TURBO SPECKLE FILTERING APPLIED TO POLSAR DATA

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ABSTRACT

Abstract— A new approach for speckle reduction in polarimetric synthetic aperture radar (PolSAR) images based on the turbo iterative principle is proposed. The turbo iterative algorithm shows high performances due to the propagation of the information between two complementary filters. One filter can boost up the results of the other by processing its residue image and retrieving valuable information in the noise subspace.

***Index Terms*—** PolSAR, speckle filtering, Turbo principle.

1. INTRODUCTION

Recently, Sun *et al*. [1] proposed a new iterative processing for SAR image restoration based on the turbo iterative principle. The turbo principle has emerged from the turbo codes which are a class of recently-developed high-performance error correction code introduced by Berrou *et al*. [2]. Such codes use two decoders in an iterative process, so called turbo iterative decoding. This processing results in an error correction approaching the Shannon limit, which is the theoretical limit of maximum information transfer rate over a noisy channel. The concept behind turbo decoding is to pass soft decisions from the output of one decoder to the input of the other decoder, and to iterate this process until they converge to a more reliable solution. The turbo iterative algorithm applied to SAR images [1] shows high performances due to the propagation of the information between two simple filters.

The encouraging results after the turbo iterative principle provide an excellent motivation to investigate a turbo method applied to PolSAR data. Our objective is to carry out an analysis of a PolSAR turbo filter. Here it is quite important to stress on the concept of iteration, where it is not a simple repetition of a filtering process but more like a recurrence of its parameter estimation. Nevertheless, one of the main constraints in such systems is to design two complementary filters that are analogous to the decoders in turbo code. Some filters, *e.g.*, Lee filter [3], tend to obtain a very smooth image while leaving some texture and feature information in the removed noise image that can be called residue image. In contrast, other filters, *e.g.*, wavelet based filter [4], tend to retain the structural information while leaving some noise in the estimated image. Therefore, the interest of turbo iterative algorithm is to make use of the advantages of both filters. One filter can boost up the results of the other by processing its residue image and retrieving valuable information in the noise subspace. In such a case, extrinsic information is exchanged resulting in a better estimation of the polarimetric reflectivity.

In section 2, a background about turbo iterative processing and a description of two elementary filters is provided. In section 3, simulations are carried out to investigate the performances of the presented approach, filtered artificial and real images are shown. Finally, section 4 goes over the main results and runs through further perspectives.

2. TURBO SPECKLE FILTER

In reciprocal backscattering case, $S_{hv} = S_{vh}$, polarimetric information can be represented by the scattering vector $\boldsymbol{k_S}$,

$$\mathbf{k}_S = \begin{bmatrix} S_{hh} & \sqrt{2}S_{hv} & S_{vv} \end{bmatrix}^T \tag{1}$$

where h and v represent respectively the transmitting horizontal and receiving vertical linear polarization, and the superscript "T" refers to the matrix transpose. From (1), the polarimetric covariance matrix $\mathbf{C}$ and the span are expressed as follows,

$$\mathbf{C} = \mathbf{k}_S \, \mathbf{k}_S^{*T} \tag{2}$$

$$span = \mathbf{k}^{*T}\,\mathbf{k} = |S_{hh}|^2 + 2|S_{hv}|^2 + |S_{vv}|^2 \tag{3}$$

where the superscript "*" refers to the complex conjugate.

$$\mathbf{I} = \left\{ C_{11}, C_{12}, C_{13}, C_{22}, C_{23}, C_{33} \right\} \tag{4}$$

2.1. Turbo Iterative Principle

In the case of a PolSAR filter, the turbo iterative principle consists in generating two component signals, $\mathbf{U_1}$ and $\mathbf{U_2}$, from the original signal **I**. As shown in Figure 1. , these two component signals, theoretically uncorrelated, result from the two operators ("*interleavers*") π_1 and π_2, described by the following equations:

$$\pi_1\Big|_k \triangleq \begin{cases} U_{1,k} = \left|\dfrac{I_k}{\psi_k\ \overline{z}_{n,k}}\right|, \ k = 2,3,5 \\ U_{1,k} = \left|\dfrac{I_k}{Z_{21,k}}\right|, k = 1,4,6 \end{cases} \tag{5}$$

$$\pi_2\Big|_k \triangleq \begin{cases} U_{2,k} = \psi_k\ \overline{z}_{n,k}\ Z_{12,k}\ e^{j\phi_k}\Big|_{k=2,3,5} \\ U_{2,k} = Z_{12,k}\ Z_{21,k}\Big|_{k=1,4,6} \end{cases} \tag{6}$$

Where the different parameters are defined as follows:

- $\overline{z}_{n,\,k}$ refers to the average Hermitian product normalized intensity value of $\mathbf{Z_{21}}$, with $\rho_k = \left|\rho_k\right|\exp\left(j\phi_{x,k}\right)$ as the complex correlation coefficient of the channel *k*.

$$\overline{z}_{n,\,k} = \frac{\pi}{4}\,{}_2F_1\left(-\frac{1}{2}, -\frac{1}{2}; 1; \left|\rho_k\right|^2\right) \tag{7}$$

- ψ_k represents the average power in the two channels of $\mathbf{Z_{21}}$

$$\psi_k = \sqrt{E\left\{\left|S_p\right|^2\right\}E\left\{\left|S_q\right|^2\right\}} \tag{8}$$

π_1 and π_2 are derived from the statistical description of polarimetric SAR data of Tough *et al.* [5].and from the PolSAR noise model presented. The signal $\mathbf{U_1}$ is defined as a multiplicative noise by López-Martínez and Fàbregas [6] and its pdf has been found relatively invariant to change in coherence values as can be seen in Figure 2. The pdf of $\left\{U_{1,k}\right\}_{k=2,3,5}$ obtained from the distribution of the Hermitian product amplitude expressed by Tough *et al.* [5] is

$$p_U\left(u\right) = \frac{4\,\overline{z}_n u}{1-\left|\rho\right|^2} I_0\left(\frac{2\,\overline{z}_n\left|\rho\right|u}{1-\left|\rho\right|^2}\right) K_0\left(\frac{2\,\overline{z}_n u}{1-\left|\rho\right|^2}\right) \tag{9}$$

where I_0 is a modified Bessel function of the first kind, K_0 is a modified Bessel function of the second kind, and ρ is defined as:

$$\rho = \frac{\left\langle S_p S_q\right\rangle}{\sqrt{\left\langle\left|S_p^2\right|\right\rangle\left\langle\left|S_q^2\right|\right\rangle}} \tag{10}$$

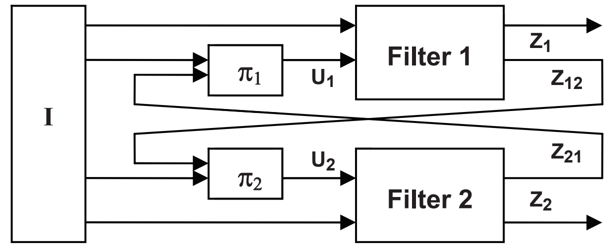


Figure 1. Scheme of Turbo Iterative Principle.

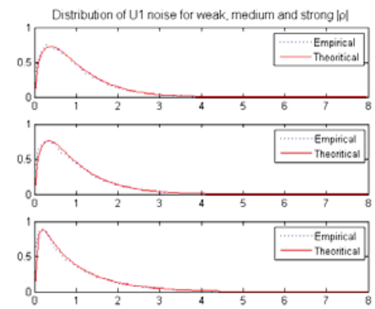


Figure 2. Empircal and Theoritical Probability Density Funcfion of $\mathbf{U_1}$.

Next, two different filters have to be chosen in a way that their performances complement each other. *Filter 1* should present a tendancy to reduce noise with a good preservation of spatial features, and should process the residue noise to recover valuable information in the noise subspace. In contrast, *filter 2* should demonstrate a speckle reduction with good polarimetric parameters estimation. Then, the output signals $\mathbf{Z_{12}}$ and $\mathbf{Z_{21}}$ are the information exchanged between both filters in order to balance the speckle filter performances. At each iteration, $\mathbf{Z_{12}}$ and $\mathbf{Z_{21}}$ are estimated to enhance the results of each filter and to compensate their costs. The iterative process stops when the change in $\mathbf{Z_{21}}$ is small.

2.2. Complementary filters

2.2.1 PolSAR Wavelet Shrinkage

For *filter 1*, a wavelet shrinkage filter developed by Farage *et al.* [4] is considered. The wavelet transform employed is based on a *Stationary Wavelet Transform* (SWT). In addition, the significant coefficient values are enhanced by summing the squared coefficients of all the channels. By squaring real edge coefficients, they tend to become larger for coarser scales, while noise coefficients become smaller. The wavelet shrinkage technique makes it possible to identify significant wavelet coefficients (*i.e.*, mainly those generated by edges and point targets) to recover the information over-filtered by *filter 2* and contained in signal $\mathbf{U_1}$. The threshold technique is based on percentile method supported by (9).

Therefore, the output of *filter 1* relates to some retrieved spatial feature information that is used by *filter 2* to improve the estimation of weighting coefficients.

2.2.2 Lee filter

One of the filters experimented for the *filter 2* in the design of the turbo algorithm is the Lee filter [3]. It is based on the estimation of the local variance statistics. The filtering weights are determined using the span image that benefits from the scattering characteristics of the HH, VV and HV intensities. The local linear minimum mean-square filter is obtained as such

$$\hat{x} = \overline{y} + b\left(y - \overline{y}\right) \tag{11}$$

where $\hat{x}$ is the filtered pixel value, $\overline{y}$ is the local mean, and b is the weighting function expressed as

$$b = \frac{\operatorname{var}\left(x\right)}{\operatorname{var}\left(y\right)} \quad and \quad \operatorname{var}\left(x\right) = \frac{\operatorname{var}\left(y\right) - \overline{y}^2\sigma_v^2}{\left(1+\sigma_v^2\right)} \tag{12}$$

where $\sigma^2{}_v$ is the speckle variance. In the turbo iterative process, the variance *var(x)* of the coefficient b is computed from the extrinsic information $\mathbf{u_2}$ in (5), and *var(y)* is determined from the original data **I**.

2.2.3 Model-Based PolSAR filter

Alternatively, the MB-PolSAR filter [7] can be used for *filter 2*. The MB-PolSAR filter is based on the multiplicative-additive speckle noise model for multidimensional SAR data stated as

$$\begin{aligned} S_p S_q^* = {} & \psi_k \overline{z}_{n,\,k} N_c n_m e^{j\phi_{x,k}} + \psi_k \left(\left|\rho_k\right| - N_c \overline{z}_{n,\,k}\right) e^{j\phi_{x,k}} \\ & + \psi_k \left(n_{ar} + j\, n_{ai}\right) \end{aligned} \tag{13}$$

where N_c is expressed as

$$N_c = \frac{\pi}{4}\left|\rho_k\right| {}_2F_1\left(\frac{1}{2}, \frac{1}{2}; 2; \left|\rho_k\right|^2\right) \tag{14}$$

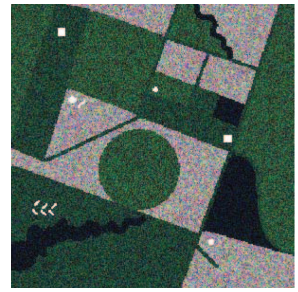
This filter approach is based on processing the elements of the covariance PolSAR data matrix according to the estimation of the complex correlation coefficient. Therefore, in the turbo iterative filter, the estimation processing of $|\rho_k|$ is conducted by the extrinsic information $\mathbf{u_2}$ in (5).

2.3. Despeckling Method

The various steps of the full non parametric filtering method are as follows:

1. Use a mask to preserve original point targets values.
2. Set initial reference image so that $\mathbf{z_{21}}$ is the low-frequency images of **I**.
3. Get the residue image $\mathbf{u_1}$ from the operator π_1.
4. Apply *filter 1* based on $\mathbf{u_1}$ and **I** according to PolSAR wavelet filter [4].
5. Apply *filter 2* and estimate b coefficient (Lee filter) or $|\rho_k|$ (MB-PolSAR filter) from $\mathbf{u_2}$ and **I**.
6. Stop iteration if change in $\mathbf{z_{21}}$ is small or else go to step 3 and change the reference image into the new $\mathbf{z_{21}}$.

(a) Ground Truth



(b) Original Image

(c) SSC 4 levels, H-α=79.5%
EP=0.161, ENL=20.27

(d) Enhanced Lee 7x7, H-α=76.9%
EP=0.260, ENL=9.65

(e) Turbo Lee7x7, iter4,
Output *filter 1*, H-α=81%
EP=0.1090, ENL=26.5

(f) Turbo MB 7x7, iter 4,
Output *filter 2*, H-α=83%
EP = 0.216, ENL=34.1

Figure 3. Display color, red = 2 $|Shv|^2$, green = $|Svv|^2$, blue = $|Shh|^2$. H-α is Entropy-Alpha classification rate.

3. RESULTS

3.1. Experiments Using Simulated Images

Speckle reduction performances are evaluated on simulated PolSAR images (single look complex), produced from the Cholesky factorization of typical samples polarimetric responses. Five areas with different scattering properties are selected within an E-SAR image (L-band, DLR, Oberpfaffenhofen area). The final PolSAR image is shown in Figure 3. , as well as the ground truth image. We evaluated the performances of the artificial PolSAR image filtering on its three power bands with the following indicators:

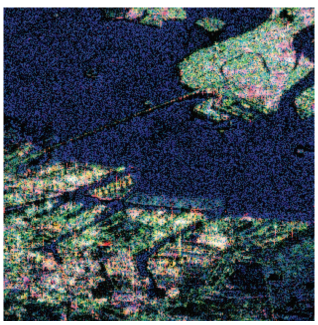
- *Equivalent number of looks* (ENL): a measure that indicates the strength of the noise reduction; we computed the ENL for each power channel and each scattering classes (we excluded point targets) and we took the mean value.

$$ENL = \frac{1}{3\times 5}\sum_{n=1,4,6}\sum_{l=1,..,5}\frac{<I_n>^2}{E\left[(I_n - <I_n>)^2 \mid l\right]} \quad (15)$$

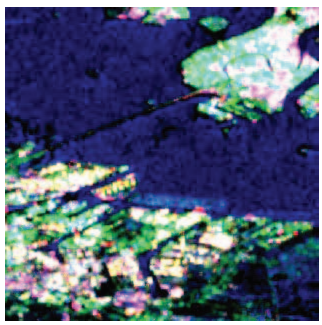
- *Edge strength preservation* (EP): preservation of the edge magnitudes of filtered image is compared to the ground truth image (the smaller the EP the more significant it is).

$$EP = \frac{1}{3\times 5}\sum_{n=1,4,6}\sum_{l=1,...,5}\left|1 - \frac{\sum_{\mathbf{x}\in Edges}\left\|\nabla I_n(\mathbf{x})\right\|}{\sum_{\mathbf{x}\in Edges}\left\|\nabla I_n^{GT}(\mathbf{x})\right\|}\right| \quad (16)$$

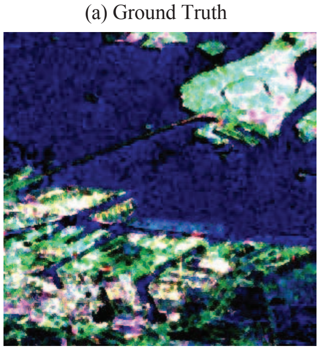
3.2. ExperimentsUsing PolSAR Images from Airborne Sensor



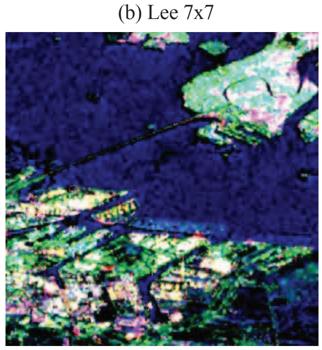
(a) Ground Truth



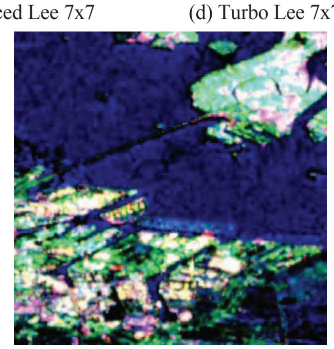
(b) Lee 7x7



(c) Enhanced Lee 7x7



(d) Turbo Lee 7x7 it. 4output *filter1*



(e) Turbo Lee 7x7 it. 4 output *filter2*

Figure 4. Display color, red =2 $|Shv|^2$, green = $|Svv|^2$, blue = $|Shh|^2$.

In case of real images, the filters were applied to the Japan Aerospace Exploration Agency (JAXA) ALOS L-band POLSAR data of a Venizia, Italy, image. These data are single look complex, and processed by all filters with a window size 7x7.

4. DISCUSSION AND CONCLUSION

It can be seen from the experiment results shown in Figure 3. that Turbo speckle filtering offers higher ENL values with better EP indexes compared to standards filters presented in the experiment (*i.e.*, enhanced Lee filter [8] and SSC wavelet filter [4]). The turbo iterative processing adaption to PolSAR data improves clearly the trade-off between the noise reduction and spatial features preservation. The Entropy-Alpha rate classification has also been enhanced and especially with the turbo-MB filter. In Figure 4. , we can observe that Turbo Lee presents a remarkable capacity to preserve edges and meaningful spatial features. The propagation of information flowing in the turbo filter allows reaching for a more optimum result.

The turbo principle applied to PolSAR data yields encouraging results, and consequently will be the subject of further studies.

5. ACKNOWLEDGMENT

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