DESPECKLING SAR IMAGES USING WAVELETS AND A NEW CLASS OF ADAPTIVE SHRINKAGE ESTIMATORS

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ABSTRACT

We propose in this paper an efficient and fast wavelet based technique for speckle removal from SAR images. It relies on realistic distributions of the wavelet coefficients which represent mainly speckle noise on the one hand and those that represent the useful signal corrupted by speckle on the other. We propose analytic models for these distributions, and compute their parameters automatically from a given SAR image. The resulting algorithm strongly suppresses speckle, while preserving image details and sharpness.

1. INTRODUCTION

For remote sensing, Synthetic Aperture Radar (SAR) is a very powerful and attractive tool due to its high spatial resolution. Yet, automatic interpretation of SAR images is extremely difficult [1] because of the speckle noise. Speckle affects all coherent imaging systems and can be regarded as multiplicative noise. Some standard speckle filters, e.g. [2], yield easily computable equations but do not preserve fine details in complex images. A recently proposed method [1] achieves high performance using Bayes estimation and random fields as texture models; however, its computational complexity is high. In order to achieve both high quality denoised images and a fast computation the wavelet transform [3] is an attractive choice. Currently, there is a great activity in the area of context-based and locally adaptive wavelet shrinkage, e.g., [4-7]. In this respect, we have proposed in [8] a specific form of a spatially adaptive shrinkage factor as a function of two variables: the first variable is the ratio of the likelihood's of the magnitude of the wavelet coefficient given noise and given useful edges, respectively; the second variable is derived from a spatial surrounding in a binary mask that indicates the estimated edge positions. The likelihood model was heuristic and parameterized.

In this paper, we further extend and improve this approach. Instead of using a heuristic likelihood model, we determine empirically the actual statistical distribution of the wavelet coefficients representing mainly noise and of those representing useful edges. Practically, we compute their histograms in the areas indicated by the corresponding mask. For SAR images, we notice the following useful property: the magnitudes of the wavelet coefficients representing mainly noise follow well scaled exponential distribution; the magnitudes of the wavelet coefficients representing mainly useful signal follow well scaled Gamma distribution. The parameters of these distributions are easily computed from the corresponding histograms. The results demonstrate the effectiveness of this approach for despeckling SAR images.

2. ADAPTIVE SHRINKAGE METHOD

Let us denote by $w_{l,j,D}$ the observed value of the wavelet coefficient at spatial position l, at the resolution scale 2^j, in the detail image with orientation D. The corresponding true, unknown value that we want to estimate is $y_{l,j,D}$. We assume the redundant wavelet decomposition, with equal number of wavelet coefficients at all scales. In particular, we use the decomposition with spline wavelets from [9], resulting in two detail images at each scale. For the sake of clarity, we shall omit the orientation index D, and the scale index j unless in cases where it is explicitly needed. With each detail image $\mathbf{w}=\{w_1,\ldots,w_L\}$ we associate a *mask* $\mathbf{x}=\{x_1,\ldots,x_L\}$ of *binary labels*, where $x_l = 0$ if w_l represents mainly noise, and $x_l = 1$ if w_l represents useful signal. Estimated values of these binary labels will be denoted by $\hat{x}_l$. Finally, the magnitude of the wavelet coefficient $|w_l|$ will be denoted by m_l. The likelihood of m_l given the label value x_l will be denoted by $p(m_l | x_l)$.

To remove noise, we apply wavelet shrinkage $\hat{y}_l = q_l w_l$, where $0 \leq q_l \leq 1$ is the shrinkage factor. In [8], we have proposed and motivated the following form for q_l:

$$q_l = \frac{\xi_l \, \eta_l}{(1+\xi_l \, \eta_l)}, \qquad (1)$$

where one parameter is the likelihood ratio at the current position l, and the other one is derived from the spatial surrounding $\partial(l)$. In particular

$$\xi_l = \frac{p(m_l \mid 1)}{p(m_l \mid 0)}, \quad \eta_l = \exp(\gamma \sum_{k \in \partial(l)} (2\hat{x}_k - 1)), \qquad (2)$$

The parameter γ controls the relative importance given to the local spatial neighborhood, for which we use the eight nearest neighbors of each pixel. Our main interest in this paper is to determine realistic likelihood models $p(m_l | x_l)$ for SAR images, and such that their parameters can be easily computed from the

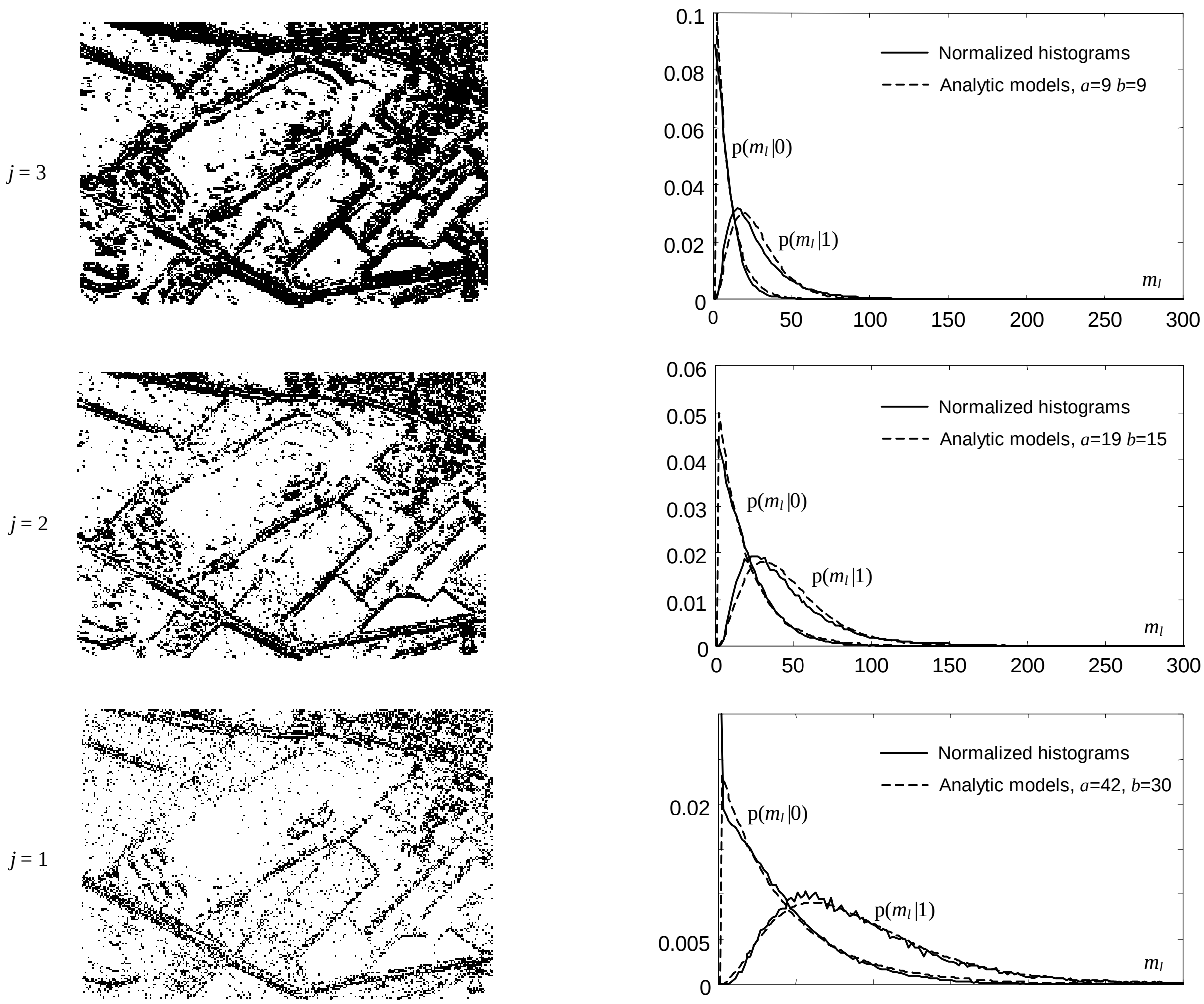

Fig.1. From top to bottom: estimated masks for one orientation of details at the resolution scale 2^j and the corresponding, estimated likelihood's $p(m_l\,|x_l)$, for the SAR image from Fig.3.

given image. Realistic conditional densities can be derived by investigating the histograms of m_l in the areas of the detail image labeled by the same value x_l. Practically, we estimate these densities for each detail image, using the corresponding, estimated mask.

Let us first introduce the global description of our algorithm, before we concentrate on its specific aspects. The global procedure is the following:

1. Compute the redundant wavelet decomposition into N resolution scales (j =1…N)
2. Apply a coarse-to-fine denoising procedure: $\hat{\mathbf{y}}_N^D = \mathbf{w}_N^D$ and for j =1…N
   - Estimate the mask using the observed detail image and the previously estimated, coarser one
   - Estimate the conditional densities $p(m_l|0)$ and $p(m_l|1)$
   - Apply the shrinkage factor from Eq (1) to each wavelet coefficient
3. Apply the inverse wavelet transform.

2.1. Mask estimation

For each detail image, we classify the binary labels as follows:

$$\hat{x}_{l,j} = \begin{cases} 0, & |w_{l,j}||\hat{y}_{l,j+1}| < \sigma_j^2 \\ 1, & |w_{l,j}||\hat{y}_{l,j+1}| \geq \sigma_j^2 \end{cases}, \qquad (3)$$

where σ_j is the standard deviation of noise at the resolution scale 2^j; in particular, we compute it as the median absolute deviation of the coefficients in a given detail image divided by 0.6745. The classification (3) is motivated in the following way: it is well known that at positions of meaningful image edges the magnitudes of wavelet coefficients tend to increase through resolution scales. In contrast, the magnitudes of the wavelet coefficients representing pure noise rapidly diminish as the scale increases. This property can be exploited in different ways to achieve a better classification of wavelet coefficients than using their magnitudes alone. For the application considered in this paper, we found that the simple classification (3) is robust and provides good results.

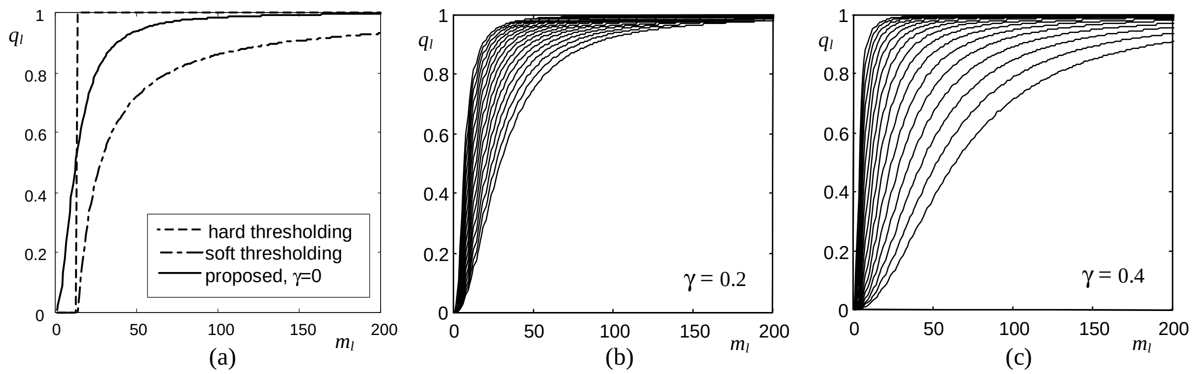

Fig.2. An illustration of the proposed adaptive shrinkage functions, derived from the estimated $p(m_l|x_l)$ for j=3 from Fig.1. (a) The resulting shrinkage function for γ=0, in comparison with standard hard- and soft-thresholding functions. (b) and (c) Families of resulting shrinkage functions, depending on the local spatial context, for γ=0.2 and γ=0.4, respectively.

2.2. Estimation of likelihood functions

Let us denote by $S_0 = \{l \,|\, l \in S, \hat{x}_l = 0\}$ and $S_1 = \{l \,|\, l \in S, \hat{x}_l = 1\}$ the two subsets of the image field $S=\{1,\ldots n\}$, containing the estimated positions of noisy and significant wavelet coefficients, respectively. We compute the histogram of the vector $\mathbf{m_0} = \{m_l \,|\, l \in S_0\}$, and normalize it (such that the total area under the curve equals one); this normalized histogram is the empirical estimate of the density $p(m_l|0)$. In the similar way, $p(m_l|1)$ is empirically estimated by computing and normalizing the histogram of the vector $\mathbf{m_1} = \{m_l \,|\, l \in S_1\}$. The empirically estimated likelihood's for several detail images of the SAR image from Fig.3 are shown in Fig.1. By inspecting these histograms in different detail images and for a number of different SAR images, we found an interesting result: the empirically estimated likelihood's $p(m_l \,|\, 0)$ and $p(m_l \,|\, 1)$ can be well approximated by scaled exponential and Gamma densities, respectively. More precisely, we use the following analytic form

$$p(m_l \,|\, 0) = \frac{1}{a} \exp(-m_l / a)\,, \tag{4}$$

$$p(m_l \,|\, 1) = \frac{1}{2b}\, (m_l / b)^2 \exp(-m_l / b)\,. \tag{5}$$

In Fig.1, we show these analytic approximations together with the empirically estimated ones. Use of these analytic expressions greatly facilitates the computation of the shrinkage factor. The parameters a and b are computed automatically during the denoising procedure, by minimizing the mean squared difference between the normalized histogram and the sampled analytic approximation.

2.3. Adaptive family of shrinkage functions

Using the likelihood models (4) and (5), one can easily compute the shrinkage factor q_l from Eq (1) for any given value m_l. Let us first examine the shape of the resulting shrinkage function without the influence of the local spatial neighborhood (i.e., for η_l =1). We illustrate it in Fig.2.a, (for likelihood models with a=b=9, as in the top row of Fig.1.), and we compare it with standard hard- and soft-thresholding functions; in the latter two cases the threshold was determined as the intersection of $p(m_l \,|\, 0)$ and $p(m_l \,|\, 1)$. One can see that the proposed shrinkage function suppresses high magnitude coefficients less than the classical soft-thresholding. This is very important for high-resolution SAR images, where strong scatterers and the sharpness of image details should be preserved. In Fig.2.b, and Fig.2.c, we illustrate the resulting families of shrinkage functions, when different relative importance γ is given to the local spatial context.

3. RESULTS AND DISCUSSION

We demonstrate the performance of the proposed method on three different SAR images. The size of the original image in Fig. 3 is 400x600 pixels, while in Fig. 4, due to limited space we show only the parts of other two SAR images. One can see that speckle noise is efficiently removed, while the sharpness and tiny details are preserved. The computation is fast, (only slightly larger than that of the simplest wavelet thresholding techniques); this is very important, since SAR images may contain huge amount of data. The method can operate fully automatically: the only parameter that is not computed directly from the input image is γ, i.e., the relative importance given to the local spatial context. By qualitative judgement of results for many different SAR images, we found that the value γ=0.2 was optimal in all cases; this value was also used for all the results presented here. For some applications, it might be desirable to have the possibility of tuning this parameter. Its higher value (see Fig.2.c) leads to greater smoothing of noise and background textures, while enhancing the main edges, which are detected in masks.

To enable an objective comparison with other methods, we also give the peak-signal-to-noise-ratio (PSNR) values for two standard test images corrupted by synthetic noise. We have used the speckle noise model from Matlab: it adds to an image I the multiplicative noise uI, where u is a uniformly distributed random variable with zero mean and standard deviation σ_u.. For the Cameraman image and σ_u equal to 15, 25 and 35 the PSNR values after despeckling are 34.78dB, 31.34dB and 28.84, respectively. For the Lena image, and the same standard deviations σ_u, the resulting PSNR values are 35.73dB, 31.75dB and 29.35dB, respectively.

Fig.3. Left: original SAR image showing a horse track, resolution 1m, source Sandia Natioanal Lab. Right: Despeckled image.

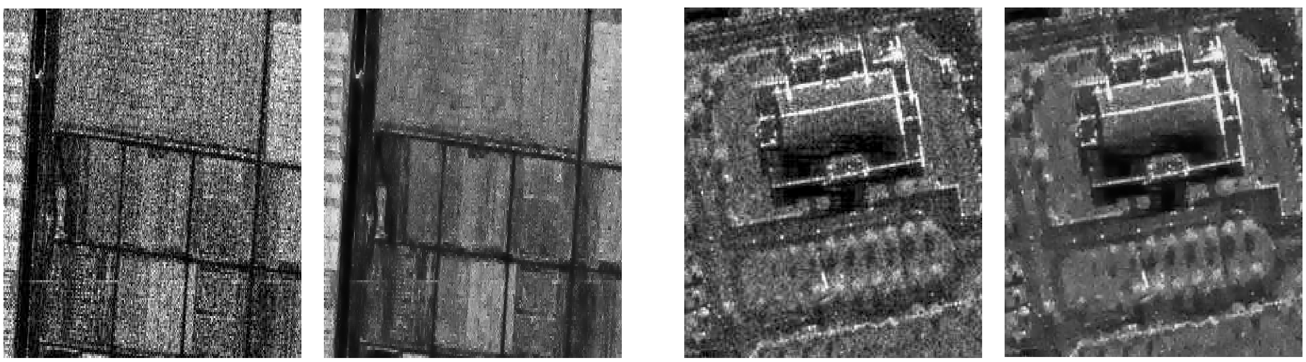

Fig.4. Parts of original (resolution 1m, source Sandia) and despeckled SAR images. Left: agricultural fields. Right: a city area.

4. CONCLUSION

In this paper, we proposed a new and efficient technique for despeckling SAR images. The main novelty is the use of realistic distributions of the wavelet coefficients which represent mainly speckle noise on the one hand and those that represent the useful signal on the other. We proposed analytic models for these distributions, and the automatic computation of their parameters directly from a given SAR image. By combining these distributions with a simple local model for spatial context, we obtained a family of adaptive shrinkage functions for the wavelet coefficients. Its use leads to fast computation and despeckling with well-preserved image details, as was demonstrated on different SAR images.

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