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Abstract

The Dual-Frequency Polarized Scatterometer (DFPSCAT) is a pencil-beam rotating scatterometer used to measure snow water equivalence (SWE). Considering the low azimuth resolution of its forward-looking region, an adaptive regularization deconvolution super-resolution method based on the scatterometer echo signal model is proposed. Compared with the classical SIR and MAP algorithms, the proposed method can better reconstruct the original signal and exhibits less noise amplification. The algorithm processing accuracy with different Kpc values is also studied, and the results show that when the Kpc value is less than 0.1, nearly all restored data can satisfy the 0.5dB accuracy requirement.

Full Text

Adaptive Regularization Method for Forward-Looking Azimuth Super-Resolution of a Dual-Frequency Polarized Scatterometer

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Abstract

The Dual-Frequency Polarized Scatterometer (DFPSCAT) is a pencil-beam rotating scatterometer designed to measure snow water equivalence (SWE). To address the low azimuth resolution in its forward-looking region, we propose an adaptive regularization deconvolution super-resolution method based on the scatterometer echo signal model. Compared with classical SIR and MAP algorithms, the proposed method better reconstructs the original signal while exhibiting less noise amplification. We also investigate the algorithm' s processing accuracy across different Kpc values, finding that when Kpc is less than 0.1, nearly all restored data satisfy the 0.5 dB accuracy requirement.

Index Terms–DFPSCAT, azimuth super-resolution, adaptive regularization method, accuracy

1. Introduction

Radar scatterometers have been widely used for ocean surface wind vector measurement, typically achieving surface resolutions of tens of kilometers (20–50 km). Super-resolution techniques have been employed to enhance radar scatterometric data resolution for specific applications such as iceberg tracking, where radiometric precision requirements are less stringent. The Water Cycle Observation Mission (WCOM) has been proposed to improve the capability of synergistic observation of key water cycle parameters [1]. DFPSCAT is one of three payloads for WCOM, alongside the Full Polarization Interferometric Radiometer (FPIR) and the Polarimetric Microwave Imager (PMI). DFPSCAT is primarily used to retrieve SWE through simultaneous measurement of both surface and volume scattering from snow cover [2, 3]. According to retrieval requirements, the surface resolution of the normalized radar backscatter coefficient (sigma0) measured by DFPSCAT should be approximately 2 km with high radiometric precision.

Due to constraints on scanning coverage and rotation speed, DFPSCAT' s beamwidth and antenna dimension are approximately 1.08° and 1.5 m, respectively. To achieve the desired spatial resolution, pulse compression is adopted along the elevation direction. Along the azimuth direction, Doppler Beam Sharpening (DBS) can be used within the side-looking region of the swath. However, for the forward-looking region, azimuth resolution remains limited by the antenna beamwidth.

Numerous super-resolution methods have been investigated to address this issue, including Wiener filtering, iterative inverse filtering, MAP deconvolution, and generalized inverse filtering methods. However, these methods suffer from reduced capability and low efficiency, particularly at low SNR. Considering the characteristics of scatterometer signals, regularization methods offer a suitable alternative. This paper first establishes the DFPSCAT echo signal model and then details an adaptive regularization method for enhancing azimuth resolution. Two simulations are conducted to evaluate algorithm performance, with results demonstrating the superior performance of the proposed method.

2. DFPSCAT Echo Signal Model

DFPSCAT is a pencil-beam rotating scatterometer whose observation geometry is shown in Fig. 1 [Figure 1: see original paper]. Assuming the transmit signal is a rectangular pulse, the echo signal after pulse compression can be expressed as:

$$y(R,\varphi) = C_0\sigma(R,\varphi) \otimes h(R,\varphi) \otimes \operatorname{sinc}\left(\frac{R}{\delta_R}\right) e^{-j\frac{4\pi R}{\lambda}} + n(R,\varphi)$$

where R is the slant range, φ is the azimuth angle, C_0 represents the radar system constant, σ is the target backscatter coefficient, λ is the electromagnetic wavelength, $c = 3 \times 10^8$ m/s, δ_R is the phase factor of the transmit signal, n is receiver thermal noise, and $\otimes$ represents convolution.

For the same slant range $R = R_0$, Eq. (1) can be simplified as:

$$y(\varphi) = \sigma(\varphi) \otimes h(\varphi) + n(\varphi)$$

For the scatterometer case, the observed data represents one section of this continuous convolution process, forming a partial convolution. The actual sampling operation can be written as:

$$\mathbf{y} = \mathbf{H}\sigma + \mathbf{n}$$

where $\mathbf{y}$ is the vector of samples from the continuous signal y in Eq. (2), $\mathbf{H}$ is an $N \times N$ circulant matrix, σ is the unknown vector of length N, and $\mathbf{n}$ is the noise vector of length N.

Note that Eq. (3) does not have a definite solution because the number of unknowns exceeds the number of equations. To address this problem, one approach utilizes a circulant matrix model, while another modifies the partial convolution into a complete convolution using an aperiodic matrix model. These two approaches achieve similar results as long as M (the sampling number of h) is much smaller than N [4]. To facilitate calculation, we choose the approximate circulant matrix model:

$$\mathbf{y} = \mathbf{H}\sigma + \mathbf{n}$$

3.1. Tikhonov Regularization Method

Due to the ill-posed nature of Eq. (5), Tikhonov proposed a regularization method that introduces a regularization operator to make equation solutions continuously depend on observed data. The Tikhonov regularization algorithm is equivalent to minimizing the following expression:

$$L(\sigma, \alpha) = \|\mathbf{H}\sigma - \mathbf{y}\|^2 + \alpha\|\sigma\|^2$$

where α is the regularization parameter that plays a key role in solving the problem. There are two criteria for selecting α: priori and posteriori. The optimal selection of the priori criterion depends mainly on experience but is often infeasible for actual problems. Therefore, the Morozov method, a commonly used posteriori criterion, is chosen to determine α. Calculating Eq. (6) is equivalent to solving the following linear equation:

$$(\mathbf{H}^T\mathbf{H} + \alpha\mathbf{I})\sigma = \mathbf{H}^T\mathbf{y}$$

3.2. Adaptive Regularization Method

The adaptive regularization method was first proposed by Ryzhikov and Biryulina in 1998 to solve inverse problems of linear equations [5]. We apply this method to achieve super-resolution of the scatterometer in the azimuth direction. With the prerequisite that $\mathbf{H}$ is reversible, the specific form of the algorithm can be expressed as:

$$\sigma = (\mathbf{H}^T\mathbf{H} + \alpha\mathbf{I})^{-1}\mathbf{H}^T\mathbf{y}$$

Comparing the above formulae, it is not difficult to find that when $\alpha \to 0$, the adaptive regularization solution approaches the true solution, while when $\mathbf{H}$ contains zero eigenvalues, the method remains stable. The results show that the adaptive regularization method can better approximate the original echo model and obtain the optimal approximation solution.

4. Algorithm Performance

To evaluate algorithm performance, one-dimensional (1-D) signal reconstruction simulation is first conducted, followed by quantitative analysis of processing accuracy.

In the 1-D signal reconstruction simulation, the test signal is a narrow sinc function with a bandlimited spectrum, while the antenna function is a wide rect function whose frequency response attenuates the high-frequency components of the signal spectrum, as shown in Fig. 2 [Figure 2: see original paper]. The antenna beamwidth is set to 1.08°. The azimuth super-resolution region is ±10° off nadir, and the test signal is sampled every 0.14°.

Noisy measurements satisfy the following relationship:

$$\mathbf{y}_{\text{noisy}} = \mathbf{y}_{\text{noise-free}}(1 + K_{pc}N(0,1))$$

where $N(0,1)$ is a zero-mean unit-variance Gaussian random variable and K_{pc} represents measurement error.

Figure 3 [Figure 3: see original paper] compares reconstructed signals and spectra for noise-free cases. All four algorithms provide good signal reconstruction, as illustrated in Fig. 3(a). However, Fig. 3(b) shows that SIR and MAP methods cannot recover the lost spectrum information caused by nulls in the antenna pattern spectrum, while both TR and AR algorithms completely restore the original spectrum.

To evaluate performance with noise, Fig. 4 [Figure 4: see original paper] demonstrates the output of resolution enhancement methods and their spectra with K_{pc} set to 0.01. Two significant observations emerge: First, MAP and AR algorithms reconstruct the original signal with less bias compared to SIR and TR algorithms. Second, the AR algorithm' s spectrum exhibits less noise amplification than MAP, SIR, and TR.

Based on the 1-D signal simulation results, we conclude that the AR method demonstrates superior reconstruction performance. We now quantitatively analyze processing accuracy to validate these algorithms for SWE retrieval. To satisfy SWE retrieval requirements, sigma0 accuracy must be better than 0.5 dB [6]. Assuming the actual backscatter coefficient varies continuously across the azimuth super-resolution region, we calculate the percentage of reconstructed sigma0 values achieving better than 0.5 dB accuracy as an index for algorithm evaluation.

Figure 5 [Figure 5: see original paper] shows algorithm processing accuracy as K_{pc} varies from 0.05 to 0.15. The AR method produces reconstructed sigma0 with higher accuracy than other methods for the same K_{pc}. Additionally, AR algorithm accuracy degrades more slowly with increasing K_{pc} compared to SIR, MAP, and TR algorithms. When K_{pc} is less than 0.1, nearly all restored data satisfy the accuracy requirement.

5. Conclusion

This paper introduces regularization methods to enhance azimuth resolution and successfully applies them to the DFPSCAT forward-looking case. Tikhonov and adaptive regularization methods are described and compared through theoretical analysis, demonstrating that both can be used for DFPSCAT azimuth super-resolution, while the proposed adaptive regularization method adapts better to noise and achieves superior performance. Simulation results show that compared to classical SIR and MAP algorithms, the proposed method achieves higher accuracy, with almost all restored data exhibiting better than 0.5 dB accuracy when K_{pc} is less than 0.1.

6. References

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

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