DETECTING DEPOLARIZING TARGETS WITH SATELLITE DATA: A NEW GEOMETRICAL PERTURBATION FILTER

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1. INTRODUCTION

The aim of this study is target detection and classification of partial targets employing a physical rather than a statistical technique. With a similar approach, the authors already developed a single target detector [1-3]. A single target exhibits a fixed polarization in time/space and its scattering behavior can be characterized using a unique scattering (Sinclair) matrix or equivalently a scattering vector: $\underline{k} = \frac{1}{2} Trace([S]\Psi) = [k_1, k_2, k_3, k_4]^T$, where [S] is the scattering matrix and Ψ is a complete set of 2x2 basis matrices under a Hermitian inner product [4, 5]. In the case of reciprocal medium and monostatic sensor, $\underline{k}$ is three dimensional complex [6]. Finally, the scattering mechanism is $\underline{\omega} = \underline{k}/|\underline{k}|$. The target observed by a SAR system is not an idealized scattering target, but a combination of different targets which we refer to as a partial target. In order to characterize a partial target the second order statistics are required. In this context the target covariance matrix can be estimated as $[C] = \left\langle \underline{k} \cdot \underline{k}^{*T} \right\rangle$, where $\langle . \rangle$ is the finite averaging operator. In general, the scattering vector in a generic basis is $\underline{k} = [k_1, k_2, k_3]^T$, with k_1, k_2 and k_3 complex numbers. If two different scattering mechanisms $\underline{\omega}_1$ and $\underline{\omega}_2$ are considered, the polarimetric coherence is: $\gamma = \dfrac{\underline{\omega}_1^{*T} \langle [C] \rangle \underline{\omega}_2}{\sqrt{\underline{\omega}_1^{*T} \langle [C] \rangle \underline{\omega}_1 \cdot \underline{\omega}_2^{*T} \langle [C] \rangle \underline{\omega}_2}}$. (1)

2. SINGLE TARGET DETECTOR

A single target detector based on eq.1 has already been developed and published in [1-3]. The aim of this section is to provide a geometrical interpretation which will allow the extension of the concept to partial target detection. It is always possible to characterize a (normalized) single target with a scattering mechanism $\underline{\omega}_T$. Moreover, the basis of the space can be chosen in order to have the target of interest limited only to one component. Hence, $\underline{\omega}_T = [1,0,0]^T$. Subsequently, a second scattering mechanism $\underline{\omega}_P$, which is close to $\underline{\omega}_T$ (in the geometrical space), is generated with a perturbation technique. The matrix corresponding to the metric of the target space can be calculated with: $[P]=diag\left(\langle|k_1|^2\rangle,\langle|k_2|^2\rangle,\langle|k_3|^2\rangle\right)$. The coherence between target and perturbed target in the new metric (normalized weighted inner product) can be calculated with

$$\gamma_d(\underline{\omega}_T,\underline{\omega}_P)=\frac{\underline{\omega}_T^{*T}\langle[P]\rangle\underline{\omega}_P}{\sqrt{\underline{\omega}_T^{*T}\langle[P]\rangle\underline{\omega}_T\cdot\underline{\omega}_P^{*T}\langle[P]\rangle\underline{\omega}_P}}=\frac{1}{\sqrt{1+\frac{|b|^2}{|a|^2}\frac{\langle|k_2|^2\rangle}{\langle|k_1|^2\rangle}+\frac{|c|^2}{|a|^2}\frac{\langle|k_3|^2\rangle}{\langle|k_1|^2\rangle}}}=\frac{1}{\sqrt{1+\frac{|b|^2}{|a|^2}\frac{P_{C2}}{P_T}+\frac{|c|^2}{|a|^2}\frac{P_{C3}}{P_T}}} \tag{2}$$

Where the first component is the target of interest and the second and third ones are the *clutter*. Finally, the detector is constructed setting a threshold on γ_d.

2. PARTIAL TARGET DETECTOR AND CLASSIFIER

The aim of this section is to extend the geometrical single target detector described in section 2 to partial targets. First step is to construct a formalism similar to the single target one which is proper for partial targets. The second order statistics are needed. A *feature partial scattering vector* is introduced: $\underline{t}=Trace([C]\Psi)=[t_1,t_2,t_3,t_4,t_5,t_6]^T=\left[\langle|k_1|^2\rangle,\langle|k_2|^2\rangle,\langle|k_3|^2\rangle,\langle k_1^*k_2\rangle,\langle k_1^*k_3\rangle,\langle k_2^*k_3\rangle\right]^T$, where Ψ is a complete set of 6x6 basis matrices under a Hermitian inner product. $\underline{t}$ lies in a subspace of C^6. In particular, it has the first three elements real positive and the second three complex. Then a change of basis is performed which makes the target of interest lie only on 1 component: $\underline{t}_T=[1,0,0,0,0,0]^T$ and $\underline{t}_P=[a,b,c,d,e,f,g]^T$. In order to calculate the weighted inner product, a matrix $[A]$ is constructed with a basis of C^6 obtained by a Gram-Schmidt ortho-normalization where the first axis is represented by the vector $\underline{t}_T$. If $\underline{u}_1=\underline{t}_T$, $\underline{u}_2$, $\underline{u}_3$, $\underline{u}_4$, $\underline{u}_5$ and $\underline{u}_6$ represent the ortho-normal basis, the $[A]$ matrix can be calculated as: $[A]=diag\left(\underline{t}_T^{*T}\underline{t},\underline{u}_2^{*T}\underline{t},\underline{u}_3^{*T}\underline{t},\underline{u}_4^{*T}\underline{t},\underline{u}_5^{*T}\underline{t},\underline{u}_6^{*T}\underline{t}\right)$. The detector is built as: $\left\langle([A]\underline{t}_T)^{*T}([A]\underline{t}_P)\right\rangle=\underline{t}_T^{*T}\langle[A]^{*T}[A]\rangle\underline{t}_P=\underline{t}_T^{*T}[P]\underline{t}_P$, where now $[P]=diag(P_1,P_2,P_3,P_4,P_5,P_6)$.

$$\gamma=\frac{\underline{t}_T^{*T}[P]\underline{t}_P}{\sqrt{(\underline{t}_T^{*T}[P]\underline{t}_T)(\underline{t}_P^{*T}[P]\underline{t}_P)}}==\frac{1}{\sqrt{1+\frac{b^2}{a^2}\frac{P_2}{P_1}+\frac{c^2}{a^2}\frac{P_3}{P_1}+\frac{|d|^2}{a^2}\frac{P_4}{P_1}+\frac{|e|^2}{a^2}\frac{P_5}{P_1}+\frac{|f|^2}{a^2}\frac{P_6}{P_1}}} \tag{3}$$

Once we obtain the partial target detector we can use it as a preliminary stage to produce a series of masks which are used to perform classification. The pixel is allocated in a class if the co-respective mask is bigger than the others. If $m_1,\dots,m_n$ are the *n* masks obtained, a pixel is located in the class c where: $m_c=\max_{i=1,\dots,n}\{m_i\}$. (4)

3. VALIDATION

In order to validate and test the potential of the classifier, this is applied on fully polarimetric SAR datasets. We are aware of the importance to develop future applications for satellite data, for this reason, we decided to validate with X band TerraSAR-X and L band ALOS PALSAR. In **figure 1** the supervised classifier is applied on TerraSAR-X data. The latter were acquired in Germany over a mix of agricultural and urban areas. **Figure 1.a** depicts the Pauli RGB image as comparison. The areas chosen as classes are labeled. We decided to use the Pauli RGB image for the selection of the areas, since for some instance we can relate the colors with physical characteristics of the scatterers. In **Figure 1.b** is presented the proposed supervised classification with 4 classes. **Figure 1.c** presents a comparison with the supervised Wishart, which uses pixel statistics (please note the color coding of the masks is different). The results appear to be in good agreement, differences are mainly to be found on regions not employed for classification training. Those areas are in between two classes therefore they can be interpreted differently by the two classifiers. Another new feature in the proposed classifier is the presence of black areas. These are regions which do not fall in any class (mainly man-made targets and buildings). It is important to identify these areas and not force them into the closest class. In case we are interested in the classification of those points, we can treat them separately with the detector. Finally, the technique proposed is fully physical; we believe that the results are subject of improvement once a subsequent iterative statistic stage will be added. **Figure 2** presents a similar scenario using an L-band ALOS PALSAR dataset. The scene is acquired in China, close to the city of Taian. In this example, another important advantage of the proposed classifier can be observed. Comparing the two classifiers, it seems that the decision of the proposed one is not affected by the total intensity of the signal. The mountainous region with layover of bare ground (right hand side) is classified as the bare ground in the valley (left hand side). Conversely, Wishart locates the layovered region in three different classes (among bare ground, forest and urban area). The new detector is not influenced by changes in overall amplitude of the coherence matrix, but exclusively on the weight of the matrix elements.

4. CONCLUSIONS

A geometric interpretation of the single target detector [1-3] has been provided. Subsequently, a new partial target detector has been developed extending the vector formulation from single targets to partially polarized targets. The partial target detector was then utilized as a first stage for a novel supervised classifier. Validation against satellite data (TerraSAR-X and ALOS) is provided showing the capability of the classifier to separate different areas. Moreover, a comparison with the Wishart supervised classifier is provided, showing two main enhancements: a) rejection of targets which do not belong to any class b) improved classification against changes in the overall amplitude of the coherence matrix, since the algorithm works solely on the polarimetric information. Therefore, changes in amplitude due to layover are not anymore a problem for the new classifier (making the algorithm particularly suited for mountainous regions). Future work will see application of this filter to improved land use classification and geophysical parameter estimation from polarimetric data from Radarsat2, Terrasar-X and ALOS_PALSAR.

5. REFERENCES

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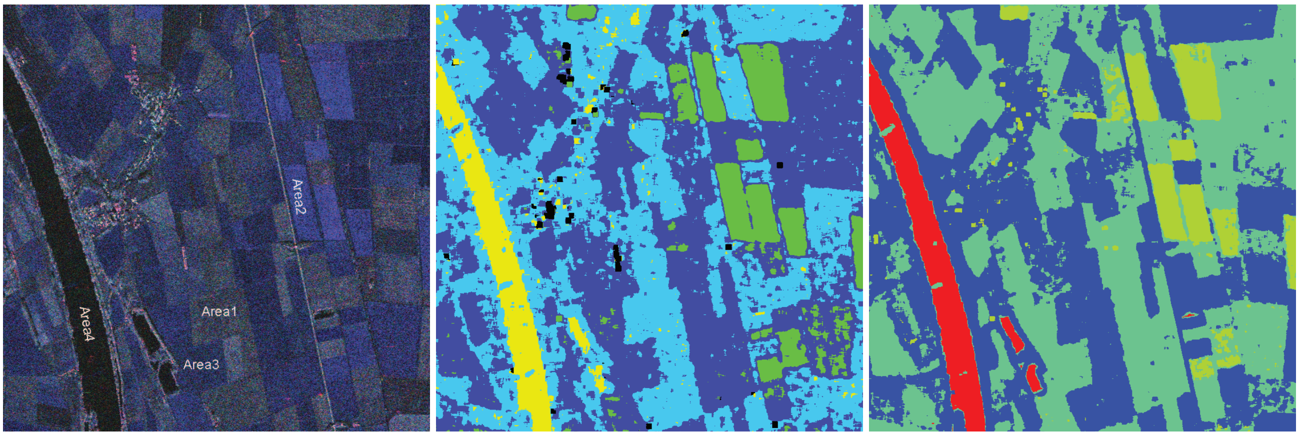
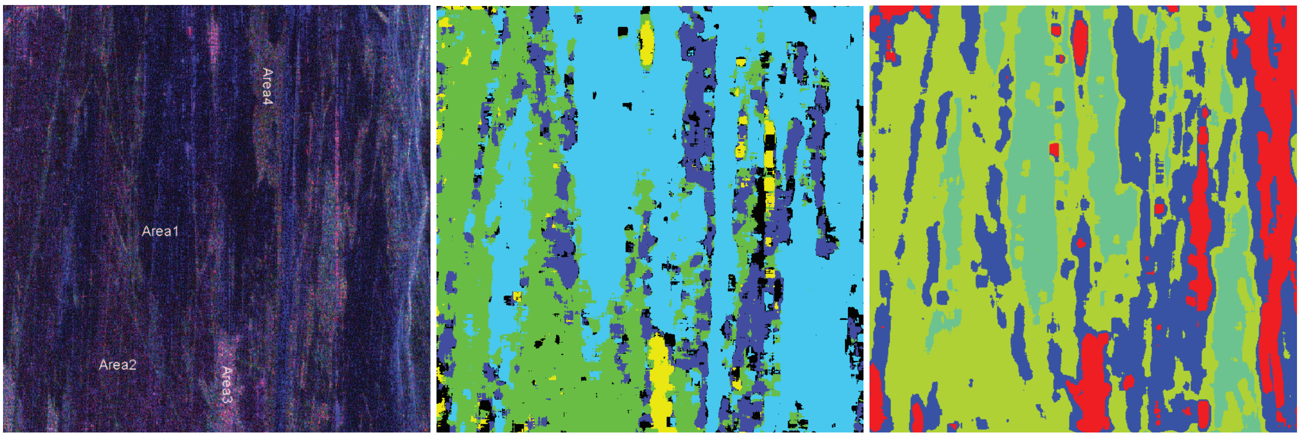


(a) (b) (c)

Figure 1. Partial target detection on TerraSAR-X data (Germany): (a) RGB Pauli image of the area (b) supervised classification after the detection of 4 partial targets (c) Wishart supervised classification (same classes as before).



(a) (b) (c)

Figure 2. Partial target detection on ALOS data (China): as **Figure 1.**