A NONLOCAL APPROACH FOR SAR IMAGE DENOISING

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1. INTRODUCTION

Because of the coherent nature of radar waves, and the subsequent coherent processing, SAR images are corrupted by a strong specific noise, called "speckle". As a consequence, detecting objects and regions of interest in SAR images may be a severe challenge even for an expert human interpreter, while automatic algorithms devoted to the same tasks are just not reliable enough for most applications. For this reason, there has been a growing interest on SAR image denoising in recent years, motivated also by the appearance of powerful techniques based on wavelet transform.

Indeed, wavelet shrinkage techniques, like that originally proposed by Donoho [1], have been readily applied to SAR images [2], with some good results. However, the wavelet shrinkage approach relies on the hypotheses of additive and gaussian noise, while SAR speckle can be better modeled as multiplicative noise. To circumvent this problem, a homomorphic transformation is typically applied on the image beforehand, so as to obtain additive noise. Then, the wavelet coefficients can be properly modeled in the log-domain and estimated by means of a bayesian approach, as proposed for example in [3] and [4], before going back to the original domain. This approach, relatively simple, has the drawback of altering the statistics of the original image, which might introduce unwanted artifacts. As an alternative, one can avoid the log-transform altogether, and model instead the data as affected by a signal-dependent additive noise, using afterwards a wavelet transform [5, 6, 7].

More recently, speckle reduction techniques based on the "nonlocal" approach have been gaining ground [8, 9, 10], building upon the nonlocal means algorithm originally proposed in [11]. This approach relies on the observation that most images present clear self-similarities, as most patches repeat almost identically over and over in the image. Once these similar patches are identified, one can carry out some form of noise filtering along such patches, wherever they are, rather than in a local neighborhood of the pixel. A significant improvement w.r.t. the original algorithm, has been the evolution towards a *multipoint* rather than *pointwise* filtering, where the nonlocal approach is combined with wavelet shrinkage in a two-step process. In the Block-matching 3D (BM3D) algorithm [12], once a group of similar patches is collected, the whole group is denoised by means of a (3D) wavelet shrinkage process. Then the partially cleaned image is used to estimate the parameters of a further denoising step based on Wiener filtering. It seems safe to say that BM3D represents the state of the art for AWGN noise.

In this work we propose a new version of BM3D which is adapted to denoise SAR images by taking into account their peculiar features. Experiments show the effectiveness of the new technique both in terms of signal-to-noise ratio (on simulated speckled images) and of subjective quality (on actual SAR images).

2. THE NONLOCAL APPROACH

Traditional denoising techniques, based on local filtering, make the implicit hypothesis that neighboring pixels have the same statistical nature. Therefore, they work quite well on homogeneous regions, significantly reducing noise power, but happen to impair severely the image quality in the presence of fine structures, details, and texture, which are typically oversmoothed. A plethora of adaptive techniques have been proposed in time to deal with this problem but results remain relatively poor.

The nonlocal approach [11] represents a complete change of perspective since the "true" value of the current pixel is not estimated anymore from the pixels that are closest to it, but from those pixels, located anywhere in the image, which have the most similar context. In more practical terms, for each pixel, we consider the patch surrounding it, then look in the whole image for the most similar patches (according to a weighted euclidean distance), and use the center pixels of such patches to estimate the pixel value. Clearly, this approach is particularly effective on quasi-periodic and textured areas, where repeated patterns abound, but also in the presence of edges and relatively small details.

Experimental results show nonlocal denoising techniques to be very effective, at least for AWGN images. However, they can be easily adapted to work with different noise models, such as the multiplicative one, provided that a suitably modified distance measure is used. In the Probabilistic Patch-Based (PPB) algorithm [8], for example, a similarity criterion based on the noise distribution model is considered, and the filtering weights are obtained through an iterative process which takes into account the similarity between restored patches. Therefore, PPB works with both additive and multiplicative noise, generalizing the original nonlocal-means (NL-means) algorithm.

NL-means itself, however, has been clearly surpassed by more recent denoising techniques based on a nonlocal *multipoint* approach, like the BM3D [12, 13], where both context and spatial correlation are taken into account to optimize results. The first action taken by BM3D, just like in NL-means, is to locate similar patches by means of a block-matching algorithm with Euclidean metric. Unlike in NL-means, however, all such patches are then collected in a 3D structure which undergoes a decorrelating transform (typically wavelet) so as to exploit both spatial and contextual dependencies. Once a sparse representation is obtained, some forms of shrinkage is used to remove noise components (collaborative filtering), before going back in the image domain. Since filtered patches can overlap, several estimates of the same pixel are typically obtained, and their weighted average must be computed to reconstruct a "basic estimate" of the denoised image.

At this point, a further denoising step is carried out, where block-matching takes place on a cleaner image (the basic estimate) so as to obtain more reliable matches, a new 3D structure is created, and its empirical energy spectrum is computed to perform Wiener filtering on the transformed noisy 3D structure.

3. MODIFIED BM3D FOR SAR IMAGE DENOISING

BM3D can be applied to SAR images as it is, provided that a homomorphic transform of the data is taken beforehand. As mentioned in the introduction, however, the log operation changes the data dynamics and, therefore, the distances among patches. Based on such a consideration, we discard the homomorphic approach, here, and work directly on the original image. The first consequence of this choice is that we cannot use hard-thresholding anymore, since it does not make any sense in this case, and must look for some other type of wavelet shrinkage suitable for multiplicative noise.

As in classic BM3D, the first step is block matching. In BM3D an L^2 distance is used to measure block similarity. Indeed, if the noise variance is low, this kind of measure is robust for independent additive noise, while if this is not the case, a preliminary thresholding on the block wavelet coefficients can be carried out to reduce noise power before computing block distances, as suggested in [12]. It is clear that we cannot use this strategy on speckled images, so we have changed the measure for block distance as suggested in PPB.

After block-matching, our modified BM3D stacks similar blocks together to form a 3D array, applies the undecimated wavelet transform, and finally performs shrinkage. The shrinkage strategy used is very similar to that proposed by Argenti et al. in [5]. Let z be the observed noisy image and x the noise-free reflectivity (we consider speckle intensity model), hence:

$$z(n) = x(n)u(n) = x(n) + [u(n) - 1]x(n) = x(n) + v(n), \tag{1}$$

where $u(n)$ is the speckle that we suppose to be stationary, uncorrelated and independent of $x(n)$. In addition, we assume that $E[u(n)] = 1$, that is $E[u(n) - 1] = 0$ which leads us to consider an additive, zero-mean, signal-dependent noise model, represented in (1) by the term $v(n)$.

In the transform domain (1) becomes

$$W_z(n) = W_x(n) + W_v(n), \tag{2}$$

where W_y is the wavelet transform of a generic signal y. As proposed in [5] we apply the following local linear MMSE estimator

$$\hat{W_x}(n) = \max(0, \frac{E[W_z^2(n)] - E[W_v^2(n)]}{E[W_z^2(n)]})W_z(n) \tag{3}$$

to every detail subband of the UDWT decomposition (which in our case is a 3D transform), and then carry out the inverse transform. For the hypotheses made on speckle noise, it is possible to estimate $E[W_v^2(n)]$ in the generic j-th subband from the space-varying second-order moment of the noisy image z, as

$$E[W_v^2(n)] = \frac{\sigma_u^2}{1 + \sigma_u^2} \sum_i h_{eq}(i) E[z^2(n - i)] \tag{4}$$

where h_{eq} is the equivalent filter of the j-th subband. Unlike in [5], where the statistics are computed pixel by pixel using a 7×7 local window, we reduce the computational burden by assuming $E[z^2(n)]$ to be constant in each 3D block, which is quite reasonable considering that they are usually quite small. This choice, together with the use of normalized filters, turns (4) into the simpler expression $E[W_v^2(n)] = \frac{\sigma_u^2}{1+\sigma_u^2} E[z_B^2]$, where $E[z_B^2]$ is the mean square value computed on the generic block.

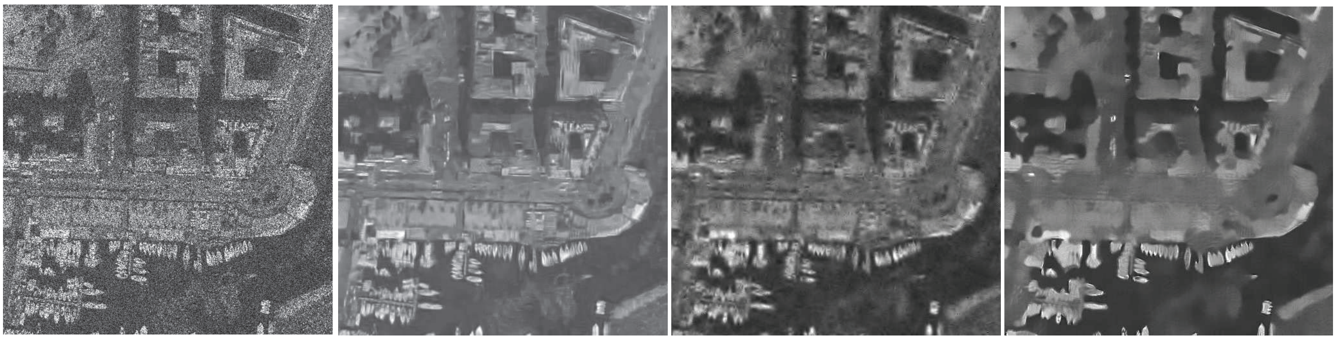
	Lena				Napoli			
	L=1	L=2	L=4	L=16	L=1	L=2	L=4	L=16
noisy	12.11	14.90	17.84	23.79	14.28	17.05	19.99	25.98
modified BM3D	**27.08**	**29.27**	31.16	34.40	**23.33**	**24.92**	**26.62**	**30.31**
SA-WBMMAE	25.09	27.13	28.94	32.42	22.00	23.21	24.57	27.46
PPB SAR 25it	26.72	28.39	29.85	32.68	21.58	23.10	24.86	28.23
BM3D	26.45	29.19	**31.24**	**34.50**	22.87	24.65	26.33	29.95
NLM	21.79	25.66	28.53	33.16	21.31	23.65	25.66	28.92
PPB 25it	25.25	27.88	29.68	32.85	21.49	23.09	24.82	27.98

Table 1: PSNR results for test images with simulated speckle.

4. EXPERIMENTAL RESULTS

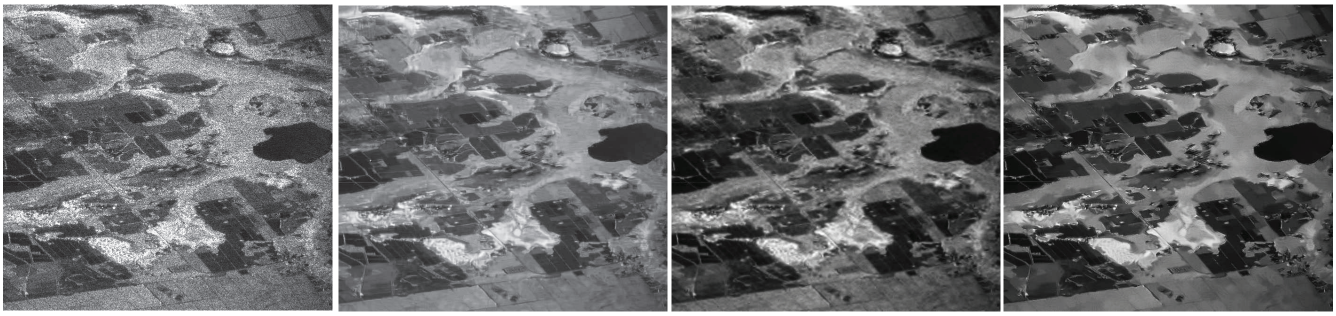
We have investigated the performance of the proposed technique with both natural images degraded by simulated speckle noise and actual SAR images. The first type of experiment allows us to compute a reliable quantitative measure of the algorithm performance, something which is not possible with real SAR images. We have selected the well-known image “Lena” to obtain results easily comparable with the literature, and an aerial photograph of the city of Naples (Fig. 1), Italy, since it has statistics more similar to those of a SAR image. Results are compared with those of the most recent techniques proposed for SAR image denoising, that is PPB-SAR [8] (nonlocal) and SA-WBMMAE [4] (local), as well as with the nonlocal algorithms for AWGN images mentioned before (NLM, PPB, BM3D). For these last techniques, we carry out preliminarily a log-transform, and then estimate and subtract the non-zero mean [4] of the noise. In Tab. 4 we report PSNR results for Lena and Napoli corrupted by speckle noise in amplitude format (square-root intensity [14]) with different number of looks. The proposed modified version of BM3D provides almost always the best performance, better than all other SAR-oriented denoising techniques, especially for the aerial image which more closely resembles an actual SAR image. A visual inspection of the filtered images further reinforces this point since the SAR-oriented PPB, despite its good PSNR level, outputs an unacceptably oversmoothed image, contrary to what happens with the proposed technique which preserves accurately all details. Only with the low-noise versions of Lena (4 and 16 looks) the homomorphic BM3D behaves slightly better. Considering that something similar happens with the two versions of PPB, this seems to confirm that with a large number of looks the log-transformed speckle is approximately gaussian [14], justifying the homomorphic approach in this circumstances. In any case, the proposed SAR-oriented version behaves clearly better than all other techniques with a small number of looks, by far the most critical and interesting case.

Finally, we show results for a real AIRSAR image from the NASA/Jet Propulsion Laboratory taken over the Collier Fig. 2. As already said, assessing the performance for actual SAR images is quite difficult, lacking a “clean” reference image, and measures like the equivalent number of looks tell very little about detail preservation. Therefore, we prefer to rely on visual inspection to compare the different techniques. Again, it seems safe to say that the proposed technique does a very good job, reducing significantly the noise power without appreciably affecting image details, while competing techniques give rise to moderate (SA-WBMMAE) or even severe (PPB-SAR) oversmoothing phenomena.



(a) Noisy image (b) modified BM3D (c) SA-WBMMAE (d) PPB SAR 25it

Fig. 1: Napoli L=1.



(a) Original image (b) modified BM3D (d) SA-WBMMAE (e) PPB SAR 25it

Fig. 2: Collier.

5. REFERENCES

[1] D. L. Donoho, “De-noising by soft-thresholding,” *IEEE Transactions on Information Theory*, vol. 41, no. 3, pp. 613–627, May 1995.

[2] H. Guo, J. E. Odegard, M. Lang, R. A. Gopinath, I. W. Selesnick, and C. S. Burrus, “Wavelet based speckle reduction with application to SAR based ATD/R,” *Proceedings of IEEE Internantional Conference on Image Processing*, vol. 2, pp. 913–917, Nov. 1994.

[3] A. Achim, P. Tsakalides, and A. Bezarianos, “SAR image denoising via Bayesian wavelet shrinkage based on heavy-tailed modeling,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 41, no. 8, pp. 1773–1784, Aug. 2003.

[4] M. I. H. Bhuiyan, M. O. Ahmad, and M. N. S. Swamy, “Spatially adaptive wavelet based method using the Cauchy prior for denoising the SAR images,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 17, no. 4, pp. 500–507, Apr. 2007.

[5] F. Argenti and A. Alparone, “Speckle removal from SAR images in the undecimated wavelet domain,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 40, pp. 2363–2374, Nov. 2002.

[6] F. Argenti, T. Bianchi, and A. Alparone, “Multiresolution MAP despeckling of SAR images based on locally adaptive generalized gaussian pdf modeling,” *IEEE Transactions on Image Processing*, vol. 15, no. 11, pp. 3385–3399, Nov. 2006.

[7] M. Dai, C. Peng, A. K. Chan, and D. Loguinov, “Bayesian wavelet shrinkage with edge detection for SAR image despeckling,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 42, no. 8, pp. 1642–1648, Aug. 2004.

[8] C. Deledalle, L. Denis, and F. Tupin, “Iterative weighted maximum likelihood denoising with probabilistic patch-based weights,” *IEEE Transactions on Image Processing*, to be published.

[9] H. Zhong, J. Xu, and L. Jiao, “Classification based nonlocal means despeckling for SAR image,” *proc. of SPIE*, vol. 7495, Oct. 2009.

[10] P. Coupé, P. Hellier, C. Kervrann, and C. Barillot, “Bayesian non local means-based speckle filtering,” *Proceedings of IEEE International Symposium on Biomedical Imaging*, pp. 1291–1294, May 2008.

[11] A. Buades, B. Coll, and J.M.Morel, “A review of image denoising algorithms, with a new one,” *Multiscale Model. Simul.*, vol. 4, no. 2, pp. 490–530, Jul. 2005.

[12] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, “Image denoising by sparse 3D transform-domain collaborative filtering,” *IEEE Transactions on Image Processing*, vol. 16, no. 8, pp. 2080–2095, Aug. 2007.

[13] V. Katkovnik, A. Foi, K. Egiazarian, and J. Astola, “From local kernel to nonlocal multiple-model image denoising,” *International Journal of Computer Vision*, to be published.

[14] H. Xie, L. E. Pierce, and F. T. Ulaby, “Statistical properties of logarithmically transformed speckle,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 40, no. 3, pp. 721–727, Mar. 2002.