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Conference Paper *in* IEEE Transactions on Geoscience and Remote Sensing · April 2012

DOI: 10.1109/TGRS.2013.2269866

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Abstract

Speckle reduction is an important problem in SAR image analysis. We present an interactive easy-to-use software package based on an evolutionary algorithm, to optimize a despeckling Bayesian nonlocal means filter with sigma preselection for reducing the image variance while preserving the image mean. As a difference from other methodologies, there is an implication of the user, which provides a subjective validation to complete the Bayesian filter design. We apply the methodology on both synthetic and real intensity SAR images and the results show the effectiveness of the proposal.

1 Introduction

For all the despeckling filtering methods [1, 2, 3], the major problem is to reach a trade-off between the output image resolution and the speckle removal. The desired result is a filtered image showing a miminum standard deviation while keeping the original mean value of the noisy image. It is known that such a filtered image is an enhanced despeckled version of the original noisy image.

To optimize a filter, there are several numerical methods such as gradient-like and quasy-Newton methods but, although providing acceptable solutions, such solutions are susceptible of showing undesirable artifacts or deformed borders or simply of lossing relevant image details. To avoid that, we propose to apply a supervised methodology to guide the efficient design of the Enhanced Bayesian NonLocal filter (EBNL filter) [4], while retaining image details. Besides, as direct numerical methods tend to get trapped in local minima, we use a robust heuristic method such as a genetic algorithm.

The paper is organized as follows: firstly, we present the Bayesian filter and its related control parameters. Secondly, the main aspects regarding the genetic algorithm are discussed. Finally, some experimental results and conclusions are presented.

2 Enhanced Bayesian Nonlocal Means Filter with Sigma Preselection

Our methodology applies the EBNL filter [4] combined with an interactive genetic algorithm to guide the design of the filter. In this section, we summarize the main features of the BNL filter [3] and we describe its enhanced version [4]. While describing the enhanced BNL filter, we focus on the filter parameters selected for its optimization through the evolutionary methodology.

The BNL means filter is the extension of the non local means filter based on Euclidean-distance criteria [5] and on a probabilistic approach which can be also applied to multiplicative noise (speckle-like noise). BNL filters, in general, proceed by minimizing the Bayesian risk under the assumption that the statistical estimations from an image patch are valid, that is, good aproximations for the true involved statistical parameters. Besides, BNL filters preserve edges while reducing the standard deviation and preserving well the original image mean [4], as other well-established despeckling filters [1, 2].

For a noise-free image u, and a noisy image v, the BNL filter [3] proceeds updating the noisy data at pixel $v(x)$ as,

$$\widehat{u}(x) = \frac{\sum_{y\in\varepsilon(x)} p(\mathbf{v}(x)|\mathbf{u}(y))p(\mathbf{u}(y))u(y)}{\sum_{y\in\varepsilon(x)} p(\mathbf{v}(x)|\mathbf{u}(y))p(\mathbf{u}(y))}, \qquad (1)$$

where $\widehat{u}(x)$ is estimated as the weighted average of all gray values $u(y)$ in the local neighborhood $\varepsilon(x)$ of x. $\mathbf{v}(x)$ and $\mathbf{u}(x)$ are the vectorized $M\times M$ image patches centered at pixel x. Under the assumption of fully developed and non-correlated speckle samples, the conditional distribution $p(\mathbf{v}(x)|\mathbf{u}(y))$ can be estimated by means of a Gamma distribution (see [6]) as,

$$p(\mathbf{v}(x)|\mathbf{u}(y)) \propto \exp\left(-\frac{1}{\rho^2}\sum_{m=1}^{M^2}\left(\frac{v_m(x)}{u_m(y)} + \ln\frac{u_m(y)}{v_m^{L'}(x)}\right)\right),$$

where ρ is the smoothing parameter, and $L' = (L-1)/L$, with L the number of looks for an intensity SAR image. The smoothing parameter ρ can be related to the number of looks, L, through $\rho = k/\sqrt{L}$, where k is an empirical factor. A good choice for the k value is $k \approx 2$, although in our proposal, k is regarded as a filter parameter to be optimized. The description of the BNL filter is completed by establishing the prior distribution $p(\mathbf{u}(y))$, which is inversely proportional to the size of the neighborhood $\varepsilon(x)$ of x, $|\varepsilon(x)|$, i.e., $p(\mathbf{u}(y)) = 1/|\varepsilon(x)|$. Authors in [4] propose a variation of the BNL filter described above in order to reduce the bias problem due to the use of $\mathbf{u}(y)$ and $u(y)$ - which are not available in a real case - instead of $\mathbf{v}(y)$ and $v(y)$. The EBNL filter is:

$$\widehat{u}(x) = \frac{\sum_{y \in N(x)} p(\mathbf{v}(x)|\mathbf{u}'(y))p(\mathbf{u}'(y))u'(y)}{\sum_{y \in N(x)} p(\mathbf{v}(x)|\mathbf{u}'(y))p(\mathbf{u}'(y))}, \qquad (2)$$

where the *a priori* mean estimation, $u'(y)$ is done using a 3×3 mean window, which shows better performances in retaining details than using a larger window, and it is also faster. In our proposal, we apply this criterium instead of the iterative method proposed in [3]. Note that equation (2) also differs from (1) in the neighborhood $N(x)$, which is a refined subset based on the sigma range, to account for the pixel preselection, as it is detailed as follows:

$$N(x) = \varepsilon(x) \cap N_1(x) \cap N_2(x), \qquad (3)$$

where the set $N_1(x)$ is a set of pixels obtaining by patch preselection to eliminate the uncorrelated pixels within the $\varepsilon(x)$ patch, and the set $N_2(x)$ accounts for pixel preselection. The $N_1(x)$ subset is calculated as,

$$y \in N_1(x), \text{ only if } \gamma < \overline{\mathbf{v}}(y)/\overline{\mathbf{v}}(x) < 1/\gamma, \qquad (4)$$

where $\overline{\mathbf{v}}(\cdot)$ stands for the mean value of the corresponding patch $\mathbf{v}(\cdot)$ and $\gamma < 1$ is a threshold defined by the user. In our proposal, we consider this parameter as a filter parameter to be optimized. Note that this parameter strongly affects to the cost computational cost involved when filtering an image and, this parameter it is also relevant because a bad choice for this parameter reduces the efficiency of the filtering process. The other set appearing in (3), $N_2(x)$, is the the set of pixels obtained by pixel preselection. Pixel preselection based on the sigma range is a useful technique for retaining details and for preservation of strong reflective scatterers, which are usually of high interest when filtering SAR images. It is also useful for excluding outliers during the calculations. The sigma range preselection reduces the speckle -smooth the image noise- by means of averaging *only* those neighborhood pixels showing intensities within a fixed sigma range of the center pixel.

For SAR images, the sigma value, ξ usually ranges from $\xi = 0.8$ to $\xi = 0.9$ as indicated in [1] for terrain and crop classification, although, for some applications, a lower value is preferred. In our proposal, we consider ξ as a filter parameter spanning in a user defined interval. To account for dark areas, we follow the approach from [4], which consists of separating the pixels with a threshold, $T = v_{max}/2$; pixels with an intensity values higher than T are preselected through the sigma range mechanism,

$$y \in N_2(x), \text{ only if } v(y) \in (u'(x)I_1, u'(x)I_2), \qquad (5)$$

where I_1 and I_2 are the range satisfying the condition $\xi = \int_{I_1}^{I_2} p_N(I)dI$, for a N-look intensity pdf $p_N(I)$.

The BNL filter and its enhanced version have been discussed. The selected filter parameters for filter optimization are: the k value (related to the smoothing parameter), the γ parameter (related to the patch preselection), and the ξ parameter associated to pixel preselection. As the filter can be applied iteratively, we consider the maximum number of iterations, n_{max}, as another filter parameter. The size of the vectorized patch M, SM, and the size of the neighborhood $N(x)$ of x, SN, are also considered filter parameters to be optimized. We write them as the decision vector $\mathbf{z} = [k, \gamma, \xi, n_{max}, SM, SN]$.

3 Optimization and Evolutionary Algorithm

For a given intensity noisy image I_v with support Ω and mean $\mu(I_v)$, and standard deviation $\sigma(I_v)$, we want to optimize the EBNL by solving:

$$\begin{aligned} &\text{minimize } \sigma(I_v(\mathbf{z})) \\ &\text{subject to } \mu(I_v(\mathbf{z})) = \mu(I_v), \end{aligned} \qquad (6)$$

where $\mathbf{z}$ is the decision vector.

The desired result is a filtered image showing a miminum standard deviation but keeping the original mean value of the noisy image. It is known that such a filtered image corresponds to the enhanced despeckled version of the original noisy image. The problem to be solved is a nonlinear contrained optimization problem (*probably*) non-convex. There are several direct numerical methods to solve the problem to get an *acceptable* non-optimal solution, such as gradient-like methods, and quasy-Newton methods. Using direct methods can be risky because, although they provide acceptable solutions satisfying the restrictions, those solutions are susceptible of showing undesirable artifacts or deformed borders or simply of lossing relevant image details. To avoid that, we propose to apply a supervised methodology to guide the efficient design of the EBNL filter while retaining image details. In addition, as direct numerical methods tend to get trapped in local minima, we prefer to use a heuristic method.

3.1 Interactive Genetic Algorithm

The basis of genetic algorithms (GAs) can be seen as the intelligent -highly efficient- exploitation of a random

search inspired by the natural evolution process [7]. GA employs a population P of individuals z_j (*chromosomes*) and evolves this population through the application of random variation and selection operators. A population, P, with its corresponding chromosomes z_i, (potential solutions to the stated optimization problem), is defined as the set, $P = \{z_i\}$, with, $z_i = (z_{i1}, ..., z_{il})$ as a vector of l genes, $z_{ij} \in [vlb_j, vub_j] \subset \Re$, and $i \in \{1, 2 \ldots, N\}$, $j \in \{1, 2 \ldots, l\}$; vlb_j and vub_j stand for the lower and upper bound for the values of the genes respectively. In our EBNL filter implementation, the gene corresponds to the decision vector $\mathbf{z} = [k, \gamma, \xi, n_{max}, SM, SN]$, and the lower and upper boundaries are given by the set $[(1.5, 2.5), (0.70, 1.0), (0.60, 0.98), 3]$ for the variables k, γ, ξ, n_{max}, while for the size patches are given by $[(3 \times 3, 5 \times 5), (5 \times 5, 7 \times 7, 9 \times 9)]$. Both sets have been fitted through a training phase over a set of SAR images.
From (6), the objective function to be optimized is $\sigma(I_v(\mathbf{z}))$, but, using the Interactive Genetic Algorithm (IGA), we solve the problem by minimizing the *fitness function* F, in the GA context. This fitness function is evaluated visually by a human operator for a given decision vector and gives a score $z \mapsto F(z) \in [0, 10]$. The IGA works like a parameter adaptation algorithm producing and evolving various filter realizations according to a subjective quality criterion. The user evaluates every filtered image attending to its variance reduction and its constant mean value which are shown on screen jointly with the original (noisy image) and the filtered image after each iteration (see **Figure** 1). The equality contraint on equation (6) is relaxed by an acceptable level of approximation (the restriction is considered satisfied by any mean value, $\mu(I_v(\mathbf{z})) \in [\mu_{min}, \mu_{max}]$). The values μ_{min} and μ_{max} are provided by the user of the algorithm according to his/her preferences.

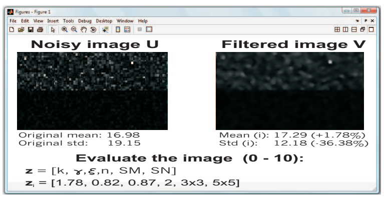

Figure 1: Interactive evaluation of the filtered image i

It is expected that, by randomly mixing (*combining*) chromosomes through the two basic variation operators, crossover and mutation, 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 a near optimal solution, that is, a selection of the best results (individuals) is accomplished in each algorithm iteration.
The original BNL filter, the EBNL filter and the evolutionary algorithm to design the filter have been embedded into a software package with a friendly graphic interface implemented in MATLAB R2008a [8]. To design a filter, the user 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 sesion takes around 15 minutes on a Pentium-IV 2.3 GHz machine. The application has been checked by different SAR users and they coincided in its suitability and its easiness training phase.

4 Experimental Setup

To validate the proposal, we have done some experiments both on synthetic SAR images and on real intensity SAR images. We compare the resuls with the EBNL filter using the $SM = 7, (7 \times 7)$ and $SN = 21, (21 \times 21)$ patches as indicated in [4], and the parameters $k = 2, \gamma = 0.8, \xi = 0.95, n_{max} = 1$. The criteria we consider for quantifying our proposal are the mean preservation, the variance reduction and the edge preservation through Pratt's figure of merit [9]. 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. Figure 2 (a) shows the 250 × 250 SAR phantom and (top right) the simulated 1 look intensity SAR image. The speckle has been simulated following the Gamma distribution with a mean value of 1 and fitted to provide an ENL = 1 (*Equivalent Number of Looks*). The degraded image and the results after applying the EBNL based filter and the optimized EBNL using our proposal are also shown in the same Figure 2. We can see that, in solution from the EBNL filter, some details are loosing (see the cars in the parkings) and, a better performance is provided by its optimized version. The quantitative results in table 1 show a better FOM for the optimized EBNL and a mean preservation nearer to the mean of the noise-free image. The relative CPU time is significantly lower for the optimized EBNL than for the EBNL filter.

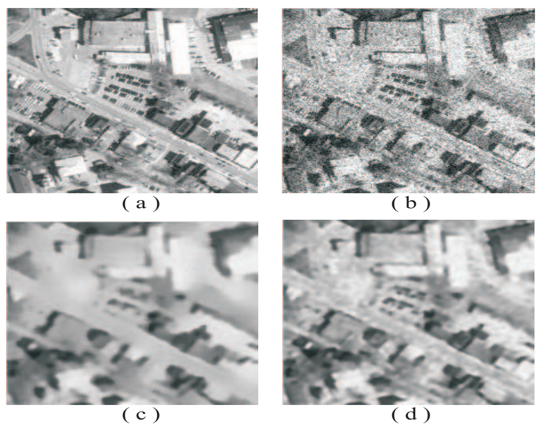

Figure 2: Results for the synthetic image: (a)Noise-free Image. (b) Image Degraded with Simulated Speckle Noise (ENL = 1).(c) The EBNL filter. (d) The optimized EBNL filter [1, 1.8, 0.75, 0.92, 5 × 5, 5 × 5]

Table 1: Quantitative evaluation for the synthetic SAR image and relative CPU time (best values in boldface)

Image	Mean	Std.	FOM	CPU Time
Noise-free image	152.30	55.98	—	—
Degraded image	148.32	63.02	—	—
EBNL	152.99	**44.22**	0.29	9.2
Optimized EBNL	**152.59**	47.62	**0.45**	**1**

The real intensity SAR image selected is the one shown in Fig. 3, (a). It is a 256 × 256 TerraSAR VV 2-looks image corresponding to the center of Prague (urban area), with a resolution of 1.55 m (acquisition date: 2008-03-24). The filtered image by the EBNL filter and by two filter realizations applying the proposed methodology are also shown in this figure. It may be observed that both filters, EBNL and the optimized EBNL, perfom well, but, from table 2, a significative CPU time reduction time is provided by both optimized EBNL filters. It means that a similar result to the one provided by the EBNL filter can be obtained but faster. The reduction in variance is significative and the preservation of the mean is $\approx 3\%$ for the EBNL and for the two optimized EBNL filter realizations.

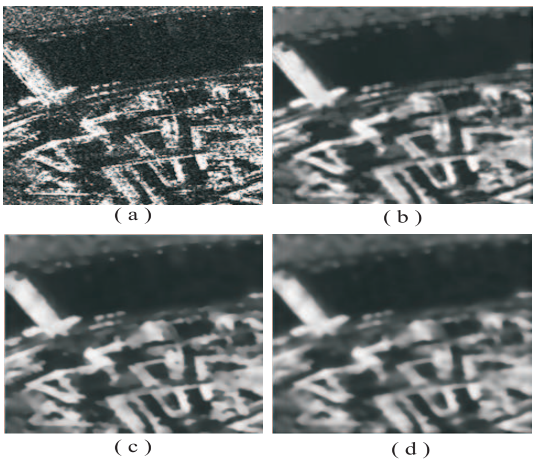

Figure 3: Results for real intensity SAR image. (a) Original SAR image. (b) The EBNL filter. (c) Solution for user 1 applying our proposal [3, 1.81, 0.72, 0.81, 3 × 3, 7 × 7]. (d) Solution for user 2 applying our proposal [1, 2.3, 0.61, 0.88, 3 × 3, 9 × 9]. (SAR images courtesy of Terra Sar-X, Infoterra GmbH and Infoterra Servicios de Geoinformación S.A.)

Table 2: Quantitative filter evaluation for the real intensity SAR image and relative CPU time (best values in boldface)

	Noisy image	EBNL	Optimized EBN by user 1	Optimized EBNL by user 2
Mean	82.59	**84.97**	85.13	85.13
Std.	70.12	56.68	54.48	**51.69**
CPU	—	5.2	1.2	**1**

5 Conclusions

We proposed an interactive easy-to-use software tool, based on an evolutionary algorithm, to optimize the EBNL filter for despeckling SAR images. As a difference from other filter design methodologies, there is a direct implication of a user which provides a subjective validation of the filtered images guiding the filter to his/her requierements. The results show the potential of the methodology for optimizing the EBNL filter.

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