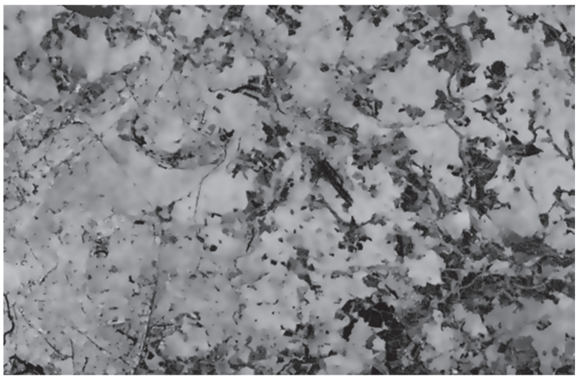
Fig. 3 Outputs of (a) SRAD with original scaling factor and (b) SRAD with hybrid scaling factor, after 300 iterations.

To verify the usefulness of our scaling factor selection strategy on real-life speckled images, we ran both SRAD with original scaling factor and hybrid scaling factor on a real SAR image shown in Fig. 4(a). It is a 570×370 SAR image of the Star City of Russia taken by NASA JPL SIR-C/X-SAR system. A 142×93 rectangular region at the top-left corner of the image was chosen as the initial region. All the experimental settings including the T_e value were kept same as the earlier experiment. At run time, p_e value was found to be 4.07%. Fig. 4(b) and 4(c) show the SRAD output after 300 iterations using original scaling factor and hybrid scaling factor, respectively. Fig. 4(b) and Fig. 4(c) verify that the edges are sharper in the output produced by SRAD with hybrid scaling factor. The hybrid scaling factor also helped to preserve finer edge details and prevented over-smoothing.



(a)

(b)



(c)

Fig. 4 (a) SAR image of the Star City, Russia (courtesy of NASA JPL), (b)—(c) outputs after 300 iterations of SRAD with original scaling factor and hybrid scaling factor, respectively.

V. Conclusion

We have introduced a hybrid scaling factor for SRAD to prevent edge dislocation and maintain the sharpness of edges. Experimental results show that the proposed hybrid scaling factor helps to prevent edge dislocation and also keeps the edges sharp. Unlike SRAD with the original scaling factor, it produces sharper edges irrespective of the homogeneity of initially selected homogeneous (or near-homogeneous) region. However, if the initial region is not homogeneous enough our strategy sacrifices de-noising performance to combat with edge dislocation and over-smoothing of edges. The proposed scaling factor selection strategy may also help to reduce human intervention in the de-noising process.

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