Fast PolSAR data visualization and classification based on Huynen canonical decomposition (Postprint)

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Abstract

A scattering preference degree parameter derived from the Huynen canonical dichotomy exhibits superior classification capability compared to the scattering similarity parameter. A scattering hue parameter is subsequently proposed and demonstrated to be superior to scattering alpha in describing scattering mechanisms. Furthermore, a scattering saturation parameter is defined, which demonstrates comparability to scattering entropy in describing scattering randomness. Finally, a Huynen dichotomy-based PolSAR data visualization scheme is developed, which not only operates more efficiently but also yields superior visual results compared to those from H/alpha. ©2014 VDE VERLAG GMBH.

Full Text

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Abstract A scattering degree of preference parameter is developed from Huynen canonical dichotomy which displays superior classification ability over the scattering similarity parameter. A scattering hue parameter is then proposed and demonstrated to be of superiority compared with scattering alpha on description of scattering mechanism. A scattering saturation parameter is further defined and shows comparable to scattering entropy on description of scattering randomness. A Huynen dichotomy-based PolSAR data visualization scheme is finally obtained which not only works more efficient but also makes the results look better than that from H/alpha.

1 Introduction these cases [1]. But N-target is clearly defective because it cannot completely reserve the non-symmetric and ir-

It is unbiased to say that it is Dr. J. R. Huynen pioneered regular target information. By referring to wave dichotthe area of polarimetric target decomposition. In his dis- omy, it is found that there still exist two other target disertation on the phenomenological theory of radar target chotomies [3]. The Pauli vectors (i.e. k2 and k3) of sin- [1], Huynen formally developed the coherent and incogle targets extracted from them are shown in (1), where herent decompositions. The coherent one expresses the k1 is that extracted from Huynen dichotomy, and Tij descattering matrix of a determined target in terms of sev- notes the element of target coherency matrix [T]. eral physical parameters, such as SPAN, orientation, and helicity, which was further extended for the well-used T11 T12 T13 1 1 1 Cameron decomposition and Touzi decomposition [2]; = k1 = T21 , k2 = T22 , k3 T23 . (1) while the incoherent one is also known as Huynen target T11 T22 T33 T31 T32 T33 dichotomy because it decomposes a random target scattering into the incoherent sum of an equivalent single Each column of [T] is just one of the Pauli vectors in (1) target scattering and a remnant noisy N-target scattering and is kept invariant to a dichotomy [1]. This decomposition has clear physical significance because they are reserved by dichotomies k1 , k2 and k3 , respectively [3]. because it prefers the real world of symmetry. However, The diagonal entries T11, T22, and T33 physically relate to it is not mathematically unique because there exist other target scattering of symmetry/regularity, irregularity, and target dichotomies, such as Holm-Barnes decomposition non-symmetry, respectively, according to Huynen pheand Yang decomposition [2]. The contributions of Holm, nomenological theory [1]. They also denote the scatter- Barnes, and Yang improve Huynen dichotomy signifi- ing similarity between [T] and the canonical scatterers, cantly, but there is no unified criterion for us to select i.e. the sphere, dihedral, and volume scatterer, respecbetween them. A Huynen canonical dichotomy is devel- tively [4]. Thus the parameter invariance may show the oped and extended for a generalized dichotomy in [3]. scattering preference of each dichotomy. This can be The dichotomy can unify the existing Huynen-like target dichotomies and clearly demonstrated in Fig. 1 on the AIRSAR data of get dichotomies and shows comparable decomposition San Francisco using the Pauli pseudo-colour illustration. and classification ability as the Cloude-Pottier decom- Comparing with the original image shown in Fig. 1(a), position [3]. This paper further focuses on Huynen ca- the dark colours of blue, red, and green in Figs. 1 (b), (c), nonical dichotomy. Our recent research shows that the and (d) clearly show the difference. Here it should note dichotomy can provide a fast and better way to visualize that the scattering preference does not mean it is just this. and classify PolSAR data, as will be detailed as follows. For example, Huynen dichotomy prefers the symmetric 2 Huynen Canonical Dichotomy and regular scatterers. This does not mean the extracted single targets from the dichotomy are all symmetric and We first give a concise introduction to Huynen canoni- regular. The actual scattering of target only depends on cal dichotomy. The original Huynen dichotomy behaves its Pauli vector. In this regarding, the preference of the well on the symmetrically and regularly dominant radar dichotomy can only provide a direct and superficial detarget. For targets of complex non-symmetry and irregu- scription of scattering information. However, in the follarity, however, it will fail. Huynen added that the atten- lowing we will show that for the purpose of visualization should turn to N-target instead of single target in tion and classification this information is enough.

Figure 1: Pauli pseudo-colour display of (a) the original San Francisco data and (b-d) the extracted single targets from Huynen canonical dichotomy, where (b), (c), and (d) correspond to vectors k1 , k2 , and k3 , respectively.

3 Fast PolSAR Data Visualization with Classification Based on Huynen Canonical Dichotomy The SPAN image and Pauli image are the two widelyused visualizations of PolSAR data. But they only convey limited information contained in the coherence matrix of a random scatterer. Some recent works [5] have dedicated to visualize PolSAR information to the most. Figure 2: San Francisco data classification based on All of them added the scattering information and purity (a) scattering similarity and (b) scattering preference. information of random target into SPAN image, a huesaturation-intensity (HSI) presentation is thus obtained. where SPANi is the power of single target extracted from The Cloude-Pottier entropy (H) and alpha parameters or the ith dichotomy. SPAN in denominator is the power of their alternative are used as saturation and hue to show random target. Thus SDoP measures the relative power the randomness and scattering mechanism, while SPAN and it is comparable to the wave degree of polarization is used as intensity. Considering the valid scope of Hue, (WDoP), which measures the relative power between Sat and Int, some simple transformations are necessary. the decomposed fully polarized wave and the original The following transformation is used in the PolSARPro: partially polarized wave. A simple classification of target can be achieved based on SDoP. For example, the

Hue= 4 (90° − α) − 60 scattering is labelled as "more preferable to irregular

Sat = 1 − H . (2) scatterer" if SDoP2 is larger than SDoP1 and SDoP3. It is

Int = Normalzie ((log SPAN)) worthy to emphasize the "preferable" further here. In fact Chen et al. [4] has recently proposed to classify a random target into sphere (SS1), dihedral (SS2), and vol- This paper is dedicated to develop a new PolSAR data ume scatterer (SS3) based on scattering similarity (SS): visualization approach still based on HSI, but our Hue and Sat descriptions are from Huynen canonical dichot- Tii omy. The Pauli vectors from this decomposition are just =SSi = , i 1, 2,3 . (4) T11 + T22 + T33 the columns of [T], thus the complex eigendecomposition operation in Cloude-Pottier decomposition can be They are in fact the normalized diagonal entries of [T] immediately avoided, and the resulted improvement of [5]. Fig. 2(b) shows the classification of San Francisco computation efficiency can be envisaged. scene based on SDoP, in which the blue colour denotes more preferable to symmetric/regular scatterer, such as 3.1 Scattering Degree of Preference and sphere; red means more preferable to irregular scatterer, Application to Classification such as dihedral; and green shows more preferable to non-symmetric target, such as volume scatterer. Fig. 2(a) The three target dichotomies prefer the sphere, dihedral, shows the classification based on SS, where the blue, and volume scatterer, respectively, thus they can be used red, and green colours denote more similar to sphere, for classification. In order to measure the preference dedihedral, and volume scatterer, respectively. By compargree of each dichotomy, here we define a scattering deing the two classifications we can observe that more ingree of preference (SDoP) parameter formation is reflected by SDoP. Particularly in the sea area, the scattering influence from radar LOS variation $\sum$ j =1T ji2 SPANi has been clearly identified and classified, which can be = SDoPi = = , i 1, 2,3 (3) SPAN T $\sum$ 3 T even comparable to the H/A/alpha-Wishart classifier [2]. ii j =1 jj The inferiority of SS to SDoP is straightforward because

SS is in fact a special SDoP. For example, let k2 =A[0, 1, 0]T, i.e. the dihedral is considered, and then SDoP degenerates to SS.

3.2 Scattering Hue Although SDoP looks attractive, it cannot quantitatively measure the scattering mechanism. To achieve this here we propose a scattering hue (SH) by comparing among SDoP1, SDoP2, and SDoP3. Two different versions of SH are developed, i.e. the smooth SH and the rugged SH:

SDoPmax = max(SDoP1, SDoP2 , SDoP3) SDoPmin = min(SDoP1, SDoP2 , SDoP3) SDoP3 − SDoP1 SDoP2 = SDoPmax , if SDoPmax − SDoPmin SDoP1 < SDoP31 SDoP2 = SDoPmax Figure 3: Colour circles of (a) smooth SH and (b) rug- SDoP − SDoP 3 1 + 6, if SDoPmax − SDoPmin SDoP3 ≥ SDoP ged SH, as well as the extracted (c) smooth SH and (d) SH smooth= 60 × SDoP1 − SDoP2 rugged SH on San Francisco data. SDoP + 2, if SDoP3 SDoP = max max − SDoPmin three groups. Taking Zone I of Group1 and Zone VI of SDoP2 − SDoP3 Group3 for example, these zones have the least prefer- + 4, if SDoP1 SDoP = max .(5) SDoPmax − SDoPmin ence to volume scatterer. However, Zone VI has more SDoP1 − SDoP3 SDoP2 = SDoPmax preference to sphere. The SDoP1 and SDoP2 values are , if SDoPmax − SDoPmin SDoP1 ≥ SDoP3 comparable in the bordering area of these two zones, SDoP2 = SDoPmax SDoP1 − SDoP3 + 6, if which infers the colour transition here should be smooth. SDoPmax − SDoPmin SDoP1 < SDoP3 The purple area around 300º in Fig. 3(a) just demon- SH rugged= 60 × SDoP2 − SDoP1 strates this. The obtained smooth SH on San Francisco SDoP + 2, if SDoP3 SDoP = max max − SDoPmin data is shown in Fig. 3(c), which not only contains the SDoP3 − SDoP2 same scattering information as the SDoP classification + 4, if SDoP1 SDoP = max SDoPmax − SDoPmin in Fig. 2(b), but also shows the similar colouring. In Fig. 3(c), we can see much purple colour across the sea and The colour circles of the two SHs are illustrated in Figs. city area, which means SDoP1 and SDoP2 are compara- 3 (a) and (b). They are divided into six zones. Zones I ble there and SDoP3 is the smallest. But in the practical and II compose the colour Group1, as shown in Fig. 3. remote sensing application, what we want mostly is not They have more preference to dihedral than sphere and the least scattering but the dominant scattering mechavolume scatterer because SDoP2 is larger than SDoP1 nism, i.e. SDoP1 is larger than SDoP2, or SDoP2 is larger and SDoP3 here. The red colour is mostly located within than SDoP1. In this regarding the smooth SH colour ilthese zones so as to well indicate the scattering of build- lustration cannot visually provide the information unless ings. The difference between Zones I and II depends on we check the original SH data. To solve this defect, we the comparison of SDoP1 and SDoP3. The sphere scat- further develop a rugged SH, as shown in Fig. 3(b). The tering has more preference in Zone I than the volume positions of Zones I and II, III and IV, V and VI are exscattering. A smooth colour transition from red to purple changed in this SH circle. Zone I is next to Zone VI in (fusion of red and blue) can be observed in this zone Fig. 3(a), but it is now 'opposite' to Zone VI. Thus the with the increase of SDoP1. In the limit when SDoP1 bordering colour ambiguity between them is resolved. equals SDoP2, the colour completely changes to purple. Zone IV is now next to Zone I and it denotes the scatter- Zone II prefers more to volume scattering than sphere. A ing preference of SDoP3>SDoP1>SDoP2, being comsmooth colour transition from red to yellow (fusion of pletely inverse to Zone I of SDoP2>SDoP1>SDoP3. The red and green) can be observed in this zone with the in- bordering colour ambiguity in this case is greatly supcrease of SDoP3, and the colour changes to yellow when pressed. The same changes also take on other five zones. SDoP1 equals SDoP2. A smooth scattering-related col- The rugged SH of San Francisco data is shown in Fig. our transition is thus achieved in Group1. Zones III and 3(d), which is much colourful than Fig. 3(c). More im- IV compose colour Group2, which prefer more to dihe- portant, the purple colour in the sea and city area in Fig. dral. The remaining Zones V and VI compose Group3, 3(c) is now coloured as cyan and orange, which denotes which indicate more preferable to the volume scattering. more preferable to sphere and more preferable to dihe- Detail analysis of these four zones is omitted here. We dral, respectively. This is in accord with the ground truth. term the SH circle in Fig. 3(a) as the smooth SH because Thus the rugged SH is more competent to visualize the it can also achieve a smooth colour transition among the scattering mechanism.

Figure 4: The (a) hue, (b) saturation, and (e) HSI visualization of Oberpfaffenhofen data based on H/alpha, as well as the (c) rugged SH, (d) SS, and (f) HSI visualization of the data based on Huynen canonical dichotomy.

Next we give a simple comparison between H/alpha hue saturation within the interval of [0, 1]. Figs. 4 (b) and (d) and SH. To well illustrate the difference, DLR ESAR show the H/alpha-based saturation and SS, respectively. Oberpfaffenhofen data is selected, which shows a more We can see that they behave nearly the same. The detail complex scattering scene including forest, runway, bare comparison is passed over here due to space limitation. land, vegetation land, and buildings. Figs. 4 (a) and (c) display alpha hue and SH, respectively. SH' s superiority 3.4 HSI Visualization over alpha hue on visualization of different scattering By integrating SH, SS, and SPAN, the final HSI illustramechanism can be clearly observed. Thus we think SH tion is obtained and shown in Fig. 4(f). Fig. 4(e) further can be a competent alternative to scattering alpha. displays the result obtained from H/alpha. The scattering details in Fig. 4(e) can all be clearly observed in Fig. 3.3 Scattering Saturation 4(f). But Fig. 4(f) looks better than Fig. 4(e) on differen- SDoP denotes the relative power of the extracted single tiation of scattering mechanism. This mainly lies in the target with respect to that of the original random target, superiority of SH. The visualization elements SH and SS as defined in (3). We can easily find that SDoP achieves can be directly obtained without any eigendecomposi-its maximum value of one when the original target is tion, thus the efficiency improvement is considerable. fully determined. On the other hand, if the target is partially determined or random, SDoP ranges from zero to 4 Conclusions one. Thus SDoP may also indicate target randomness or purity, just like WDoP to measure the depolarization of Huynen decomposition is used for fast PolSAR data viwave. Section 2 shows that the canonical dichotomy can sualization and classification. The visualization is comindependently extract three single targets with different parable and even better than that based on H/alpha, bescattering preference. This on the other hand may also sides the high efficiency. The classification is much betshow that the extracted three single targets can probably ter than that based on SS because of the power of SDoP, provide three different and independent understandings from which we not only can obtain SH to show the scatof the ensemble scatterer. Thus a statistical model can tering mechanism, but also can obtain SS to describe the be obtained with the pseudo-probability as shown in (6). scattering randomness. SH and SS perform comparable Then a mean estimation of SDoP is achieved: to and even better than the scattering alpha and entropy.

SPANi References = Pi = , i 1, 2,3 ∑ j =1 SPAN j [1] J. R. Huynen: Phenomenological Theory of Ra- ∑ j =1 SPAN 2j 3 dar Targets, Tech. Univ. Delft, 1970. SDoP = ∑ j P SDoP j = . (6) SPAN ∑ j =1 SPAN j 3 [2] J.-S. Lee and E. Pottier: Polarimetric Radar Im- j =1 aging: From Basics to Applications, CRC Press, 3 1 = SS 2 SDoP − 2 2009. [3] D. Li and Y. Zhang: Huynen Dichotomy-based Radar Target Adaptive Extraction, Proc. PIERS, The mean is one for the determined target, is 1/3 for the pp. 881-885, 2013. random noisy target, and is between for the distributed [4] Q. Chen et al.: IEEE TGRS, vol. 51, no. 3, pp. target. Thus it can measure the scattering randomness 1817-1825, 2013. and be used as saturation just like the scattering entropy. A scattering saturation (SS) parameter is developed by [5] J. Praks, E. C. Koeniguer, and M. T. Hallikainen: simply transforming the average SDoP so as to keep the IEEE TGRS, vol. 47, no. 7, pp. 2262-2274, 2009.

Note: Figure translations are in progress. See original paper for figures.