Characterization of Mixed Target Scattering Using Random Similarity (Postprint)

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Abstract

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Full Text

Preamble

Characterization of Mixed Target Scattering Using Random Similarity

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Abstract

This paper proposes a random similarity parameter that can measure not only the scattering similarity between any two scatterers but also the degree of scattering randomness. The parameter generalizes both the similarity parameters developed by Yang et al. and Chen et al., and provides a fast and effective alternative to the widely-used scattering entropy H parameter. The superior target discrimination capability of the proposed parameter is demonstrated through its application to terrain classification.

1 Introduction

Polarimetric radar remote sensing of the Earth has received intensive attention in recent years. Fully polarimetric measurements can acquire both the geometrical structure and physical scattering characteristics of a target. This information is stored in the scattering matrix (for a single scatterer) or the coherence matrix (for a mixed scatterer). By processing and analyzing these matrices, we can obtain an understanding of the scattering mechanisms. Among the various approaches available for this purpose, polarimetric decomposition is the most popular, as it interprets target scattering by identifying dominant or average scattering mechanisms or by expanding the target scattering in terms of several canonical scattering components. Another widely-used approach was developed by Yang et al. based on scattering similarity, which measures the correlation between two scattering matrices [?]. By examining the similarity between a given (unknown) scatterer and several known canonical scatterers, direct characterization of the scatterer can be achieved. However, Yang' s parameter can only measure the similarity between two single scatterers. For a general mixed scatterer created by the coherent addition of multiple single scatterers, this parameter fails to analyze its scattering behavior.

Chen et al. extended Yang' s parameter to measure the similarity between a mixed scatterer and a canonical single scatterer [?]. Discrimination of the mixed scatterer is then obtained by calculating its similarity to canonical scatterers such as surface, dihedral, and /4-rotated dihedral. The /4-rotated dihedral is used to model volume scattering and accounts for cross-polar HV scattering. Nevertheless, volume scattering is usually created by the mixture of randomly oriented spheroidal scatterers or by the mixture of odd-bounce and even-bounce scattering. It is therefore often modeled as a mixed scatterer rather than a simple rotated dihedral. Many canonical mixed volume models have been developed to date, which have been widely used in model-based polarimetric decompositions [?]. However, a problem arises when these mixed volume scatterers are utilized because Chen' s parameter cannot measure the similarity between two mixed scatterers.

In this paper, we develop a random similarity parameter that covers both Yang' s and Chen' s parameters and provides a general similarity measurement. From this general parameter, we derive a self-similarity parameter and a mirror-similarity parameter that serve as fast and effective alternatives to the widely-used entropy parameter for describing scattering randomness. The superiority of the proposed parameter for target discrimination is demonstrated through its application to terrain classification.

2 Random Scattering Similarity

The scattering of a single scatterer can be described by the scattering matrix S. In the monostatic backscattering case, we have SHV = SVH.

For a mixed scatterer subject to spatial and/or temporal variations, we can no longer model its scattering using a fixed scattering matrix. Instead, the coherence matrix T is formed through the statistical average of all acquired scattering information:

$$T = \langle k \cdot k^H \rangle = \begin{bmatrix} \langle |k_1|^2 \rangle & \langle k_1 k_2^* \rangle & \langle k_1 k_3^* \rangle \\ \langle k_2 k_1^* \rangle & \langle |k_2|^2 \rangle & \langle k_2 k_3^* \rangle \\ \langle k_3 k_1^* \rangle & \langle k_3 k_2^* \rangle & \langle |k_3|^2 \rangle \end{bmatrix}$$

where $\langle \cdot \rangle$ denotes ensemble averaging and k is the Pauli vector:

$$k = \frac{1}{\sqrt{2}} [S_{HH} + S_{VV}, \quad S_{HH} - S_{VV}, \quad 2S_{HV}]^T$$

The superscripts T and H in the equations denote transpose and conjugate transpose operations, respectively. The averaging operation is removed in the single scatterer case.

For a given mixed scatterer T and a canonical mixed scatterer T_c, their random scattering similarity r_{rrr} is defined as:

$$r_{rrr}(T, T_c) = \frac{\mathrm{Tr}(T \cdot T_c)}{\sqrt{\mathrm{Tr}(T^2)}\sqrt{\mathrm{Tr}(T_c^2)}} = \frac{\sum_{i=1}^{3} \lambda_i \lambda_{ci} |\langle u_i, u_{ci} \rangle|^2}{\sqrt{\sum_{i=1}^{3} \lambda_i^2}\sqrt{\sum_{i=1}^{3} \lambda_{ci}^2}}$$

where $\mathrm{Tr}(\cdot)$ denotes the matrix trace operation.

From this definition, we can derive that:

$$r_{rrr}(aT, bT_c) = r_{rrr}(T, T_c) \quad \text{and} \quad r_{rrr}(U_r T U_r^H, U_r T_c U_r^H) = r_{rrr}(T, T_c)$$

where a and b are arbitrary complex numbers and U_r is an arbitrary SU(3) matrix. The first equation indicates scale invariance, while the second shows invariance to unitary transformation, meaning the similarity remains unchanged even if we replace coherence matrices with corresponding covariance matrices.

The matrices T and T_c can be eigendecomposed as follows:

$$T = UDU^H = \sum_{i=1}^{3} \lambda_i u_i u_i^H$$

$$T_c = U_c D_c U_c^H = \sum_{i=1}^{3} \lambda_{ci} u_{ci} u_{ci}^H$$

where $D = \mathrm{diag}(\lambda_1, \lambda_2, \lambda_3)$ and $D_c = \mathrm{diag}(\lambda_{c1}, \lambda_{c2}, \lambda_{c3})$ are diagonal matrices composed of the eigenvalues λ_i and λ_{ci} (i = 1, 2, 3) of T and T_c, respectively, and $U = [u_1, u_2, u_3]$ and $U_c = [u_{c1}, u_{c2}, u_{c3}]$ are unitary matrices composed of the corresponding eigenvectors u_i and u_{ci}.

It is easy to validate that the value range of r_{rrr} is:

$$r^l_{rrr} \le r_{rrr} \le r^u_{rrr}$$

where r^l_{rrr} and r^u_{rrr} are the lower and upper bounds of r_{rrr}, respectively.

The upper bound is approached when $U_c = U \cdot \mathrm{diag}(e^{j\phi_1}, e^{j\phi_2}, e^{j\phi_3})$, where ϕ_i are arbitrary phases that can be omitted. In this case, T and T_c share the same unitary eigenvector matrix U.

The lower bound is achieved when $U_c = [u_3, u_2, u_1]$. Here, matrices T and T_c still have the same eigenvectors u_i, but the arrangement of u_i in U_c is the mirror image of that in U. We name U_c as the mirror matrix of U.

If the canonical scatterer T_c degenerates to a single scatterer, we have $T_c = k_c \cdot k_c^H$, and the expression can be arranged as:

$$r_{rrr}(T, T_c) = \frac{k_c^H T k_c}{\sqrt{\mathrm{Tr}(T^2)}||k_c||_2^2}$$

where $||\cdot||_2$ denotes the 2-norm. In this case, the proposed parameter becomes identical to Chen's parameter r_r, which measures the similarity between a mixed scatterer and a single scatterer [?]. The range then changes to:

$$0 \le r_{rrr} \le \frac{||k_c||_2^2}{\sqrt{3}||k_c||_2^2} = \frac{1}{\sqrt{3}}$$

This range is more accurate than Chen' s range of [0, 1] when scatterer T is a non-degenerate mixed scatterer.

If scatterer T also degenerates to a single scatterer, i.e., $T = k \cdot k^H$, then the expression can be further simplified to:

$$r_{rrr}(T, T_c) = \frac{|k^H k_c|^2}{||k||_2^2||k_c||_2^2}$$

This is precisely Yang's parameter r measuring the similarity between two single scatterers [?]. The range then becomes $0 \le r_{rrr} \le 1$, which is consistent with Yang' s result.

Thus, the random similarity parameter encompasses both Yang' s and Chen' s parameters and extends them to the general case. It remains valid even when the rank of T and/or T_c is 2, and is also applicable to bistatic scattering scenarios.

3.1 Self-Similarity Parameter

The self-similarity parameter r_{rrs} is obtained when $T = T_c$:

$$r_{rrs}(T) = r_{rrr}(T, T) = \frac{\mathrm{Tr}(T^2)}{\mathrm{Tr}(T)^2} = \frac{||D||_F^2}{(\mathrm{Tr}(D))^2}$$

where $||\cdot||_F$ denotes the Frobenius norm. Here, r_{rrs} is not always equal to 1 but depends on the eigenvalues. One can easily verify that r_{rrs} equals 1 for a single scatterer, equals 1/3 for a randomly noisy scatterer, and resides between 1/3 and 1 for other scatterers. It can thus measure scattering randomness.

To validate this, we compare r_{rrs} with the scattering entropy H, which has been widely used to describe randomness and is defined as:

$$H = -\sum_{i=1}^{3} P_i \log_3 P_i, \quad \text{where} \quad P_i = \frac{\lambda_i}{\sum_{j=1}^{3} \lambda_j}$$

Figures 1(a) and 1(b) illustrate the obtained H and r_{rrs} for the DLR L-band ESAR data of Oberpfaffenhofen. The two parameters exhibit inverse behavior, and Figure 1(d) further shows their relationship. Good correspondence is observed for scatterers with high and low H values, but poor correspondence arises for scatterers with medium H due to the nonlinear logarithmic operation in H' s calculation. The right side of the equation provides another derivation of r_{rrs} that is independent of eigendecomposition, making its computation significantly faster than H. Therefore, the self-similarity parameter serves as a fast alternative to entropy.

3.2 Mirror-Similarity Parameter

In the mirror-similarity scenario, T and T_c share the same eigenvalue matrix, indicating identical scattering randomness. However, their eigenvector matrices are mirror images of each other, as shown in the lower bound condition. Consequently, the Cloude-Pottier angles of T and T_c are also "mirrored" –if T' s angle is 0, the angle of T_c would be /2. These two angles correspond to surface scattering and dihedral scattering, respectively. We term such T_c as the mirror target (T_m) of T.

The mirror-similarity r_{rrm} is then defined as:

$$r_{rrm}(T) = r_{rrr}(T, T_m) = \frac{\sum_{i=1}^{3} \lambda_i \lambda_{4-i}}{\sum_{i=1}^{3} \lambda_i^2}$$

We can also obtain that $0 \leq r_{rrm} \leq 1/3$. This parameter equals 0 for a single scatterer, equals 1/3 for a noisy scatterer, and resides between 0 and 1/3 for other scatterers. Thus, it can also depict scattering randomness. Figure 1(c) shows r_{rrm} obtained for the Oberpfaffenhofen scene. Comparing it with Figure 1(b), one can clearly observe the inverse relationship between r_{rrm} and r_{rrs}. Further comparison of Figure 1(c) with Figure 1(a) reveals good coherence between r_{rrm} and entropy H. It appears that r_{rrm} can provide even better target discrimination than H, as the contrast in Figure 1(c) looks superior to that in Figure 1(a). To validate this, Figures 1(e) and 1(f) display the histograms of H and r_{rrm}, respectively. The histogram in Figure 1(f) is much flatter than that in Figure 1(e), demonstrating better contrast. Therefore, the mirror-similarity parameter is a competent alternative to entropy.

Target randomness arises from nonstationary target scattering, system noise, and environmental clutter. These factors cause target scattering to become decorrelated and depolarized. Hence, by investigating the correlation of the obtained polarimetric scattering information, a measure of scattering randomness can be achieved. The similarity parameter in (4) is in fact a correlation-like measure, which is why we term it random scattering similarity.

4 Random Similarity-Based Classification

The random similarity parameter is applied to classification in this section. The classification scheme follows Chen's approach, which characterizes target scattering based on similarity, but incorporates four widely-used mixed volume scattering models T_{cvi} (i = 2–5) as summarized in Table 1 . Volume scattering directly relates to cross-polar HV scattering, which is generally produced by both odd-bounce objects (such as vegetation) and even-bounce structures (such as oriented buildings), making it difficult to discriminate between these two scatterer types [**?**]. The first two models, T_{cv1} and T_{cv2}, are used to model dihedral-related HV scattering. T_{cv1} corresponds to the /4-rotated dihedral used in Chen' s classification for volume scattering, but it is only suitable for depicting low-randomness volume scatterers because it is a single scatterer model. T_{cv2} was proposed by Sato et al. [**?**] to extend T_{cv1} to mixed scatterer scenarios, enabling it to model high-randomness, dihedral-induced volume scatterers.

The remaining three volume models aim to model vegetation scattering. T_{cv3} was developed by Freeman and Durden to describe volume scattering from a forest canopy, modeled as a cloud of dipole scatterers with uniform orientation angle distribution [**?**]. T_{cv4} and T_{cv5} were proposed by Yamaguchi et al. for vegetated areas where vertical or horizontal structures are dominant, such as tree trunks and branches [**?**]. These cases adopt nonuniform cosine or sine orientation distributions, corresponding to T_{cv4} or T_{cv5}, respectively.

By substituting T_{cvi} into (4), we obtain the similarity r_{rrcvi} between T_{cvi} and T, as formulated in Table 1.

For a given scatterer T, Chen et al. first calculated the similarities between T and the canonical surface scattering T_{cs}, dihedral scattering T_{cd}, and volume scattering T_{cv1}, which yield r_{rrcs}, r_{rrcd}, and r_{rrcv1}, respectively, as shown in

Table 1. Chen et al. then assigned r_{rrcd}, r_{rrcv1}, and r_{rrcs} to red, green, and blue colors to construct a pseudo-color classification map:

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} r_{rrcd} \\ r_{rrcv1} \\ r_{rrcs} \end{bmatrix}$$

Figure 2(a) shows Chen' s classification of the Oberpfaffenhofen scene. If we preserve r_{rrcs} and r_{rrcd} but substitute r_{rrcv2}, r_{rrcv3}, r_{rrcv4}, and r_{rrcv5} for r_{rrcv1} in the classification, we obtain four additional classifications, as shown in Figures 2(b)-(e). Compared to Figure 2(a), the improvement in Figure 2(b) is not obvious, but Figures 2(c), (d), and (e) provide better classifications. The framed area in Figure 2(e) shows an airport with runway and parking apron. It is difficult to discriminate between the scattering of the runway and the parking apron in Figure 2(a). However, when we select an appropriate volume model to describe the scattering from the parking apron (which comprises grass), it can be well differentiated from the runway, as shown in Figures 2(d) and (e). Further comparison of the results in Figures 2(c), (d), and (e) reveals that the scattering from the parking apron in Figure 2(d) is much clearer, indicating that vertically oriented grass appears to be dominant in the parking apron area, which is consistent with ground truth. Nevertheless, Figure 2(e) provides better characterization of some man-made objects than Figure 2(d).

Since each T_{cvi} is designed to model a specific volume scattering mechanism, the resulting r_{rrcvi} is only appropriate for certain scatterers. To achieve an integrated picture of the target, we should combine several r_{rrcvi} values. Here, we consider two combination strategies. Yamaguchi et al. devised a branch selection method to adaptively identify T_{cv3}, T_{cv4}, and T_{cv5} for modeling volume scattering [**?**]. Our first strategy employs this branch selection to construct an r_{rrcv} parameter from the corresponding r_{rrcv3}, r_{rrcv4}, and r_{rrcv5}:

$$r_{rrcv} = \begin{cases} r_{rrcv3}, & \text{if } 10\log_{10}\left(\frac{\lambda_1}{\lambda_3}\right) > \text{tol} \\ r_{rrcv4}, & \text{if } 10\log_{10}\left(\frac{\lambda_1}{\lambda_2}\right) > \text{tol} \\ r_{rrcv5}, & \text{otherwise} \end{cases}$$

where tol denotes a target-dependent tolerance. By replacing r_{rrcv1} in (19) with r_{rrcv} for the green channel, we obtain the classification shown in Figure 2(f), which effectively fuses Figures 2(c), (d), and (e).

Our second strategy extracts the maximum of r_{rrcv3}, r_{rrcv4}, and r_{rrcv5} as r_{rrcv}:

$$r_{rrcv} = \max(r_{rrcv3}, r_{rrcv4}, r_{rrcv5})$$

Figure 2(g) displays the classification result, which shows minimal visual difference from Figure 2(f). This indicates that Yamaguchi' s branch selection is essentially an optimal selection.

The above strategies treat r_{rrcv3}, r_{rrcv4}, and r_{rrcv5} as competitive–once one of them (e.g., r_{rrcv4}) is selected to describe a scatterer, the other two are omitted. Our third strategy discards r_{rrcs} and r_{rrcd} and directly uses r_{rrcv3}, r_{rrcv4}, and r_{rrcv5} to construct the classification map:

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} r_{rrcv3} \\ r_{rrcv4} \\ r_{rrcv5} \end{bmatrix}$$

Figure 2(h) shows the resulting classification. We observe excellent target discrimination that appears even better than Figures 2(f) and (g). This result indicates that the three volume scatterers T_{cv3}, T_{cv4}, and T_{cv5} in Yamaguchi decomposition are not competitive but cooperative.

5 Conclusions

Yang' s and Chen' s similarity parameters have proven successful for characterizing target scattering. These two parameters are extended to a general parameter for measuring the similarity between two mixed scatterers. The developed random similarity parameter encompasses both Yang' s and Chen' s parameters and can measure the similarity between any two scatterers. An additional utility of the parameter is in characterizing scattering randomness. The self-similarity parameter provides a fast alternative to the entropy parameter, while the mirror-similarity parameter can achieve consistent yet superior target discrimination compared to entropy. The parameter is applied to classification using three different strategies, and its superior discrimination of radar targets over Chen' s parameter is clearly demonstrated using real airborne data.

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