Postprint: Stochastic Gradient Minimum Variance Pursuit SAR Super-Resolution Reconstruction Algorithm Based on Attribute Scattering Information

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Abstract

In both military and civilian synthetic aperture radar (SAR) application domains, the expectations and demands for achieving higher resolution and finer description of targets are extremely urgent. Under the sparse representation framework, an SAR reconstruction observation model is constructed based on the attribute scattering center model (ASC) component-level local scattering model; a scattering center attribute parameter space classification strategy based on the signal domain is proposed, and combined with frequency domain extrapolation, a component-level super-resolution SAR reconstruction algorithm based on stochastic gradient minimum variance tracking is proposed. The final super-resolution SAR image of this algorithm is obtained via FFT, which improves algorithmic efficiency; moreover, the algorithm simultaneously acquires high-precision attribute-level features of target scattering centers while reconstructing super-resolution SAR images. Simulated synthetic data and electromagnetic computed data verify the super-resolution capability of the algorithm, and the Cramér-Rao bound for ASC attributes is employed to evaluate the attribute estimation performance of the algorithm.

Full Text

Superresolution SAR Reconstruction Algorithm Using Stochastic Gradient Minimum Variance Pursuit with Attributed Scattering Priors

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Abstract: Both military and civilian synthetic aperture radar (SAR) applications have pressing needs and high expectations for achieving higher resolution and more detailed target description. This paper first constructs a SAR reconstruction observation model based on the attributed scattering center (ASC) model for object-level local scattering characterization within a sparse representation framework. It then proposes a signal-domain classification strategy for scatterer attribute parameter space and, combined with frequency extrapolation, introduces an object-level superresolution SAR reconstruction algorithm based on stochastic gradient minimum variance pursuit (SGMVP). The algorithm finally obtains the superresolution SAR image via FFT, which improves computational efficiency. Moreover, the algorithm simultaneously achieves high-precision target scattering center attribute-level features while reconstructing the superresolution SAR image. Simulated synthetic data and electromagnetic computation data validate the algorithm' s superresolution capability, and the Cramér-Rao lower bound (CRLB) of ASC attributes is used to evaluate the algorithm' s attribute estimation performance.

Key Words: synthetic aperture radar (SAR); attributed scattering center (ASC) model; sparse representation; spectrum extrapolation

0 Introduction

Traditional SAR target reconstruction techniques are often based on ideal point target assumptions. However, the selection of regularization parameters significantly impacts final reconstruction performance. In reality, target scattering centers originate from physical scattering components of real-world objects. In recent years, increasing research has investigated non-ideal scattering characteristics in SAR echoes, demonstrating that incorporating target anisotropic scattering and dispersive scattering information during SAR reconstruction can effectively improve performance. Fasoula et al. [1,2] divided the azimuth observation aperture into multiple sub-apertures of equal size and performed anisotropic scattering detection jointly across sub-apertures, with the final SAR image formed through incoherent superposition of images reconstructed from each sub-aperture. However, this sub-aperture independent processing approach suffers from azimuth resolution loss. To mitigate this issue, Cetin et al. [3] utilized regularized sparse optimization techniques to model non-ideal scattering, proposing SAR reconstruction algorithms with superresolution and feature enhancement capabilities.

Jackson et al. [6–8] introduced scattering mechanism-driven parametric models (such as the geometrical theory of diffraction model [9] and canonical shape feature models [10]) into SAR reconstruction, transforming the problem into a parameter estimation task. However, this approach entails high computational cost for nonlinear non-convex optimization, particularly when model order determination is considered. To overcome these challenges, this paper combines compressive sensing (CS) theory [12,13] with attributed scattering priors [11] to propose a novel SAR reconstruction algorithm. CS theory indicates that high-dimensional sparse signals can be reconstructed with high probability by solving an underdetermined sparse constrained optimization problem. Under ideal point target assumptions, Liu, Zhang et al. [14,15] and Xiang et al. [16] proposed three CS-based SAR reconstruction algorithms capable of efficiently obtaining SAR images.

The main contribution of this paper is the simultaneous consideration of spatial sparsity of scattering centers and attribute scattering information of scatterers in constructing the SAR reconstruction algorithm. Through classification of scattering center attribute parameter space, the original multi-attribute joint estimation problem is appropriately decomposed to reduce computational burden. The proposed SGMVP attribute parameter estimation algorithm comprises three processes: dictionary-based pursuit, optimal adaptive filtering, and residual update. The algorithm not only obtains superresolution SAR images but also provides high-precision physically-relevant attributed scattering features.

1 Attribute Scattering Information-Driven Observation Model

1.1 Attributed Scattering Center Description

Man-made targets can be intuitively approximated as decompositions into simple geometric primitives, as illustrated in [Figure 1: see original paper]. Electromagnetic theory indicates that these geometric structures, known as canonical scattering components, exhibit predictable scattering responses as functions of frequency and incidence angle [17]. The attributed scattering center model is an effective electromagnetic scattering parameterization model that captures and describes anisotropic and dispersive scattering characteristics of scatterers, providing a physically-relevant concise description of target scattering responses. Derived from the GTD model, the unified approximate expression for the attributed scattering amplitude response of a canonical scattering component located at position can be written as:

$$(,;)/\mathrm{expsinsincsin}_{pppcppp}Skjkkklck\alpha\phi\sigma\beta\phi\phi\phi\pi$$

where is the complex scattering coefficient, is the frequency-dependent attribute parameter, is the azimuth-dependent attribute parameter, represents the length attribute parameter, and denotes the orientation angle attribute parameter. The seven-attribute set for the th scattering center is . The ASC model roughly categorizes canonical scattering components into localized scattering centers and distributed scattering centers. Rectangular plates, lying cylinders, and dihedral corners belong to distributed scattering centers, for which the azimuth-dependent attribute . Localized scattering centers primarily include spheres, trihedrals, and top-hat structures, for which both the projected effective length and orientation angle on the radar line-of-sight plane are constant and equal to zero. Additionally, the frequency-dependent attribute parameter is an integer value related to the local curvature of the scatterer surface.

1.2 ASC-Based SAR Observation Model

SAR data acquisition relies on the antenna platform' s motion to collect pulse data from multiple azimuth angles over the region of interest. Since spatial position information and geometric shape information of scatterers modulate the phase and amplitude of SAR phase history respectively, algorithms can be developed to simultaneously obtain spatial position attributes and geometric structure attributes. Unlike ideal point target models whose scattering response is constant-amplitude and independent of frequency and azimuth, this paper presents an object-level scattering-characterized SAR reconstruction model based on the ASC model.

The phase history of canonical scatterers can be expressed as:

$$\{,\}_1(,,,)\exp 2(,,)Ppppppprkhxykjkxy\phi\phi\rho\phi == -\sum$$

where represents the position offset, denotes the number of scattering centers in the scene, and the scattering function is explicitly written as . For a given spatial location, the ASC-based scattering function can be represented as , where is the attribute parameter set. Considering that shape attributes are not identifiable when signal bandwidth is less than 4 GHz, this paper temporarily neglects this attribute [17]. Therefore, the ASC-based SAR observation model can be written as:

$$\{,\}_1(,,,)\exp 2(,,)vUPVvuvuppppppvurkSkjkxy\phi\sigma\phi\rho\phi ==== \Re - \sum\sum\sum$$

where is the scattering center type index, represents the number of basis vectors in the overcomplete dictionary after discretization of attribute parameter space for scattering center type , containing both localized and distributed canonical scatterers. Assuming phase history measurements have frequency points and azimuth points, we can easily obtain , where is the sub-dictionary corresponding to type . By defining and letting denote element-wise matrix multiplication and as the all-ones vector, we obtain a concise linear representation:

$$\{,\}_1(,,,)\exp 2(,,)vUPVvuvuppppppvurkSkjkxy\phi\sigma\phi\rho\phi ==== \Re - \sum\sum\sum$$

where is the overcomplete dictionary corresponding to all spatial positions, is complex white Gaussian noise, and is the complex scattering coefficient vector.

Equation (4) constitutes the attributed scattering information-based observation model.

2 Principle of SGMVP-Based SAR Superresolution Reconstruction Algorithm

Although the SAR reconstruction model (4) captures non-ideal scattering behavior, the diversity of scattering center attributes and the potentially thousands of spatial positions cause the column dimension of overcomplete dictionary to increase dramatically. Directly solving problem (4) encounters high memory requirements and computational complexity. Furthermore, approximating canonical scatterer responses using ideal point scattering models would characterize them as superpositions of multiple point scatterers at different spatial positions, introducing errors that severely impact estimation accuracy of other attributes and may cause complete failure of attribute feature estimation.

To address these issues, this paper combines attributed scattering information with improved stochastic gradient minimum variance pursuit (SGMVP) techniques to propose a novel physically-scattering-characteristic-related superresolution SAR reconstruction algorithm. The six attributes of the ASC model are estimated hierarchically in SGMVP, which comprises three major processing stages: (a) Pursuit process: discriminates scattering center type while estimating first-class attributes (spatial position and effective length); (b) Optimal adaptive filtering process: obtains second-class attributes (azimuth dependence for localized centers and orientation angle for distributed centers) and third-class attributes (complex scattering coefficients); (c) Residual update process.

In the pursuit process, by initializing second and third-class attributes to zero and using random compressive sampling of observations , we obtain a dimensionality-reduced overcomplete dictionary , where the effective length attribute is discretized into values. The correlation vector is computed as , where is the residual vector at the th iteration. As iterations increase, the residual gradually approaches zero. When it reaches or falls below a preset threshold, the final estimate of complex scattering coefficients is output. The first-class attributes of the th scattering center are obtained by identifying the maximum element of the correlation vector: . If the effective length attribute is non-zero, the th scattering center is classified as a distributed canonical scatterer, and the azimuth-dependent attribute for localized scatterers is assigned zero. Conversely, if the effective length estimate is zero, the th scattering center is classified as localized, and its orientation angle attribute is set to zero.

Given the known scattering center type, the orientation angle attribute and azimuth-dependent attribute cannot both be non-zero for the same scattering center. An appropriate optimal adaptive filtering process estimates the second and third-class attributes. Using the ASC model and estimated first-class attributes, we construct a search subspace for auxiliary parameter as . When the scattering center is classified as localized, auxiliary parameter represents its orientation angle attribute . When classified as distributed, represents its azimuth-dependent attribute , where is the number of discrete samples of , and parameter set denotes the attribute set excluding the parameter represented by . The auxiliary parameter is estimated via minimum variance method:

$$\{\}_2^1 \text{argmin}(;)(;)^H \tau\tau\tau\tau\tau\tau\xi\xi\xi\xi - = \Re\Re SCSD$$

where denotes the main diagonal, is the phase history covariance matrix, and is a noise-related diagonal loading parameter. For the true value of auxiliary parameter , equation (5) represents an ideally optimal filtering process that maximizes energy at the true parameter value while minimizing energy at other values. Thus, using the estimated first-class attributes and auxiliary parameter representing second-class attributes, we can easily determine the atom index of the attribute-related basis vector for the th scattering center in overcomplete dictionary . The optimal support set is updated as , and the selection matrix is extended as , where is the th column of the overcomplete dictionary.

The third-class attributes (complex scattering coefficients) are then estimated recursively via LMS under MMSE criterion using the selection matrix. The LMS gradient descent recursion is expressed as:

$$()\tau()(1)()\tau\tau\tau\Omega = \Omega -$$

where represents the th row of selection matrix , is the th element of , and is the step size parameter. denotes a complex coefficient vector whose dimension equals the number of elements in the current support set. Through this recursion, the complex coefficient vector is continuously updated from to . The third-class attribute estimate at the current iteration is .

In the residual update process, the residual is updated using . The algorithm iteratively increases until or . Finally, using the estimated scattering center attributes and ASC model, the SAR target' s frequency-domain observation spectrum is extrapolated. To further reduce model error effects and preserve weak detail features from the original echo, the central portion of the phase history generated by the ASC model is replaced with the original echo. The final unweighted superresolution SAR image is obtained via FFT-based algorithms (e.g., PFA). The detailed reconstruction flow is summarized in the SGMVP algorithm below.

SGMVP Algorithm

Initialization: Initial coefficient vector ; geometry-related dictionary ; parameters and ; termination thresholds and .

While do a) Use pursuit process to estimate first-class attributes of th scattering center and discriminate type based on whether effective length is zero. b)

Assign appropriate second-class attribute to auxiliary parameter and estimate via improved minimum variance technique. c) Determine basis vector index in overcomplete dictionary using estimated first two attribute classes, and update support set and selection matrix . d) Estimate third-class attributes using LMS recursion under MMSE criterion with selection matrix , where denotes matrix main diagonal. e) Increment . **End while**

f) Extrapolate phase history data using estimated canonical component attributes and ASC model.
g) Replace central portion of ASC-regenerated observation spectrum with original echo, and obtain final superresolution SAR image using FFT-based methods.

3 Simulation Experiment Verification

To validate the performance advantages of the proposed SAR reconstruction algorithm, experimental evaluation focuses on two aspects: scattering center attribute estimation accuracy and superresolution reconstruction capability. First, SAR phase history data with theoretical resolution of 0.3 m $\times$ 0.3 m is generated using the SAR system model, with system parameters listed in . The synthetic scene comprises twelve canonical scattering components: three lying cylinders, two top-hats, two trihedrals, three rectangular plates, one dihedral, and one sphere, as shown in Figure 2: see original paper. Complex white Gaussian noise with known variance is added to the phase history data. Independent repeated experiments are obtained through multiple noise realizations. The Cramér-Rao lower bound (CRLB) is used to evaluate the estimation performance of the proposed SGMVP algorithm.

Figure 2: see original paper shows the scattering center attribute estimation variance versus SNR curves. SNR is defined as the ratio of peak phase history signal energy to noise variance. As expected, estimation accuracy for all six attributes improves with increasing SNR. However, it should be noted that due to parameter space discretization and initial value settings in the numerical optimization process, the estimation variances cannot achieve the CRLB.

To further demonstrate the superresolution advantages, the proposed algorithm is compared with two baseline SAR reconstruction algorithms: conventional Polar Format Algorithm (PFA) and sparsity-driven Quasi-Newton Algorithm (QNA). Figure 3: see original paper(c)(e) show 2$\times$2 superresolution reconstruction results of the three algorithms at 30 dB SNR, displayed using contour plots to clearly illustrate the superresolution advantages of QNA and the proposed algorithm, both with compression sampling rate . Figure 3: see original paper(d)(f) present corresponding one-dimensional slice images at azimuth range y = 0.075 m. Black circles and black dotted lines indicate accurate amplitude values and range bins of scattering centers. The results show that both QNA and the proposed algorithm outperform PFA in superresolution reconstruction of localized scattering centers. Moreover, by incorporating physically-relevant attributed scattering priors, the proposed algorithm demonstrates stronger superresolution capability for distributed scattering centers than QNA.

For quantitative performance evaluation, reconstruction RMSE is defined as . Figure 2: see original paper shows RMSE performance curves from 50 Monte Carlo experiments at each SNR. By incorporating object-level scattering information, the proposed algorithm achieves lower reconstruction error than the ideal point target model-based QNA algorithm at high SNR. Figure 2: see original paper presents the SAR superresolution reconstruction image from the proposed algorithm at 27 dB SNR. However, empirical results indicate that when SNR falls below 15 dB, error propagation significantly affects reconstruction performance. Improving low-SNR performance represents future research.

In terms of computational efficiency, since PFA' s runtime is much smaller than the other two algorithms, we primarily compare QNA and the proposed algorithm. For the scenario in Figure 2: see original paper, across 50 Monte Carlo experiments, QNA' s average successful reconstruction time is 16.71 s, while the proposed algorithm' s is 29.43 s. Due to the introduced object-level model attribute parameter estimation process, the proposed algorithm has higher computational complexity and resource consumption than ideal point target model-based algorithms. Reducing computational load and improving efficiency are also subjects for future study.

Finally, the proposed algorithm is validated using high-frequency electromagnetic computation data from a simplified tank target generated by combining geometric optics and physical optics. The data acquisition system operates over 8.75–9.25 GHz, with azimuth angle range 88.35°–91.65° and elevation angle 60°. Figure 4: see original paper shows the tank target photo with dimensions 9.51 m (length) $\times$ 3.56 m (width) $\times$ 2.57 m (height). The incident wave is horizontally polarized plane wave. Figure 4: see original paper–(e) present 2×2 superresolution SAR images from PFA, QNA, and the proposed algorithm, respectively. Regions A and B highlight the superresolution advantages of the proposed algorithm. Scattering center type discrimination results are overlaid on the superresolution images in Figure 4: see original paper, where yellow rectangles and green triangles denote distributed and localized scattering centers, respectively. The attributed features and type information obtained simultaneously with superresolution imaging can effectively support advanced SAR processing modules such as automatic target recognition.

4 Conclusion

This paper proposes a signal-domain scattering center attribute parameter space classification strategy combined with frequency extrapolation, introducing an object-level superresolution SAR reconstruction algorithm based on stochastic gradient minimum variance pursuit. The algorithm achieves at least 2× superresolution in SAR images, with scattering center attribute parameter estimation variance approaching the CRLB. It successfully obtains high-precision target scattering center attribute-level features while reconstructing superresolution SAR images.

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