A NON-LOCAL APPROACH FOR SAR AND INTERFEROMETRIC SAR DENOISING

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1. INTRODUCTION

Recently, non-local approaches proved relevant for image restoration. Unlike local filters, the non-local (NL) means introduced in [1] decrease the noise while well preserving the resolution. In the proposed paper, we suggest the use of a non-local approach to estimate single-look SAR reflectivity images or to construct SAR interferograms. SAR interferogram construction refers to the joint estimation of the reflectivity, phase difference and coherence image from a pair of two co-registered single-look complex SAR images. This abstract is composed of four sections. Section 2 recalls the non-local (NL) means. Weighted maximum likelihood is then introduced in Section 3 as a generalization of the weighted average performed in the NL means. In Section 4, we propose to set the weights according to the probability of similarity which provides an extension of the Euclidean distance used in the NL means. Eventually, experiments and results are presented in Section 5 to show the efficiency of the proposed approach.

2. NON-LOCAL MEANS

Non-local (NL) approaches have been proposed by Buades *et. al* in [1] to denoise images damaged by additive white Gaussian noise. While local filters lead to biases and resolution loss, NL techniques are known to efficiently reduce noise and preserve structures. Instead of combining neighbor pixels, the NL means average similar pixels. NL means assume there are enough redundant pixels (pixel having identical noise-free value) in the image to reduce the noise significantly. Let v_s be the observed noisy value at site s and u_s its underlying noise-free value, NL means provides the estimate $\hat{u}_s$ defined by:

$$\hat{u}_s = \frac{\sum_t w(s,t) v_t}{\sum_t w(s,t)} \tag{1}$$

where t is a pixel index and $w(s,t)$ is a data-driven weight depending on the similarity between pixels with index s and t. For robustness reason, pixel similarity is evaluated by comparing surrounding patches around s and t with the use of the Euclidean distance:

$$w(s,t) = \exp\left(-\frac{\sum_k (v_{s,k} - v_{t,k})^2}{h}\right) \tag{2}$$

where $_{s,k}$ and $_{t,k}$ denote respectively the k-th pixels in the patches centered on s and t, and h is a filtering parameter. Equation (1) and Equation (2) are well adapted to estimate noise-free values and to evaluate patch-similarity when the observed image is damaged by additive white Gaussian noise. We describe in the following how this approach can be extended to handle speckle noise.

3. WEIGHTED MAXIMUM LIKELIHOOD

The weighted average performed by NL means can be seen as a particular case of the weighted maximum likelihood (WML) estimation. ML based filters assume there exists redundant pixels and search the value which maximizes the likelihood over the set of redundant pixel values. Since this set is unknown, we propose to approach its indicator function with weights, which leads to the WML estimation:

$$\hat{u}_s = \arg\max_u \sum_t w(s,t) \log p(v_t|u). \tag{3}$$

If we consider SAR amplitude images damaged by multiplicative speckle noise, described by a Rayleigh distribution [2], the WML estimate is given by:

$$\hat{R}_s = \frac{\sum_t w(s,t) A_t^2}{\sum_t w(s,t)} \tag{4}$$

where A is the noisy amplitude image and R the noise-free reflectivity image. For InSAR data damaged by speckle noise, described by a zero-mean complex circular Gaussian distribution [2], the WML estimate is given by [3]:

$$\begin{aligned}
\hat{R}_s &= \frac{a}{2N}, \\
\hat{D}_s &= \frac{2}{a}\left(x \cos\hat{\beta}_s + y \sin\hat{\beta}_s\right), \\
\hat{\beta}_s &= -\arg\left(x + jy\right) && (5) \\
\text{with} \quad a &= \sum_t w(s,t)\left(|z|_t^2 + |z'|_t{}^2\right), \\
x &= \sum_t w(s,t) Re\left[z_t z_t'^*\right], \\
y &= \sum_t w(s,t) Im\left[z_t z_t'^*\right], \\
N &= \sum_t w(s,t) && (6)
\end{aligned}$$

where z and z' are two co-registered single-look complex SAR images, and R, D and β are respectively the noise-free reflectivity, the coherence and the phase difference such that:

$$\mathbb{E}\left\{\begin{pmatrix} z \\ z' \end{pmatrix}\left(z^* z'^*\right)\right\} = R\begin{pmatrix} 1 & De^{j\beta} \\ De^{-j\beta} & 1 \end{pmatrix}.$$

4. SETTING OF THE WEIGHTS

As mentioned in Section 3, the weights should approach the indicator function of the set of redundant patches. In order to consider the statistical nature of the observed image, we use the probabilistic criterion introduced in [4], where the weights are set to :

$$w(s,t) = \prod_k \left[Pr(v_{s,k}, v_{t,k}|u_{s,k} = u_{t,k}) Pr(u_{s,k} = u_{t,k})\right]^{1/h}. \tag{7}$$

In the following the pixels ${}_{s,k}$ and ${}_{t,k}$ will be denoted respectively by ${}_1$ and ${}_2$. The first term $Pr(v_1, v_2|u_1 = u_2)$ reflects the likelihood to have identical (unknown) noise-free values with respect to the observed noisy image. A similar criterion has been applied in [5] to data damaged by additive white Gaussian noise. We extend here its definition as follows

$$Pr(v_1, v_2|u_1 = u_2) = \left|\frac{d\Phi}{dv_1}(v_1)\right|^{-1}\left|\frac{d\Phi}{dv_2}(v_2)\right|^{-1}\int p(v_1|u_1 = u)p(v_2|u_2 = u)\mathrm{d}u \tag{8}$$

where the Jacobian terms are introduced to take into account the change of variables due to a mapping function Φ. The mapping Φ is introduced to obtain a dimensionless weight. The second term $Pr(u_1 = u_2)$ tries to measure the *prior* probability to have equal noise-free values at site ${}_1$ and ${}_2$. In [6], the authors propose to use the Kullback-Leibler divergence on an estimate $\hat{u}$ of u as a statistical test of the hypothesis $u_1 = u_2$. We have also observed good

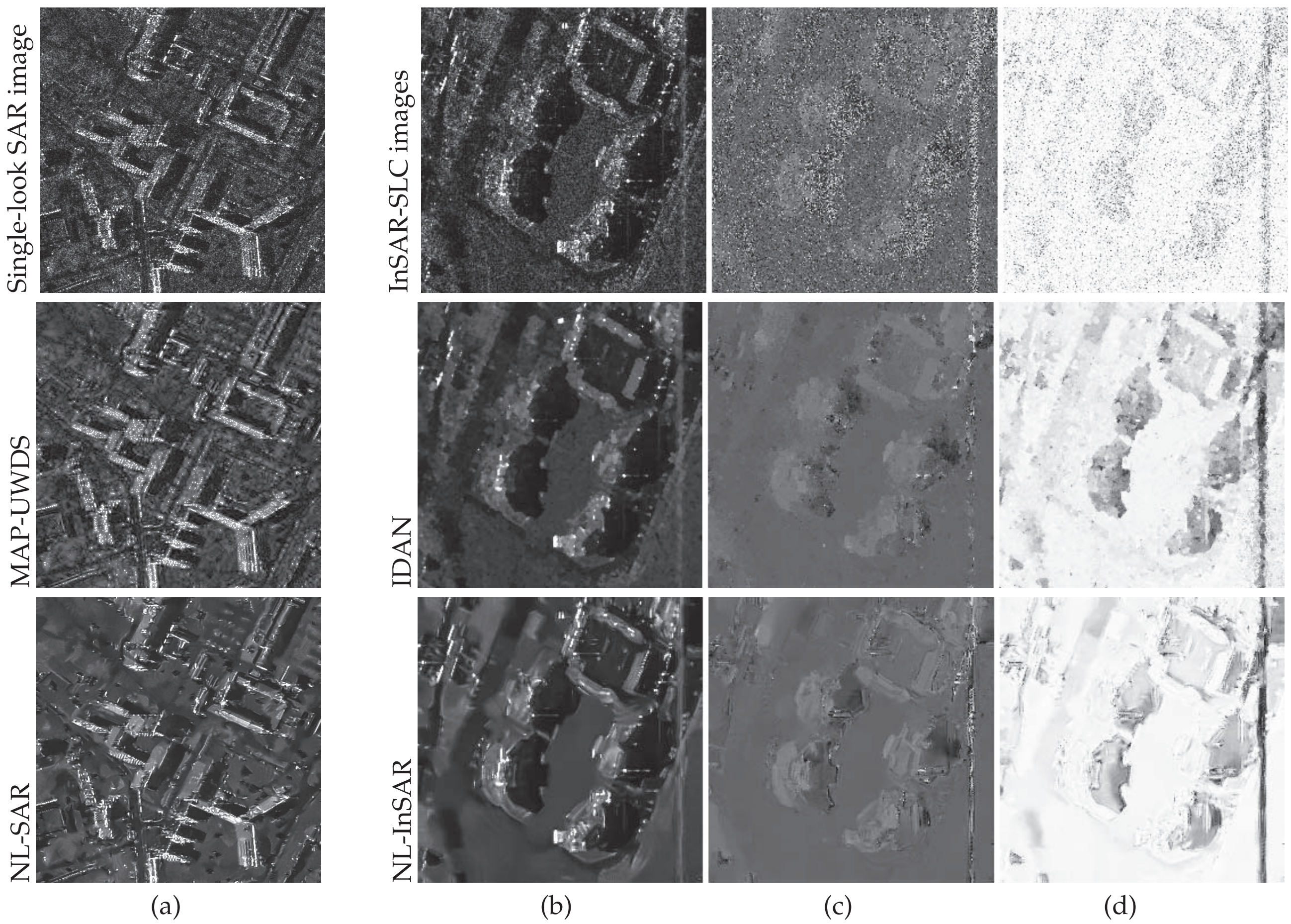

Fig. 1. (a) Reflectivity of Toulouse (France) sensed by TerraSAR-X ©DLR obtained by the single-look SAR image, the MAP-UWDS estimator [8], and the NL-SAR filter. (b) Reflectivity, (c) phase difference and (d) coherence of Saint-Pol-sur-Mer (France) sensed by RAMSES ©DGA ©ONERA, obtained from top to bottom by the SLC images (maximum likelihood estimator of [3]), the IDAN estimator [9] and the NL-InSAR estimator.

performances in practice of such a definition:

$$\begin{aligned} Pr(u_1 = u_2) &= \exp\left[-\frac{1}{T} SD_{KL}(\hat{u}_1, \hat{u}_2)\right] \\ \text{where } SD_{KL}(\hat{u}_1, \hat{u}_2) &= \int (p(v|\hat{u}_1) - p(v|\hat{u}_2)) \log \frac{p(v|\hat{u}_1)}{p(v|\hat{u}_2)} \, \mathsf{d}v \end{aligned} \tag{9}$$

where $\hat{u}$ is an estimate of u and T a filtering parameter. In practice, this estimate is refined iteratively by the use of the proposed algorithm. Both terms can be obtained in closed form in the case of SAR and InSAR data. A more detailed description of the algorithm can be found in [4, 7].

Non-local approaches are known to leave a high variance in regions where there are to few redundant patches. In order to enforce a minimum amount of smoothing, different adaptive approaches have been proposed. In our filter, we suggest to select when required, the ten most similar pixels according to the similarity between the patches.

5. EXPERIMENTS AND RESULTS

We have applied our methodology in case of SAR and InSAR data, resulting in two different filters denoted respectively by NL-SAR and NL-InSAR. Both use search windows of size 21×21, patches of size 7×7 and the parameters

h and T are set as explain in [4]. The NL-SAR filter has been applied successfully on a single-look amplitude image of the CNES in Toulouse (France) sensed by TerraSAR-X. Results are given on Figure 1.a and compared to the original amplitude image and the MAP-UWDS filter [8]. The NL-InSAR filter has been applied on a pair of two co-registered single-look complex SAR images from Saint-Pol-sur-Mer (France) sensed by RAMSES and provided by the CNES. The result is given on Figure 1.b,c,d and compared to the SLC images and the IDAN filter [9]. The proposed NL-SAR and NL-InSAR filters provide the best quality images. The noise is well reduced while the resolution is well preserved. The article will give numerical results, realized over synthetic data, such as the signal to noise ratio values to show the efficiency of the proposed approach.

6. CONCLUSION

A new methodology is described which can be used to denoise SAR images and to construct SAR interferograms without significant loss of resolution. The proposed filters are based on non-local approaches. They combine similar pixels according to the similarity between their surrounding patches. The patch based similarity is defined with respect to the noise distribution model and is adapted to the specific nature of SAR data or InSAR data. Once the weights are computed, a weighted maximum likelihood estimation is performed for each pixel of the image. Then, the process is repeated to refine the weights and the quality of the final estimate. This abstract describes the general methodology used to compute the weights. In the final paper, the closed form expression for SAR and InSAR data will be given with a description of their behavior. Finally, experimental results are given to illustrate the efficiency of the algorithm, these results will be completed with quantitative criteria such as the signal to noise ratio values.

7. REFERENCES

[1] A. Buades, B. Coll, and J.M. Morel, “A Non-Local Algorithm for Image Denoising,” *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, vol. 2, 2005.

[2] NR Goodman, “Statistical analysis based on a certain multivariate complex Gaussian distribution (an introduction),” *Annals of Mathematical Statistics*, pp. 152–177, 1963.

[3] MS Seymour and IG Cumming, “Maximum likelihood estimation for SAR interferometry,” in *The 1994 International Geoscience and Remote Sensing Symposium.*, 1994, vol. 4, pp. 2272–2274.

[4] C.A. Deledalle, L. Denis, and F. Tupin, “Iterative Weighted Maximum Likelihood Denoising with Probabilistic Patch-Based Weights,” *IEEE Transactions on Image Processing*, 2009.

[5] Y. Matsushita and S. Lin, “A Probabilistic Intensity Similarity Measure based on Noise Distributions,” in *IEEE Conference on Computer Vision and Pattern Recognition, 2007. CVPR'07*, 2007, pp. 1–8.

[6] J. Polzehl and V. Spokoiny, “Propagation-separation approach for local likelihood estimation,” *Probability Theory and Related Fields*, vol. 135, no. 3, pp. 335–362, 2006.

[7] C.A. Deledalle, L. Denis, and F. Tupin, “NL-InSAR : Non-Local Interferogram Estimation,” *Rapport de recherche Télécom ParisTech, 2009D021*, 2009.

[8] T. Bianchi, F. Argenti, and L. Alparone, “Segmentation-Based MAP Despeckling of SAR Images in the Undecimated Wavelet Domain,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 46, no. 9, pp. 2728–2742, 2008.

[9] G. Vasile, E. Trouvé, J.S. Lee, and V. Buzuloiu, “Intensity-driven adaptive-neighborhood technique for polarimetric and interferometric SAR parameters estimation,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 44, no. 6, pp. 1609–1621, 2006.