Evolutionary Expert-Supervised Despeckled SRAD Filter Design for Enhancing SAR Images

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Abstract—We present an interactive easy-to-use software package, based on an evolutionary algorithm, to perform adaptive anisotropic diffusion speckle filtering for synthetic aperture radar (SAR) images. As a main difference from other methodologies, there is an integration of a SAR-image human expert who provides a subjective validation to complete the diffusion filter design. We have applied an interactive methodology to a set of SAR images, and we compared the results with those obtained by other speckle reduction filters. The results, through the evaluation of objective and local quality criteria, show the potential of the proposal.

Index Terms—Adaptive filtering, artificial intelligence, diffusion filter, image processing.

I. INTRODUCTION

SYNTHETIC aperture radar (SAR) is a powerful tool for remote sensing due to its capability to produce high-resolution images under all weather conditions. Modern airborne and satellite-borne SAR systems (high-resolution systems, new bands, and high-resolution SAR interferometry [1]) are capable of producing high-quality images of the surface of the Earth while avoiding some of the limitations of other remote imaging systems [2]. SAR civilian applications such as topographic mapping and Earth observation have focused on the related research for the last decades, but SAR applications are increasing every year, spanning from ship detection (see, for instance, [3]) to other specific objectives (see [4] for road network extraction, [5] for forest mapping, or [6] for urban building analysis).

SAR systems generate the images by means of coherent processing of the scattered signals, and consequently, they are susceptible to speckle. SAR systems show a limited bandwidth, and there is a need to filter in obtaining fine detail images even for images having low speckle.

Several conventional speckle filtering algorithms, such as median filters [7], low-pass and averaging filters [8], edge preserving [9], filters based on underlying image statistics [10], and diffusion-like filters [11], have been researched during the past years. An interesting variation is the speckle reducing anisotropic diffusion (SRAD) filter [12], which has been successfully applied to reduce speckle for both B-mode ultrasound and SAR images. SRAD is adaptive and is based on the same minimum mean-square-error approach to filtering as the Lee filter [10]. Other filtering techniques based on the curvelet transform can be consulted in [13].

In this letter, we propose a modified version of the evolutionary SRAD filter. Our proposal is based on the following hypothesis: The desired filtered image can be better obtained if the filter design is expert supervised. As it is defined in [15], interactive evolutionary computation is an optimization method that adopts the evolutionary computation from all the system optimization based on subjective human evaluation. Typically, a user sees and evaluates system outputs—under his/her knowledge or preferences—and the evolutionary algorithm optimizes the target system to get the desired output.

Therefore, as a main difference from the normally used methodology, we introduce a SAR-image human expert to guide the design of the despeckling filter. The design parameters of the filter and an image contrast enhancement are adapted online through an interactive evolutionary algorithm (interactive genetic algorithm (GA) (IGA)).

This letter is organized as follows: In Section II, we present the SRAD filter and its related control parameters. In Section III, the main aspects regarding the evolutionary algorithm are discussed, and the software implementation of the proposal is presented. Experimental results are presented in Section IV to show the potential of the proposed methodology for reducing the speckle in SAR images. Finally, in Section V, the conclusions are drawn.

II. SRAD FILTER

Our methodology applies the SRAD filter [12] combined with an IGA. In this section, we summarize the main features of the diffusion filter and focus on the filter parameters, and the next section is devoted to the evolutionary algorithm.

SRAD filter can be seen as a mixture of the classical anisotropic diffusion filter [11] and the adaptive speckle Lee filter [10]. The original Lee filter proved efficient for SAR speckle removal and has been applied to both simulated and real ultrasound B-mode still images, as well as to SAR images. The authors in [12] propose an anisotropic diffusion version of the Lee filter, showing the effectiveness of SRAD filter. The SRAD filter better preserves and enhances edges while efficiently removing speckle in homogeneous regions. The SRAD anisotropic diffusion filter for smoothing a given image can be stated according to the following nonlinear partial differential equation:

\[
\begin{align*}
\frac{\partial I(u,v,t)}{\partial t} &= \text{div} \left[ c(q) \cdot \nabla I(u,v,t) \right] \\
I(u,v,0) &= I_0(u,v)
\end{align*}
\]

\[\frac{\partial I(u,v,t)}{\partial t} \bigg|_{\Omega} = 0 \tag{1}\]
with \( I(u,v,t) \) as the intensity image evaluated at position \( u,v \) at time instant \( t \). \( I(u,v,0) \) stands for the initial image at \( t = 0 \). \( \partial \Omega \) denotes the border of the image support \( \Omega \), while the \( n \) is the outer normal vector to the image border. The divergence operator is \( \text{div}[\cdot] \), and \( \nabla \) is the gradient operator. The diffusion coefficient \( c(q) \) is expressed as in [12]

\[
c(q) = \frac{q_0^2(t) (1 + q_0^2(t))}{q^2(u,v,t) + q_0^2(t)}
\]

with \( q_0(t) \) standing for the speckle scale function. This coefficient is related to the local statistic of the image (mean and intensity variance over a homogeneous area at each \( t \) instant), but to do automatic image processing, it can be approximated by \( q_0(t) \approx q_0 \exp[-\rho t] \), where \( \rho \) and \( q_0 \) are two positive parameters less than or equal to one. The authors in [12] recommend setting \( q_0 = 1 \) for fully developed speckle for ultrasound images and setting \( q_0 = 1/\sqrt{N} \) for \( N \)-look SAR intensity data.

In our filter implementation, we set both parameters free to be optimized using the evolutionary algorithm.

As it is detailed in [12], \( q(u,v,t) \) is called the instantaneous coefficient of variation, and it is calculated from the image pixel intensity \( I \), normalized gradient magnitudes \( |\nabla I|/I \), and the normalized Laplacian \( \nabla^2 I/I \) as

\[
q(u,v,t) = \sqrt{\frac{(1/2)(|\nabla I|/I)^2 - (1/4)(\nabla^2 I/I)^2}{[1 + (1/4)(\nabla^2 I/I)^2]^2}}.
\]

To detect an image edge (or a boundary), the gradient magnitude is used by noting that, in (2), with \( c(q) \rightarrow 1 \) and \( q \rightarrow q_0 \), the filter performs an isotropic diffusion, i.e., Gaussian filtering. For the case \( c(q) \rightarrow 0 \) and \( q \rightarrow \infty \), the diffusion stops at the edges. As the filter proceeds, some instability may appear (when the denominator in (2) approaches zero much faster than the numerator). Fortunately, this can be easily avoided by simple control routines.

To improve contrast in the filtered image, we applied the same contrast enhancement method used in [14], which notably improves the image contrast. In order to make this letter self-consistent, we detail the method. After performing SRAD on the input image, the output despeckled image undergoes a linear contrast stretch [17], spanning over the full dynamic range: 0–255. A tol fraction of the image pixels is saturated (saturation of equal fractions at low and high pixel values). From the image histogram, the bottom tol\% pixels corresponding to the upper and lower tails, respectively, are identified. Next, the upper threshold is the minimum of the upper tol\% pixel intensities, and the lower threshold is the maximum of the lower tol\% pixel intensities. Saturation means that all pixel values above the upper threshold are given the intensity of the upper threshold, while pixels below the lower threshold are given the intensity of the lower threshold. The tol parameter is an input variable to the interactive evolutionary algorithm.

### III. IGA

From an operational research perspective, the basis of a GA can be understood as the intelligent highly efficient exploitation of a random search inspired by the natural evolution process [19]. GA employs a population \( P \) of individuals \( x_j \) (which are

known as chromosomes) and evolves this population through the application of random variation and selection operators. GA paradigm has been applied to several problems, mainly combinatorial problems in the realm of artificial intelligence. There are also applications to complicated nonlinear problems, and the results compared favorably to more traditional methods [20]. A population \( P \) with its corresponding chromosomes \( x_i \) (potential solutions to the stated optimization problem) is defined as the set \( P = \{x_i\} \), with \( x_i = (x_{i1}, \ldots, x_{in}) \) as a vector of \( l \) genes, \( x_{ij} \in [vlb_j, vub_j] \subset \mathbb{R} \), and \( i \in \{1,2,\ldots,N\} \), \( j \in \{1,2,\ldots,l\} \); \( vlb_j \) and \( vub_j \) stand for the lower and upper bounds for the values of the genes, respectively. In our filter implementation, the gene corresponds to the decision vector \( x = (q_0, \rho, \text{tol}, t_{\max}) \), and the lower and upper constraints are given by the set \([0, 5; 0, 0.75; 0, 0.30; 1, 50]\), which has been fitted through a training phase over a set of SAR images with speckle. The objective function to be optimized \( F(x) \) is called the fitness function in the GA context. The fitness function is evaluated visually by a human SAR expert (see Fig. 1) for a given decision vector and yields a score \( x_i \mapsto F(x_i) \in [0,10] \). The IGA works like a parameter adaptation algorithm producing and evolving various filter realizations according to a subjective quality criterion. It is expected that, by randomly changing the chromosomes through the two basic variation operators, namely, crossover (mixing) and mutation (small change), and by selecting the best solution, the algorithm evolves, increasing the average fitness of the population. Although the optimal solution is not guaranteed, it is also expected that the final population contains the near optimal solution (see, for example, [19]).

To reduce the interactive designing phase evaluation, in order to make it less time consuming for the expert supervision task, an agglomerative hierarchical tree clustering methodology with a consistency level has been applied. Each chromosome \( x_k \) to be evaluated is placed in a separate table or history of evaluations \( \Xi \), with a zero fitness initially \( F(x_k) = 0 \). The entries in \( \Xi \) are tuples \((x_i, F(x_i))\). All members of \( \Xi \) undergo a clustering procedure. Clustering applies to the first elements in the tuples \((x_i)\). For instance, if \( x_k \) falls within some cluster \( \chi \), \( F(x_k) \) is calculated as the average fitness of chromosomes in \( \chi \), excluding \( x_k \) itself, i.e.,

\[
F(x_k) = \frac{1}{(|\chi| - 1)} \sum_{j=1,j \neq k}^{|\chi|} F(x_j).
\]

If \( \chi \) is a one-element cluster, then the evaluation of \( x_k \) is deferred to the human evaluator (the expert). In the first generation
The filters have been coded in MATLAB. The curvelet-based filtering, and the original SRAD filter. All comparison with other filtering strategies, such as the Lee filter, speckle noise in amplitude format. The results include a visual (subjectively. In subsequent generations (iterations), chromosomes are evaluated subjectively with some periodicity (a parameter of the algorithm suited to the availability of the expert). The rest of the chromosomes are evaluated using the clustering strategy described. To reduce the workload of the expert, the images showing spurious pixels related to the instability of the diffusion process must be eliminated from the evaluation mechanism [see (2)]. As it is well known, the diffusion speckle filters—when they are not well designed—tend to present a salt-and-pepper-like additional noise. This effect becomes more critical for long diffusion times (see Fig. 2), and consequently, the filtered images are unacceptable. To fully complete the description of the IGA, an elitist replacement of the worst individual in each generation with the previous best individual has been used to prevent losing the best filter realization.

A. Implementation Issues

The interactive genetic diffusion filter [interactive genetic SRAD (IGSRAD)], the simple contrast enhancement mechanism, and the evolutionary algorithm to design the filter have been embedded into a software package with a friendly graphic interface implemented in MATLAB R2008a [18]. To design a filter for an image, the user—the expert—runs the application on an input SAR image, and after a few iterations running the IGA algorithm (scoring the images according to his/her quality criteria), an output image suited to the desired particular needs is obtained. A typical design session takes around 10 min on a Pentium-IV 2.3-GHz machine.

Once the filter has been efficiently tuned, the user can build, in a preprocessing stage, a filter library and later employ it in daily practice. The application has been checked by different SAR experts, and they coincided in its suitability and its easy training phase.

IV. EXPERIMENTAL SETUP

To validate the human-in-the-loop proposed methodology, a set of experimental results has been obtained, processing simulated SAR images and real ones. For the simulated SAR images, we are also interested in computing the Peak-Signal-to-Noise Ratio (PSNR) estimator and Pratt’s figure of merit (FOM) estimator, for which an image has been degraded with speckle noise in amplitude format. The results include a visual comparison with other filtering strategies, such as the Lee filter, the curvelet-based filtering, and the original SRAD filter. All the filters have been coded in MATLAB.

A. Estimators to Evaluate the Performances of Our Proposal

For the simulated SAR images, a quantitative analysis is performed through well-established statistics estimators (mean and standard deviation): the FOM and PSNR estimators. We refer the reader to [21] and [22] for a complete description.

The mean preservation and the variance reduction measured within a region (or through the entire image) indicate a successful filter operation. The PSNR measures the signal level with respect to the remaining noise with a least squares criterion. A higher PSNR indicates a higher quality filtered image. The FOM calculates an empirical distance between the ground truth contours $I_{ref}$ and those obtained after the segmentation of the noisy image. As indicated in [21], this estimator is one of the most frequently applied in image processing, although it has no theoretical proof. $FOM \in [0, 1]$ with unity for ideal edge detection.

B. Results for an Image Degrade With Speckle

The first results are for an original speckleless image which has been degraded with simulated speckle in amplitude format. Proceeding as in [2], we selected the aerial image from MATLAB’s Image Processing Toolbox due to its similarities to the content of real SAR images. From that image (2956 × 2215 pixels), a region of interest (ROI) of 512 × 512 pixels was selected by a SAR expert, and it is shown in Fig. 3 (top left).
The speckle has been simulated following the Gamma distribution with a mean value of one and fitted to provide an equivalent number of looks $ENL = 1$. The degraded image and the results after applying the curvelet-based filtering, the Lee filter, and the original SRAD filter ($T = 5$) are also shown in Fig. 3. Three results are obtained by applying the IGSRAD filter, although only one of the solutions is illustrated (bottom left).

To avoid the user’s subjective component while tuning the filter, first, the user applied the aforementioned filters, and after a convenient lapse of time to eliminate a biased result, the user applied the interactive methodology. However, in a real situation, there is no need to avoid a previous solution obtained by other filters.

As it can be seen, both the curvelet-based filtering and the Lee filter clearly reduce speckle, but the IGSRAD filter seems to get the best performance, preserving edges while smoothing speckle. The SRAD filter applied is the original one with parameters as indicated in [12]. After SRAD filtering, the uniform areas and the clearings appear more homogeneous, but some artifacts also show up due to the instability of the SRAD filter when working with the actual parameters [see (2)]. However, this result can be notably improved by using our proposed technique (IGSRAD result, bottom right), which achieves a higher contrast without speckle smoothing degradation.

This subjective qualitative conclusion can be objectively analyzed (see Table I). The Lee filter gets the best mean preservation and the best $PSNR$ values. The best $FOM$ is for the IGSRAD filter optimized by expert $E_1$, and the best variance reduction is also for the IGSRAD filter realizations. Note that the $PSNR$ and mean values are also similar to the best ones from the Lee filter. The CPU times are considerably shorter for the diffusion filters than for the Lee filter and the curvelet-based filtering. Moreover, it is important to note the flexibility brought by the interactive proposal, which allows for the filter designer to get not an optimal solution but a desired one that better suits his/her needs according to, for example, mean preservation or higher $PSNR$. The aforementioned filters have been applied to a selected homogeneous region, and the conclusion obtained is similar, as expected.

C. Real Image Results

The first SAR image selected is the one shown in Fig. 4 (top left). It is a TerraSAR VV two-look image corresponding to the center of Prague (urban area), with a resolution of 1.55 m (acquisition date: March 24, 2008). We apply the Lee filter and the original SRAD filter ($t_{\text{max}} = 5$). From this figure, it may be observed that, although the Lee and the SRAD filter perform well, the solution obtained by means of the interactive proposal, IGSRAD, gives the best performance in terms of effectively preserving details while smoothing speckle. The contrast has been also notably enhanced, improving the visual aspect of the original noisy image.

The estimators that we used to evaluate the performance of the filters were the mean preservation, the variance reduction, and the ENL. Once the image has been filtered, we recalculate the ENL through the study of the ratio image [23]. The best filter is the one providing an ENL closer to the number of looks (i.e., closer to two for this first image) while preserving the original mean of the image (see Table II). This result for the conventional SRAD filter strengthens our interactive proposal that we regard as an interesting methodology to efficiently tune the SRAD diffusion filter. Once again, the CPU time has been notably reduced.

It is hard to give a sound comparison between the training times of IGSRAD and the other automatic filtering methods.
The second SAR noisy image selected is a subimage from the one-look HH SAR image corresponding to the Wellling area (Oberpfaffenhofen, Germany). Due to its large size and to speed up the subjective evaluation by the expert, an ROI (256 × 256 pixels) was selected (see Fig. 5). We apply the curvelet-based filtering and the Lee filter to compare the results obtained by denoising with the IGSRAD filter. The obtained values for the estimators and CPU times for all the filters are given in Table III, where it can be seen that the IGSRAD filter provides the best values for the aforementioned estimators and also the best CPU time.

V. CONCLUSION

In this letter, we have proposed a methodology based on an evolutionary algorithm that guides the design of an SRAD filter to a desired filter realization to be applied in SAR images. The main advantage of IGSRAD is that it offers a simple tool to fully tailor a SAR-image filter according to specific user criteria. Moreover, the proposed method is not limited to SRAD filters but can be extrapolated to other parametrizable filtering techniques or filtering kernels. The expected limitations of such interactive filtering strategies come from the limitations of the automatic filtering kernel employed. The results show the potential of the methodology for improving the quality of the image suited to the requirements predetermined by a user.

REFERENCES