Speckle Removal by Distance-Driven Anisotropic Diffusion of SAR Temporal Stacks

Nazia Tabassum, Andrea Vaccari, Member, and Scott T. Acton, Fellow, IEEE
Charles L. Brown Department of Electrical and Computer Engineering
University of Virginia
Charlottesville, Virginia
{nt5rc, av9g, acton}@virginia.edu

Abstract—Radar images are often collected over the same region over time. To provide smoothing of such imagery without effacing temporal changes in the scene, we put forth an anisotropic diffusion technique. Traditionally, with synthetic aperture radar images, the mean of time series is utilized to produce a single despeckled image that discards temporal information. In contrast, we propose a statistical approach designed to reduce speckle noise in each image. The new filter incorporates temporal information essential to detection of potential change events for transportation infrastructure. Results demonstrate the efficacy of the approach, showing lower mean squared error than leading methods.

Keywords—speckle noise, anisotropic diffusion, synthetic aperture radar image, remote sensing, image analysis for infrastructure inspection

I. INTRODUCTION

Resulting from subresolution scatterers, speckle observed in imaging is often represented as multiplicative noise proportional to gray level intensity [6]. Adaptive speckle filters have been used to address speckle noise within synthetic aperture radar (SAR) imagery. These filters include the Median, Lee [8]-[10], Frost [11], Kuan, Gamma MAP, etc. [3]. While these filters do remove speckle, they are affected by several shortcomings such as oversensitivity to window size, lack of edge enhancement, non-directional smoothing, and hard thresholding [6].

One of the most traditional smoothing algorithms designed to preserve edges by reducing noise within similar regions while preserving boundaries between regions is anisotropic diffusion [7]. While this approach works well for additive noise, in the case of large gradients introduced by speckle, anisotropic diffusion can result in a preservation of distortion, as shown in Section II of this paper. Often, additive noise filters can be used on multiplicative noise by taking the log of the image, which transforms multiplicative noise into an additive noise problem. However, useful information may be lost during log compression. A method derived from traditional anisotropic diffusion, speckle reducing anisotropic diffusion (SRAD) [6], reduces image artifacts due to speckle by using the inverse coefficient of variation, rather than the gradient, as a boundary detector. SRAD smooths images and preserves edges by taking advantage of better characterization of speckle noise statistics without working on log-compressed data. As SRAD combines a gradient term with a Laplacian term, edges and features are better preserved than when using traditional smoothing algorithms.

All these approaches have been originally developed to be applied to individual images, but, in the last decade, introduction of novel analysis techniques (such as persistent scatterer interferometric SAR) have made new methods possible [2]. These new algorithms rely on availability of a stack of several SAR images of the same region acquired over time. These novel speckle mitigation approaches take advantage of the temporal axis [1]. When dealing with large datasets of images taken over the same area, a common approach is to average acquisitions to reduce noise and keep details [4]. However, this type of averaging results in the loss of temporal information which is often critical to determine changes within the imaged scene [5]. In this paper, we propose a statistically-driven extension to SRAD that takes advantage of the large number of images while still preserving their temporal uniqueness. The dataset we use consists of a stack of 67 SAR images of a 40x40km area, centered in Augusta County in central Virginia, collected from August 29, 2011 to November 24, 2014.

In Section II, we will review anisotropic diffusion and SRAD. In Section III, we will introduce distance-driven SRAD, our method for incorporating temporal information for enhanced smoothing. In Section IV, we will provide results, both qualitative and quantitative. Section V will conclude this paper.

II. ANISOTROPIC DIFFUSION AND SRAD

A. Anisotropic Diffusion

Anisotropic diffusion was first proposed by Perona and Malik in 1987. This smoothing approach uses a nonlinear partial differential equation,

\[
\begin{align*}
\frac{\partial I}{\partial t} &= \text{div}[c(|\nabla I|) \cdot \nabla I] \\
I(t = 0) &= I_0
\end{align*}
\]  

(1)

In (1), div is the divergence operator, $|\nabla|$ is the magnitude of the gradient, $I_0$ is the initial image, and $c(x)$ is the coefficient of diffusion. A coefficient of diffusion is given by:

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\[ c(x) = \frac{1}{1+(x/k)^2} . \]  

A discretized version (in space and time) of the anisotropic equation (1) can be written as

\[ I_s^{t+\Delta t} = I_s^t + \frac{\Delta t}{|\bar{\eta}_s|} \sum_{p \in \eta_s} c(\nabla I_{s,p}^t) \nabla I_{s,p}^t . \]  

\( I_s^t \) is the pixel value at position \( s = (s, p) \) and time \( t \), \( \Delta t \) is the size of the time step, \( \bar{\eta}_s \) is the spatial neighborhood of \( s \) (usually 4-connected), and \( \eta_s \) is the number of pixels within the neighborhood. The value of \( k \) (diffusion or flow constant) provides the discrimination between regions where diffusion should occur (small gradients) and boundaries across which it should be inhibited (large gradients). In (2), if we substitute \( |\nabla I| \) for \( x \), we can see that when \( |\nabla I| \gg k \), then \( c(|\nabla I|) \rightarrow 0 \). In this case, anisotropic diffusion emulates an all-pass filter. On the contrary, if \( |\nabla I| \ll k \), then \( c(|\nabla I|) \rightarrow 1 \), and we approach isotropic diffusion.

### B. Speckle Reducing Anisotropic Diffusion (SRAD)

SRAD builds off traditional anisotropic diffusion but incorporates two new terms into the coefficient of diffusion \( c(x) \). The first is the instantaneous coefficient of variation, or the ICOV. We can think of the ICOV as the limit of the coefficient of variation \( c_v = \frac{\sigma}{\mu} \) as our region of interest, in \( \nabla I \), shrinks to one pixel. The ICOV can be defined as:

\[ q(x, y; t) = \sqrt{\frac{\text{var}(x(t))}{x(t)}} . \]  

The ICOV combines a gradient magnitude operator and a Laplacian operator \( \nabla^2 I \), which work together to act as an edge detector, in bright and dark regions. The second term in the smoothing coefficient is the speckle scale function, which controls the amount of smoothing performed on the noisy image. The speckle scale function, which is similar to the \( k \) term in (2), is defined as

\[ q_0(t) = \sqrt{\frac{\text{var}(x(t))}{x(t)}} . \]  

and is taken over a homogeneously speckled region in the image \( x(t) \), and is specified by the user at \( t = 0 \). The diffusion coefficient for SRAD combining both the ICOV and the speckle scale function can take a form similar to (2):

\[ c(q) = \frac{1}{1+q^2(x,y,t)-q_0^2(t)[q_0^2(t)+q^2(t)]} . \]  

\( q \) is the temporal median of \( x \) for each iteration. If the temporal median of \( x \) for each iteration. If we substitute \( q \) for \( x \) in (2), we can see that when \( |\nabla I| \gg k \), then \( c(|\nabla I|) \rightarrow 0 \). In this case, anisotropic diffusion emulates an all-pass filter. On the contrary, if \( |\nabla I| \ll k \), then \( c(|\nabla I|) \rightarrow 1 \), and we approach isotropic diffusion.

### III. DISTANCE-DRIVEN SRAD

The concept behind distance-driven SRAD is to take the traditional SRAD algorithm and expand it to the three dimensional case, where the third dimension is provided by time. We replace the gradient of the image in (4), by the distance between neighboring pixel time series. For example, if we consider two classes of pixels, belonging to a road and to a field, we expect that the temporal behavior of intensities observed within each class would be similar, while differing across classes. Furthermore, if the road is paved over the course of a year and the field is mowed or sown we want our approach to be able to detect these changes within the smoothed images. If throughout time we can distinguish between road and field pixel behavior, then we can use characteristics of pixel behavior over time as an edge map. We propose to evaluate the “distance” between neighboring pixels throughout time to determine if an edge lies on the boundary of neighboring pixels.

\[ q(x, y; t) = \sqrt{\frac{(1/2)(\Sigma D^2/I)^2-\Sigma D/I}{1+(1/4)(\Sigma D/I)^2}} . \]  

In (7), \( D \) refers to the distance taken between pixels in the north, south, east, and west directions. \( \Sigma D^2 \) signifies summing each directional distance before summing the four squared distances up. Similarly, \( \Sigma D \) sums the four unsquared directional distances, where the directional distances are all positive. For our approach we used the root sum of squares and the Kolmogorov-Smirnov distance. To find the full form of \( c(x) \) for DD-SRAD, we substitute the new \( q(x, y; t) \) in (7) for the \( q \) in (6).

#### A. Distance: Root Sum of Squares (RSS)

Root sum of squares, or RSS, distance is taken as the distance between time series of two neighboring pixels. Pixel...
intensity values are taken as vectors. Neighboring vectors are differenced – four neighbors are considered: north, south, east, and west. The difference vector between two neighbors is then squared and summed, to ensure positive differences. The square root of the sum is taken as the RSS value between two pixels’ time series. If RSS distance is high, pixels are said to be very different throughout time. If RSS distance is low, then pixels may belong to the same region in an image.

B. Distance: Kolmogorov-Smirnov (KS)

Kolmogorov-Smirnov (KS) distance provides a non-parametric measure of the difference between two cumulative distribution functions (CDF) by evaluating the maximum distance between them [12]-[14]. We build empirical distributions functions (EDFs) from pixel time series by assigning probabilities to gray level intensity values based on frequency of occurrence. Neighboring pixel empirical distribution functions (EDFs) are compared using KS distance. The KS distance is bounded between 0 and 1, so no negative distances are possible. There are a number of other distance metrics that can be taken between probability distributions, such as Bhattacharyya distance [15], or Kullback-Liebler divergence [16].

A benefit to distance-driven (DD-SRAD) is that no hard thresholds are used. The decision to smooth is based on the distance metric. If the distance is small, then the assumption is made that the two pixels are similar throughout time and there is no edge between them. Therefore, we smooth across similar pixels. If the distance is large, then an edge is perceived and the smoothing factor is diminished so that our filter tends towards all-pass.

![Image of original and de-speckled images](image-url)

![Image of edgemaps](image-url)

**Fig. 2. Despeckled SAR images.**

**IV. RESULTS AND DISCUSSION**

DD-SRAD using RSS distance was first tested on stacks of varying sizes, i.e., stacks of 4, 8, 30, 57, and 67 SAR images. The results of 100 iterations of DD-SRAD using KS distance on a 67 image stack can be seen in Fig. 2. The original image and the edges of the original image are shown in the left panel of the figure. The right panel shows the first image in the 67-image stack after running DD-SRAD, and its resulting edge map. Despeckled SAR Image refers to an image that has gone through speckle noise removal processing. The edge maps of the despeckled and enhanced versions of the image show more clear outlines of features in the image, such as roads and the small lake. Much of the noise has been removed, without losing any defining features of the image. A quantitative measure of quality is necessary for testing this method, so we tested DD-SRAD on synthetic data.

The base synthetic image shown in Fig. 3 was created by CREATIS Laboratory, at the Institut National Des Sciences Appliquées (INSA) in Lyon [1]. We created a stack of 14 noisy images with this synthetic base image. Noise variance was randomly chosen between 0 and 1, non-inclusive. The base image was then multiplied by uniformly distributed random noise distributions with mean of 0 and 14 different variances chosen as described above. We then smoothed the stack of images using anisotropic diffusion, SRAD, Detail Preserving Anisotropic Diffusion (DPAD) [17], and DD-SRAD using RSS distance. The RSS distance was chosen in this case because using RSS versus KS distance for synthetic data yielded better results, i.e., more smoothing, clearer edges. This may be due to the nature of temporal variation in the randomly generated stack, as there is no real information varying over time within this stack as there is in a SAR image stack.

![Image of synthetic test image](image-url)

**Fig. 3. Synthetic test image.**

Mean Square Error (MSE) was used to assess quality of the images. MSE is the mean of the squared errors, or differences from ground truth. The MSE is normalized by the number of pixels in the image. MSE values for each image are averaged, and the standard deviation is taken over the stack. MSE results of three algorithms versus DD-SRAD can be seen in Table 2. The MSE for SRAD and DPAD are high due to artifacts being introduced into denoised images during smoothing. The MSE for DD-SRAD and anisotropic diffusion are relatively low; however, an anisotropic diffusion result can be seen in Fig. 4. The original speckled image is shown to the left. The result on the right-hand side is over smoothed and does not retain edges. For comparison, an DD-SRAD result is shown in Fig. 5. The original noisy image is shown on the left. This method has the lowest average MSE compared to other methods.
Table I. MSE Results for Denoising Algorithms.

<table>
<thead>
<tr>
<th>Method</th>
<th>MSE Avg</th>
<th>MSE Min</th>
<th>MSE Max</th>
<th>MSE St. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anisotropic Diffusion</td>
<td>.0042</td>
<td>.0025</td>
<td>.0098</td>
<td>.0023</td>
</tr>
<tr>
<td>SRAD</td>
<td>.0772</td>
<td>.0002</td>
<td>.2954</td>
<td>.1035</td>
</tr>
<tr>
<td>DPAD</td>
<td>.0985</td>
<td>.0985</td>
<td>.0985</td>
<td>4.2x10^-6</td>
</tr>
<tr>
<td>DD-SRAD (RSS)</td>
<td>.0028</td>
<td>.0001</td>
<td>.0083</td>
<td>.0028</td>
</tr>
</tbody>
</table>

![Fig. 4. Anisotropic diffusion result.](image)

![Fig. 5. DD-SRAD results.](image)

To further impress the earlier point that DD-SRAD can keep temporal information unlike averaging the stack, we use a stack of 40 synthetic test images that introduces a new feature over time. This stack of images was also created by the CREATIS Lab at INSA in Lyon [1]. A large circle is slowly introduced to images in the stack on the bottom center of the images. We added speckle noise to this stack of images, using noise variance between 0 and .015, non-inclusive, and zero mean. The median of these images is seen in Fig. 6, which produces a smooth image with the circle in the bottom center of the image. However, there is no temporal information about circle behavior. In Fig. 7, results are of using DD-SRAD on the stack are shown (images 1, 10, and 20 in the stack.) The bottom row shows the results of DD-SRAD, while the top image shows the noise added to the first image in the stack. The results are also smooth and mostly noise-free, however, we retained temporal information.

![Fig. 6. Median of time-varying stack.](image)

![Fig. 7. DD-SRAD results on stack.](image)

One thing to note is that because we use the temporal information to define smoothing boundaries, there is the potential to introduce a ghosting artifact in some of the images as it is possible to notice in the first image in Fig. 7, where there are traces of boundaries of the feature that does not appear until later on in time. We are planning to address this issue by either smoothing the images in smaller groups across the stack or by introducing a variable weight decaying in time.

V. Conclusions and Future Work

In this paper, we have described a new algorithm for speckle removal on temporal stacks called DD-SRAD. This new method takes advantage of availability of a time series of images by evaluating distances between pixels. This distance is then used to evaluate the SRAD smoothing coefficient. We have shown that DD-SRAD can make use of a large number of images distributed through time to produce a result that is smoother than other leading speckle denoising methods yet still preserves edges. Furthermore, DD-SRAD preserves temporal information, unlike multi-look averaging.

There are a number of directions to further investigate. For instance, we would like to experiment with different distance metrics. KS distance may be more sensitive to noisy measurements because KS distance is the distance calculated between two points in the EDF that are the farthest away from each other. There are other distance metrics that can be incorporated. As mentioned at the end of Section IV, we would like to implement a version of DD-SRAD that gives higher preference to temporal information that is grouped closely in time. This should prevent “ghost” features in images. We hope that smoothing time series using DD-SRAD will prove smoother results than other leading methods, allowing us to better use the information present in these SAR image stacks.
REFERENCES


