Polarimetric Speckle Noise Effects in Quantitative Physical Parameters Retrieval

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Abstract

Quantitative physical parameters retrieval has become a very promising application of multidimensional SAR imagery as it has been demonstrated by diferent studies in the related literature. These data are employed as the input for electromagnetic inversion algorithms, which extract the physical information from the measured data. Nevertheless, SAR data are affected by speckle. In this paper, the auhors analyze the influence of the multidimensional speckle noise in the quantitative estimation of surface parameters from polarimetric SAR data.

1 Introduction

The sensitivity of microwaves to the different characteristics and properties of natural targets make SAR systems a valuable tool for the quantitative estimation of parameters that describe these targets. The complexity associated with the scattering process, as well as, the involved structure of natural target prevents quantitative estimation by means of one-dimensional SAR systems. Nevertheless, this estimation is feasible by acquiring different SAR images between which, one or more imaging parameters vary. In these cases, the increase of information comes from the fact that more data channels are available, but also, from the fact that these channels are correlated.

Polarimetry plays an important role in the estimation of surface parameters, as it allows a direct or indirect separation of roughness, rms height *s*, and moisture *mv* [vol. %] induced effects on the backscattered signal. Several algorithms have been proposed in the literature for the retrieval of surface parameters from polarimetric SAR data. Most of them are based on the evaluation of the backscattering amplitudes. However, there are several works addressing the evaluation of second order statistical parameters (correlation coefficients between different polarisations) with respect to surface parameter estimation [1].

SAR data are characterized by the high spatial resolution about which information can be estimated. In the dimension perpendicular to the sensor's movement, i.e., range, spatial resolution is achieved by techniques based on pulse compression. Nevertheless, in the orthogonal dimension, i.e., azimuth, the spatial resolution is attained through a coherent processing of the returned waves. This coherent nature is also the origin of one of the most important problems of SAR data, i.e., speckle noise. Despite being a true electromagnetic measurement, the spatial resolution at which SAR systems operate provoke that speckle has to be considered as a noise source. Consequently, speckle must be reduced in order to have access to the useful information, and hence improving quantitative inversion.

In the case of one-dimensional SAR systems, the speckle noise problem can be considered as solved, as it is already known that it is characterized by a multiplicative nature. For multidimensional SAR data, this model can not be extended due to the correlation between the channels. For this case, it has been recently demonstrated that speckle noise, in the case of multidimensional SAR data, is characterized by two noise mechanisms with multiplicative and additive natures. The combination of both noise components is determined precisely by the multidimensional SAR data correlation structure [2].

In the following, the authors present a first study to determine which are the effects of the different noise sources, identified in the new multidimensional speckle noise model, in the quantitative estimation of physical data. In particular, surface parameters are considered for quantitative inversion.

2 Surface Parameters Retrieval

Roughness and dielectric constant information are coupled in the measured backscattering intensity, so that a scattering model has to be introduced in order to decouple their contributions. Furthermore, an extension of the target vector is required for an estimation of both: roughness and dielectric properties. The most promising (and mostly used) way for this, is the introduction of polarisation diversity. The recently developed model, the extended-Bragg model [1] is used in the following to provide some qualitative insights on the influence of speckle filtering in the estimation of surface roughness and dielectric constant. The model is an extension of the small perturbation model and assumes reflection symmetry surfaces, where the mean normal to the surface vector defines the axis of symmetry. It accounts for cross-polarised backscattering as well as depolarisation effects. In this case, the coherency matrix **T** has the following scattering model

$$\mathbf{T}=\begin{bmatrix} C_1 & C_2\,\mathrm{sinc}(2\beta_1) & 0 \\ C_2\,\mathrm{sinc}(2\beta_1) & C_3\left(1+\mathrm{sinc}(4\beta_1)\right) & 0 \\ 0 & 0 & C_3\left(1-\mathrm{sinc}(4\beta_1)\right) \end{bmatrix} \quad (1)$$

The coefficients C1, C2, and, C3 describing the Bragg component of the surface, and are given by

$$C_1=\left|R_S+R_P\right|^2 \quad C_2=\left(R_S+R_P\right)\left(R_S^*-R_P^*\right)$$
$$C_3=(1/2)\left|R_S-R_P\right|^2 \quad (2)$$

where

$$R_S=\frac{\cos\theta-\sqrt{\varepsilon-\sin^2\theta}}{\cos\theta+\sqrt{\varepsilon-\sin^2\theta}} \quad R_P=\frac{(\varepsilon-1)(\sin^2\theta-\varepsilon(1+\sin^2\theta))}{(\varepsilon\cos\theta+\sqrt{\varepsilon-\sin^2\theta})^2}. \quad (3)$$

3 Multidimensional Speckle Noise Model

3.1 Multidimensional Speckle Noise Model

The multidimensional speckle noise model presented in the following is based on the covariance matrix **C** representation. This formulation facilitates, with respect to formulations based on the coherency (**T**) or the Mueller (**M**) matrices, the analysis of speckle, since all the entries of **C** consist of the Hermitian product of a pair of SAR images. Besides, it is possible to transform between **C** and **T** in a deterministic way. A multidimensional SAR system measures the target vector

$$\mathbf{k}=\left[S_1,\ldots,S_m\right]^T \quad (4)$$

which, under the Gaussian scattering hypothesis, is characterized by a zero-mean, complex, multidilmensional Gaussian distribution. For distributted scatterers, the vector **k** is unable to characterize them. Consequently, this characterization must be obtained from higher order information descriptors. Multidimensional data, under the Gaussian scattering hypothesis, is completely characterized by the covariance matrix

$$\mathbf{C}=E\left\{\mathbf{k}\mathbf{k}^H\right\}=\begin{bmatrix} E\left\{S_1S_1^*\right\} & \cdots & E\left\{S_1S_m^*\right\} \\ \vdots & \ddots & \vdots \\ E\left\{S_mS_1^*\right\} & \cdots & E\left\{S_mS_m^*\right\} \end{bmatrix} \quad (5)$$

where * indicates the complex conjugate, ^{H} is the transpose complex conjugate and $E\{x\}$ is the ensemble average. The matrix **C** needs to be estimated from the available data, which consists on the one-look sample covariance matrix defined as follows

$$\mathbf{Z}=\mathbf{k}_i\mathbf{k}_i^H \quad (6)$$

where $\mathbf{k}_i$ represents the target vector of a given pixel of the image. Since the vector $\mathbf{k}_i$ is a multivariate random variable, the sample covariance matrix is also a random variable, but characterized by the Wishart distribution [3].

The process to estimate **C** from (6), consists of a speckle noise reduction process. In order to reduce this noise, one option is to do it through the knowledge of a multidimensional speckle noise model, i.e, a relation that establishes how speckle corrupts useful information. Since every element of (6) consists of the Hermitian product of two components of the scattering vector, all the entries of **Z** can be writen as follows

$$S_pS_q^*=\left|S_pS_q^*\right|\exp\left(j\left(\phi_p-\phi_q\right)\right)=z\exp\left(j\phi\right). \quad (7)$$

In [5], through an extensive statistical study of the different properties of (7), the authors proposed a noise model for the Hermitian product $S_p S^*_q$

$$S_pS_q^*=\underbrace{\psi N_c\bar{z}_n n_m e^{j\phi_x}}_{Multiplicative\ term}+\underbrace{\psi\left(\left|\rho\right|-N_c\bar{z}_n\right)e^{j\phi_x}+\psi\left(n_{ar}+jn_{ai}\right)}_{Additive\ term} \quad (8)$$

where the average power is

$$\psi=\left(E\left\{\left|S_p\right|^2\right\}E\left\{\left|S_q\right|^2\right\}\right)^{1/2} \quad (9)$$

and $\bar{z}_n$ is the normalized amplitude of $S_p S^*_q$. The phase ϕ_x refers to the average phase of $S_p S^*_q$. Finally, $|\rho|$ is the amplitude of the correlation coefficient of the Hermitian product $S_p S^*_q$ and N_c takes the value, for $n=1$,

$$N_c=\frac{\pi}{4}\left|\rho\right|{}_2F_1\left(\frac{1}{2},\frac{1}{2};2;\left|\rho\right|^2\right). \quad (10)$$

In (8), the first noise term is given by n_m, with an expectation and a variance equal to one. Hence, this noise term is characterized by a multiplicative nature. On the contrary, the two additive noise terms n_{ar} and n_{ai} have a mean equal to zero, and the following variance

$$\mathrm{var}\left\{n_{ai}\right\}=\mathrm{var}\left\{n_{ar}\right\}\simeq(1/2)\left(1-\left|\rho\right|\right)^{1.32}. \quad (11)$$

Consequently, the additive noise terms n_{ar} and n_{ai} are not homogeneous as they depend on the level of coherence between S_p and S_q.

3.2 Polarimetric Speckle Noise Reduction Algorithm

The model given by (8) is taken as a basis to define a new polarimetric speckle noise reduction algorithm. As one can deduce, the multidimensional speckle filter has to face with the reduction of two noise components: a homogeneous multiplicative component given by n_m, and a non-homogeneous additive component given by the complex term $n_{ar}+jn_{ai}$. According to this fact, the strategy to filter out speckle in the case of multidimensional data consists of a two steps process. The first process will reduce the additive speckle, whereas the second one will face the reduction of the multiplicative speckle component. An scheme of this filter approach, which is applied to every element of the sample covariance matrix (6), is shown in Fig. 1.

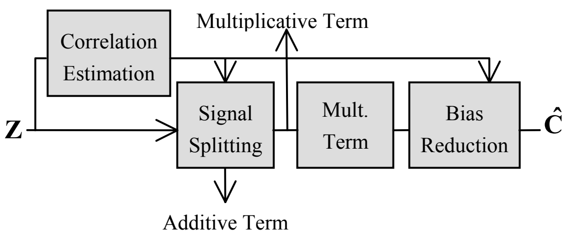

Fig. 1: Polarimetric filtering approach based on the WT.

In a first stage, the data's correlation structure is estimated via the Wavelet Transform (WT)[4] in order to preserve data's spatial resolution. This information is employed in the following, in order to separate the multiplicative and the additive speckle noise components, see (8). Finally, since the multiplicative part of (8) contains the most of the useful information, this component is filtered by means of the polarimetric refined Lee filter [5], as this approach if optimum to filter multiplicative speckle. The final step consists of a bias elimination, since, as mentioned, the multiplicative component of (8) does not contain all the average value of the Hermmitian product of a pair of SAR images. It must be mentioned, that this bias does not represent a problem, since it is deterministic.

4 Experimental Results

4.1 Polarimetric Parameters

After the conduction of the multidimensional filter on the covariance matrix **C**, the eigenvector/eigenvalue demposition has been performed [6]. Different filtering processes has been applied: the refined polarimetric Lee filter [5], and the approach presented in the previous section, which difference is to consider the additive speckle noise component.

For the evaluation of the polarimetric parameters: Entropy (H), Anisotropy (A) and the alpha angle (α) [6], two SAR data sets over bare surfaces

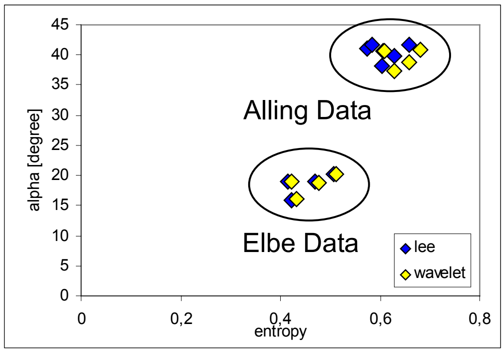

Fig. 2: Polarimetric parameters H/α for different filtering processes.

have been used: "Elbe" data from 1997 and "Alling" data from 2000. Both dada sets were acquired by the ESAR system, which is operated by DLR (Germany)

The obtained H/α values in both data sets, after reducing speckle from data with the two filtering approaches mentioned above, are presented in Fig. 2. As one can clearly observe, the H values derived with the polarimetric filter presented in Section 3.2 are clearly higher than those derived with the polarimetric Lee filter. This higher values in H values are due to the fact that the additive speckle noise component is eliminated by the filter based on the WT. Whereas the differences are small for Elbe data, these differences are visibly higher for the Alling data set. Despite not shown in Fig. 2, these differences are higher for higher H values. On the contrary, it has been observed that the values of A obtained with the filtering approach presented in Section 3.2 are clearly lower than those derived with the Lee approach.

4.2 Inversion Results

During the data acquisition campaigns, ground data were collected over test fields with heterogeneous surfaces. Soil roughness was estimated with a needleboard. Soil moisture values were measured in depths of 4-8 cm using traditional gravimetric sampling and time domain reflectometry (TDR). Due to the presence of vegetation, only four bare agricultural fields were available for validation in the case of Elbe data, see Table 1. Nevertheless, as the four fields are located at different ranges (covering an incident angle range from 47 up to 52 degrees) with different roughness and moisture values they are valuable for the validation of inversion results.

After SAR processing and polarimetric calibration, the scattering matrix data are transformed into a covariance matrix **C** where the multidimensional speckle noise reduction approaches have been applied. Then, the eigenvector decomposition is performed, followed by the computation of H/A/α. Surface scattering is characterised by a strong dominant scattering mechanism, represented by the first eigenvalue. The amplitudes of the secondary scattering effects, expressed by the second and third eigenvalues are, in comparison, very small, and therefore, more affected by noise.

In a pre-selection step, areas where H > 0.45 and alpha > 45 degrees have been masked out in order to select only surface scatterers. Consequently, Alling data are not valid to estimate surface parameters, especially if the polarimetric waveler filter is considered. For the Elbe data set, surface parameters estimation is feasible. The ks values are evaluated directly from A values. The correlation between the estimated and measured ks values is shown in Fig. 4.

In a second step, the computed H and α images are used for the estimation of the dielectric constant. The estimation can be performed directly in terms of a lookup table which delivers the dielectric constant as a function of entropy/alpha values for each range line accounting in this way the variation of incident angle across the image. The correlation between the estimated and measured values for the four test fields is shown in.

As it can be observed in the case of the Elbe data, the type of filtering does not affect inversion results. On the contrary, since the X-Bragg model does not apply for high H values, inversion results can not be presented for Alling data. As mentioned above, for this data set, noticeable differences in H/A estimated values are observed between data processed with the two different speckle filtering approaches.

Ground Measurements Test Site Elbe			
Field No.	**Cultivation**	**mv [vol. %]**	**ks (λ ~23 cm)**
10	Harrowed	18.5	0.46
12	Seed bed	19.5	0.57
13	Coarse harrowed	21	0.75
16	ploughed	23	0.95

Tab. 1: Ground measurements of the Elbe (1997) test site.

5 Conclusions

In Section 3.2, a novel polarimetric filtering approach considering the multiplicative-additive speckle noise nature of multidimensional SAR data has been presented. For surface scattering, i.e., low entropy, the multiplicative speckle noise component seems to be dominant. Hence, filtering does not affect inversion of surface parameters. On the contrary, for medium and high entropy values, the additive speckle component seems to dominate the data. Hence, to filter this noise component specifically leads to changes in the H/A values. Consquently, this will affect the estimation of physical parameters.

6 Acknowledgements

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7 References

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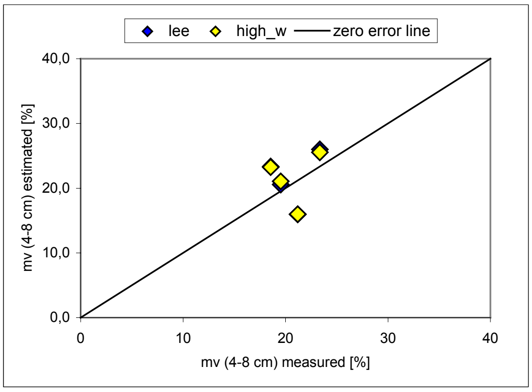

Fig. 4: Estimated versus measured volumetric soil moisture for different filtering processes. (high_w refers to the wavelet apprach).

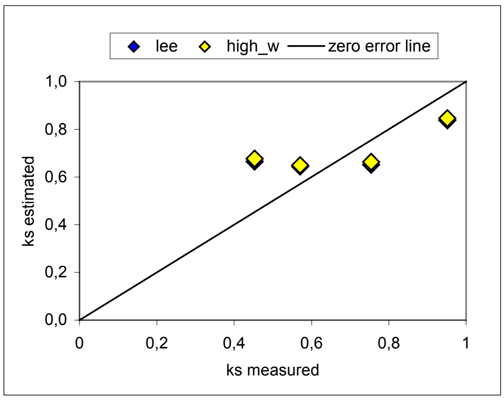

Fig. 3: Estimated versus measured surface roughness for different filtering processes (high_w refers to the wavelet apprach).