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

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Date: 2017-03-10T00:00:00+00:00

Abstract

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Full Text

Preamble

An Improved Adaptive Regularization Method for Forward-Looking Azimuth Super-Resolution of a Dual-Frequency Polarized Scatterom-

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Abstract

The Dual-Frequency Polarized Scatterometer (DFPSCAT) is a pencil-beam rotating scatterometer designed for snow water equivalent (SWE) measurement, and the Doppler Beam Sharpening (DBS) technique is proposed for DFPSCAT to achieve azimuth resolution. However, the DBS technique is inapplicable for forward-looking and afterward-looking regions. Based on an approximate aperiodic model of scatterometer echo signal, an improved adaptive regularization deconvolution algorithm with gradient histogram preservation (GHP) constraint is implemented to address this problem. To investigate its performance in resolution enhancement and resulting accuracy, both synthetic backscattering coefficient ( ) field reconstruction and SWE reconstruction are carried out. The results show that the proposed method can recover the true signal and achieve azimuth resolution of 2 km with the designed scatterometer system, which is required by SWE retrieval. Moreover, the relative errors of reconstructed are less than 0.5 dB, satisfying the accuracy requirement for SWE retrieval, and comparisons with observed results show error reductions of more than 0.03 dB. Meanwhile, a comparison between the proposed algorithm and existing resolution enhancement methods concludes that the proposed method can obtain comparable resolution enhancement as the L1 method with less noise. The technique is also verified with ASCAT scatterometer data.

Index Terms: Dual-Frequency Polarized Scatterometer (DFPSCAT), snow water equivalent (SWE), azimuth super-resolution, reconstruction accuracy

Introduction

Spaceborne radar scatterometers primarily provide wide-area measurements of ocean surface wind vectors and have been widely used in oceanographic and meteorological investigations. With advantages of wide swath, rapid global coverage, and high measurement accuracy, scatterometers have become desirable candidates for land and ice applications [1]. For conventional scatterometers, resolution in the range dimension is processed to a few kilometers using range gating, while resolution in the azimuth dimension remains determined by the antenna beamwidth of a few tens of kilometers. For land and ice applications, spatial resolution comparable to visible/IR imaging radiometers—i.e., the 1-5 km resolution Advanced Very High Resolution Radiometer (AVHRR)—is demanded [2].

To achieve the required resolution while maintaining the advantage of wide swath, several high-resolution reconstruction methods have been proposed for scatterometer image reconstruction, such as the additive algebraic reconstruction technique (AART), multiplicative algebraic reconstruction technique (MART), and scatterometer image reconstruction (SIR) [3, 4]. As an improved version of MART, SIR has the fastest convergence and least noise amplification, and has been applied to scatterometric data for specific applications such as ice mapping and iceberg tracking. In addition, Williams established a Bayesian-based scatterometer reconstruction framework that considered scatterometer noise [5]. The maximum a posteriori (MAP) estimator developed by Williams can obtain results consistent with the well-established SIR algorithm but significantly enhances resolution at the expense of noise amplification.

The Water Cycle Observation Mission (WCOM) is proposed to improve the capability of synergistic observation of key water cycle parameters. The Dual-Frequency Polarized Scatterometer (DFPSCAT) is one of the payloads proposed for WCOM, along with two others: the L-S-C tri-frequency Interferometric Microwave Imager (IMI) and the Polarimetric Microwave Imager (PMI). DFPSCAT is dedicated to retrieving snow water equivalent (SWE) by simultaneously measuring surface and volume scattering from snow cover [6, 7]. According to SWE retrieval requirements, the spatial resolution of DFPSCAT should be less than 2 km to mitigate retrieval errors related to mixed-pixel problems, and its radiometric precision should be better than 0.5 dB [8]. Since existing scatterometer systems and technology cannot satisfy these resolution and accuracy demands, the Doppler Beam Sharpening (DBS) technique is proposed for DFPSCAT to achieve the desired azimuth resolution. However, the DBS technique is inapplicable for forward-looking and afterward-looking regions where Doppler discrimination is confused with range discrimination [9]. Therefore, it is necessary to find alternative super-resolution methods to overcome this difficulty.

Guan et al. derived a forward-looking radar echo model for airborne radar and concluded that the radar echo is equivalent to a convolution operation between the target normalized radar backscatter coefficient ( ) and the antenna pattern [10]. The echo model can then be solved by deconvolution methods to achieve high resolution. With this motivation, the sampling rate of DFPSCAT in the azimuth direction is increased to meet the desired resolution requirement, and deconvolution methods are utilized to improve azimuth resolution for forward- and afterward-looking regions.

However, noise and antenna pattern nulls make deconvolution an ill-posed problem. The Wiener filter eliminates antenna nulls in the frequency domain by introducing a constant regularization term, but the algorithm requires high signal-to-noise ratio (SNR) [11]. To address this problem, Richards proposed a constrained iterative algorithm to reduce SNR requirements, but it remains strongly influenced by noise [12]. Guan introduced a statistical optimization method to reduce noise sensitivity, but the method amplified noise locally during iteration [10]. Zou proposed a norm regularization method for radar azimuth super-resolution and obtained promising results [13]. Both L2 and L1 norm regularization models were established, and results showed that the latter could obtain more effective resolution improvement, especially for sparse target signals. Additionally, Wang utilized a total variation regularization (TV) method for scatterometer image reconstruction of the rotating fan-beam scatterometer (RFSCAT) and achieved improved quality in resolution enhancement and noise reduction [14].

This paper aims to develop a theoretical framework that allows the scatterometer forward-looking echo signal model to be appropriately solved by deconvolution methods. Two approximate models (circulant matrix model and aperiodic matrix model) are introduced. Considering the oversmoothness of the adaptive regularization method, an improved adaptive regularization deconvolution algorithm with gradient histogram preservation (GHP) constraint has been implemented to solve the echo model. The improved adaptive regularization algorithm integrates gradient histogram preservation into the adaptive regularization method, which can better preserve the fine variations of . To illustrate the feasibility of the deconvolution framework and the effectiveness of the proposed algorithm, both simulation and actual scatterometer data validation are conducted. The performance of resolution enhancement and processing accuracy of the proposed method is investigated and compared with conventional approaches.

This paper is organized as follows. Section II deduces a DFPSCAT echo signal model for super-resolution processing. Section III proposes an improved adaptive regularization deconvolution algorithm and describes its iterative specification. Section IV discusses the performance of resolution enhancement and processing accuracy for the proposed algorithm. Section V validates the feasibility of the deconvolution framework and the effectiveness of the proposed algorithm using real scatterometer data. Finally, Section VI concludes this paper.

II. DFPSCAT Echo Signal Model

A. The Instrument

DFPSCAT is a real aperture radar operating at X-band (9.6 GHz) and Ku-band (17 GHz) frequencies using both vertical and horizontal polarization (i.e., VV, HH, and HV polarization). It transmits long pulses with linear frequency modulation, and the received echoes are processed with a de-chirping technique to achieve range resolution enhancement. The original range resolution is about several hundred meters, with transmitted signal bandwidth of about 5 MHz, and can be further averaged into 2–5 km spaced slices along elevation before being downlinked to ground.

The DBS technique is utilized in the outer swath regions of DFPSCAT, resulting in azimuth resolution of 1–3 km. For the forward- and afterward-looking region of 200–300 km, the azimuth resolution is still determined by the antenna beamwidth in the azimuth direction. Fig. 1 [Figure 1: see original paper] illustrates the observation geometry of DFPSCAT. The center of each pencil beam has a nominal off-nadir angle of 39° together with an altitude of 600 km to ensure a swath of about 1000 km. In the figure, "High Resolution" denotes the DBS processing region, and "Low Resolution" represents the forward- and afterward-looking region for super-resolution algorithm processing.

The preliminary designed system parameters of DFPSCAT are shown in Table 1 . The antenna 3 dB beamwidths are 1.2° and 1.0° for X-band and Ku-band, respectively. Considering the accuracy of SWE retrieval, which is greatly influenced by spatial resolution, a resolution of 2–5 km for DFPSCAT is required. Based on the previous illustration, the pulse repetition frequency (PRF) of DFPSCAT is designed to satisfy a 1 km sampling rate in the azimuth direction.

B. Echo Model

From Fig. 1, we can see that the echo of DFPSCAT varies with slant range R and azimuth angle . The amplitude of the echo is the result of filtering and weighting of the backscattering distribution of the observed targets. Assuming the transmit signal is a rectangular pulse signal where represents transmit time, rect( ) denotes the rectangular pulse envelope, f_c is carrier frequency, and ( ) is phase factor.

The echo signal after pulse compression can be expressed as

$$\varphi(2R/c) = \mathrm{rect}(\tau)e^{j2\pi f_c \tau + \phi(\tau)}$$

$$y(R,\varphi) = C_0 \int \sigma^0(R,\varphi) \otimes h(R,\varphi) \otimes \mathrm{sinc}\left(\frac{2R}{c}\right) e^{-j\frac{4\pi R}{\lambda}} dR$$

where C_0 is the radar system constant, is the normalized radar backscatter coefficient, which is a function of slant range R and azimuth angle , h represents antenna pattern, is the electromagnetic wavelength, c is the speed of light, and represents convolution.

In the forward-looking region of DFPSCAT, the slant ranges are the same for the same slice. Then, Eq. (2) can be simplified as

$$y(\varphi) = h(\varphi) \otimes \sigma^0(\varphi)$$

Fig. 2 [Figure 2: see original paper] shows the azimuth sampling schematic of DFPSCAT. The continuous echo signal y can be discretized as

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} h_1 & h_2 & \cdots & h_M & 0 & \cdots & 0 \\ 0 & h_1 & h_2 & \cdots & h_M & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & h_1 & h_2 & \cdots & h_M \end{bmatrix} \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \vdots \\ \sigma_{N+M-1} \end{bmatrix}$$

where N and M indicate the sample numbers of y and h, respectively.

Due to the number of unknowns exceeding the number of equations, there is no definite solution to Eq. (4). To settle this problem, one approach is to utilize a circulant approximate model, which first spares the front M-1 columns of the matrix in Eq. (4) and then modifies the remaining part into a periodic structure [15]. The corresponding circulant model is

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} h_1 & h_2 & \cdots & h_M & 0 & \cdots & 0 \\ 0 & h_1 & h_2 & \cdots & h_M & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ h_2 & \cdots & h_M & 0 & \cdots & 0 & h_1 \end{bmatrix} \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \vdots \\ \sigma_N \end{bmatrix}$$

The other approach is to modify the partial convolution of Eq. (4) into a complete convolution [15], namely the aperiodic approximate model. Then, Eq. (4) can be modified as

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{N+M-1} \end{bmatrix} = \begin{bmatrix} h_1 & h_2 & \cdots & h_M & 0 & \cdots & 0 \\ 0 & h_1 & h_2 & \cdots & h_M & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & h_1 & h_2 & \cdots & h_M \end{bmatrix} \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \vdots \\ \sigma_{N+M-1} \end{bmatrix}$$

Compared with the circulant model, the aperiodic model is an overdetermined problem, which is more favorable for solving the problem. Therefore, we adopt the aperiodic model and the matrix-vector form which can be expressed by

$$\mathbf{y}_a = \mathbf{H}_0 \sigma_0$$

where H and _0 denote the matrix and vector in Eq. (6), respectively. Thus, y_a can be obtained through the following expression

$$\mathbf{y}_a = \mathbf{H} \sigma_0$$

where H_0 represents the convolution matrix of Eq. (4). In fact, the boundary values are unknown in real situations. Tekalp proposed using observed values to replace the boundary values, which produced large errors at the boundary of y_a [16]. Instead, this paper proposes to utilize the previously described circulant model to calculate the unknown values in Eq. (8). The results show that y_a obtained through our proposed method is closer to the complete convolution results.

For scatterometry, the measurement error mainly consists of three components: transmission error caused by radar fading effects and receiver thermal noise, calibration error resulting from uncertainty in radar system parameters, and model error introduced because the inverse model and calibration model are inconsistent with the real scene. Usually, the error value is denoted by its normalized standard deviation, which is defined in terms of a so-called Kp parameter. For the scatterometer, the noisy measurement can be represented as

$$\mathbf{y} = \mathbf{H}\sigma_0 + \varepsilon_a$$

where ε_a denotes the standard normal distribution and Kp denotes the normalized standard deviation of measurement error.

III. Regularization Algorithm

Based on the previous analysis, azimuth super-resolution is equivalent to a deconvolution problem. Due to the ill-posed nature of deconvolution, a popular solution method is the regularization-based technique, which makes equation solutions continuously depend on observed data by introducing regularization operators [17]. The desired can then be obtained by

$$\hat{\sigma}_0 = \arg\min_{\sigma_0} \left[\|\mathbf{y} - \mathbf{H}\sigma_0\|_2^2 + \alpha \cdot \Psi(\sigma_0) \right], \quad \alpha > 0$$

where Ψ denotes some regularization term that depends on priors and is the regularization parameter.

A. Selection of Ψ

In most practical applications, scatterometer image reconstruction is ill-posed, requiring some form of regularization to estimate the image from scatterometer measurements. The proposed AART, MART, SIR, and MAP algorithms all have a built-in regularization term. Specifically:

- AART: $\Psi = \|\sigma_0\|_2^2$
- MART (SIR): $\Psi = \sum_i \log(\sigma_{0,i})$
- MAP: $\Psi = \text{avg}\|\sigma_0 - \sigma_a\|_2^2$

These algorithms can be equivalent to the classical Tikhonov regularization algorithm (referred to as TR algorithm) where $\Psi = \|\sigma_0\|_2^2$ in Eq. (11). Their solution may be written as

$$\hat{\sigma}_0 = (\mathbf{H}^T\mathbf{H} + \alpha\mathbf{I})^{-1}\mathbf{H}^T\mathbf{y}$$

Additionally, an adaptive regularization method (denoted as AR) has been proposed to solve inverse problems of linear equations and shows promising results [18]. With the prerequisite that $\mathbf{H}^T\mathbf{H}$ is reversible, the specific form of the algorithm is

$$\hat{\sigma}_0 = (\mathbf{H}^T\mathbf{H} + \alpha\mathbf{H}^T)^{-1}\mathbf{H}^T\mathbf{y}$$

Let $\mathbf{s} = \mathbf{H}^T\mathbf{y}$, then Eqs. (8), (12), and (13) can be expressed in the form of $\mathbf{s} = \mathbf{H}^T\mathbf{H}\sigma_0$. The corresponding F expression in Eqs. (8), (12), and (13) can be written as $\mathbf{F}_{TR} = \alpha\mathbf{I}$, $\mathbf{F}_{AR} = \alpha\mathbf{H}^T$, and $\mathbf{F} = \mathbf{0}$, respectively. Comparing these formulae, it is not difficult to find that when $\alpha \to 0$, both $\mathbf{F}_{AR}$ and $\mathbf{F}_{TR}$ approximate $\mathbf{F}$, whereas when $\mathbf{H}^T\mathbf{H}$ contains zero eigenvalues, $\mathbf{F}_{AR} \to \mathbf{0}$, which indicates Eq. (13) is a better approximation of Eq. (8). Therefore, the optimal solution of the echo model can be obtained using the adaptive regularization algorithm.

To evaluate algorithm performance, one-dimensional (1-D) signal reconstruction simulation has been conducted, as shown in Fig. 3 [Figure 3: see original paper]. The test signal is set as a narrow sinc function with a bandlimited spectrum. The antenna pattern is assumed as a wide rect function whose frequency response attenuates the high-frequency components of the signal spectrum [3].

The reconstructed signal and its corresponding spectrum for different algorithms are investigated, as shown in Fig. 4 [Figure 4: see original paper]. It is obvious that both AR and MAP algorithms can reconstruct the original signal with less bias compared with SIR and TR algorithms, whereas the AR algorithm has the least noise amplification.

B. An Improved Adaptive Regularization Method

Considering that the above L2-norm based adaptive regularization method might result in an over-smoothed solution, this section proposes an improved version of the adaptive regularization method. Since a good reconstructed should have a similar gradient distribution to the original, a gradient histogram preservation (GHP) term is integrated into the adaptive regularization method [19]. The new proposed method is referred to as an improved adaptive regularization method with GHP constraint.

The adaptive regularization method with GHP constraint can be expressed as

$$\hat{\sigma}_0 = \arg\min_{\sigma_0} [\|\mathbf{y} - \mathbf{H}\sigma_0\|_2^2 + \alpha \cdot \|\nabla\sigma_0\|_2^2 + \vartheta \cdot \|G(\nabla\sigma_0) - h_G\|_2^2]$$

subject to $h_G = h_{\nabla\sigma_0}$, where G denotes some odd function with monotonically non-descending property, represents the gradient operator, h_G is the histogram of $G(\nabla\sigma_0)$, $h_{\nabla\sigma_0}$ is the gradient histogram of σ_0, and and are two regularization parameters.

To solve Eq. (14), the gradient histogram of σ_0, $h_{\nabla\sigma_0}$, should be estimated accurately. Zuo introduced an estimation method for reference gradient histogram from noisy images [19]. However, the method is only suitable for denoising cases. This paper substitutes σ_0 with the gradient histogram of noise-free observation g, obtaining the following adaptive regularization with GHP constraint model:

$$\hat{\sigma}_0 = \arg\min_{\sigma_0} \left[\|\mathbf{y} - \mathbf{H}\sigma_0\|_2^2 + \alpha \cdot \|\nabla\sigma_0\|_2^2 + \vartheta \cdot \|G(\nabla\sigma_0) - h_{\nabla g}\|_2^2 \right]$$

where $\mathbf{g} = \mathbf{H}\sigma_0$.

C. Gradient Histogram Estimation for ∇g

To estimate the desired $h_{\nabla g}$ from y using Eq. (15), the reference histogram should be determined, which is supposed to be the histogram of noise-free observation g in this paper. Substituting $\mathbf{g} = \mathbf{H}\sigma_0$ into Eq. (10) gives $\mathbf{y} = \mathbf{g} + \mathbf{n}$, where n denotes measurement error and can be modeled as Gaussian white noise with variance ². The relationship $\nabla\mathbf{y} = \nabla\mathbf{g} + \nabla\mathbf{n}$ can be obtained, where y are independent and identically distributed with probability density function (PDF) $p_{\nabla y}$. Since n follows a Gaussian distribution N(0, ²), the corresponding PDF for n can be well approximated as follows [20]:

$$p_{\nabla n} = \frac{1}{\sqrt{2\pi}\delta} \exp\left(-\frac{\nabla n^2}{2\delta^2}\right)$$

Assuming g and n are independent, and g satisfies independent and identically distributed with PDF $p_{\nabla g}$, then $p_{\nabla y}$ can be expressed as

$$p_{\nabla y}(\nabla y) = \int p_{\nabla g}(\nabla g) \cdot p_{\nabla n}(\nabla y - \nabla g)\, d(\nabla g)$$

Since the normalized histogram can be regarded as a discrete approximation of $p_{\nabla y}$, $h_{\nabla g}$ and $h_{\nabla n}$ can be approximated by $p_{\nabla g}$ and $p_{\nabla n}$, respectively. Then Eq. (17) can be rewritten as

$$h_{\nabla y} = h_{\nabla g} \otimes h_{\nabla n}$$

where   denotes the convolution operator.

Using this relationship, the estimation of $h_{\nabla g}$ is equivalent to a deconvolution problem. Generally, the gradient histogram of $\mathbf{H}\sigma_0$ can be modeled as a generalized Gaussian distribution [21] with the following expression:

$$p_{\nabla g}(\nabla g) = \frac{\beta}{2\Gamma(1/\gamma)} \exp\left(-|\nabla g/\beta|^{\gamma}\right)$$

where Γ represents the complete gamma function,   is a scale parameter, and   is a shape factor that is inversely proportional to the decreasing rate of the Gaussian distribution peak. Then the estimation of $h_{\nabla g}$ is converted into estimation of parameters [,].

D. Iterative Specification of the Improved Adaptive Regularization Method with GHP Constraint

Considering the complexity of the optimization problem in Eq. (15), an iterative method based on the steepest descent algorithm has been chosen. The iterative specification for the proposed mixed regularization method is summarized in Algorithm 1, described in Table 2 .

Define an objective function as

$$J(\sigma_0) = \|\mathbf{y} - \mathbf{H}\sigma_0\|_2^2 + \alpha \cdot \|\nabla\sigma_0\|_2^2 + \vartheta \cdot \|G(\nabla\sigma_0) - h_{\nabla g}\|_2^2$$

Its gradient can be written as

$$\nabla J(\sigma_0) = -2\mathbf{H}^T(\mathbf{y} - \mathbf{H}\sigma_0) + 2\alpha\nabla^T\nabla\sigma_0 + 2\vartheta\nabla^T\left(G(\nabla\sigma_0) - h_{\nabla g}\right) \cdot \frac{\partial G}{\partial \nabla\sigma_0}$$

The steepest descent algorithm satisfies

$$\sigma_0^{(k+1)} = \sigma_0^{(k)} - \mu \cdot \nabla J(\sigma_0^{(k)})$$

where   is the step size.

Another problem is selecting an optimal $G(\nabla g)$ to satisfy the requirement of $h_{\nabla g}$. In this paper, $G(\nabla g)$ is defined as follows [22]:

$$G(\nabla g) = T(\nabla g) \cdot |\nabla g|$$

where T represents a feasible monotonic non-parametric transform that makes the histogram of $G(\nabla g)$ as similar as possible to $h_{\nabla g}$.

Table 2: Algorithm 1 Specification

Algorithm 1: Iterative Specification of the Improved Adaptive Regularization Method with GHP Constraint

1. **Initialization:** Set the initial estimate $\sigma_0^{(0)} = \mathbf{y}$, k = 0; set initial regularization parameters , , and step length .
2. **Loop:** Iterate on k = 0, 1, ···, maxiter
   - (a) Let $\mathbf{g}^{(k)} = \mathbf{H}\sigma_0^{(k)}$

- (b) Update $h_{\nabla g}^{(k)}$
- (c) Define $G(\nabla g^{(k)}) = T(\nabla g^{(k)}) \cdot |\nabla g^{(k)}|$
- (d) Compute $\nabla J(\sigma_0^{(k)})$
- (e) Update $\sigma_0^{(k+1)} = \sigma_0^{(k)} - \mu \cdot \nabla J(\sigma_0^{(k)})$
- (f) k ← k + 1 until stop criteria satisfied

There are two regularization parameters (and) in our proposed algorithm. In the simulation, is first determined by the Morozov method, and is set empirically. Since balances the regularization term with the histogram preservation term, a large is preferred. However, cannot be set too large due to estimation errors in reference histogram estimation. In the simulation, and are set to 1 and 0.25, respectively. For gradient histogram estimation of $\mathbf{H}\sigma_0$, we use the same strategy as [23], where the range of is between 0.001 and 5, and is from 0.1 to 2.5.

IV. Algorithm Performance

This section investigates algorithm performance, focusing on two crucial aspects: quantitative evaluation of resolution enhancement and algorithm processing accuracy.

A. Resolution Enhancement

While various definitions of effective resolution exist, two common working definitions are used: the resolving capability for two closely spaced objects and the 3 dB beamwidth of the spatial response of a point target. Objects are considered individually "resolved" if there is a 3 dB change in value between them against a high-contrast background. To assess the resolution enhancement of the proposed method, we use a synthetic field including these features as an example, shown in Fig. 5 Figure 5: see original paper. In the synthetic field, the left squares are 1 km × 1 km in size and spaced 2 km apart, the right square is 2 km × 2 km, and the widths of the narrow and broad lines are 1 km and 2 km, respectively.

The synthetic field reconstruction is conducted using Monte Carlo simulation. In our simulation, the "slice" measurements of the scatterometer are used to verify the resolution enhancement of reconstruction. Based on the measurement model described in Section II, the measurement result is shown in Fig. 5(b). Fig. 5(c)-(h) illustrate the reconstructed using three classical scatterometer image reconstruction methods (SIR, AART, and MART), Tikhonov regularization method (TR), and two L1-norm based regularization methods (TV and L1). The reconstructed result of the proposed method is displayed in Fig. 5(i). Note that due to the equivalence of the MAP method proposed by Williams [5] and the TR method, the MAP result is not described repeatedly.

As expected, the SIR result is excessively smooth and seriously spread out, with the least noise amplification. The AART, TR, and TV methods produce better resolution enhancement than SIR but make the output field noisier. The L1 and our proposed method obtain the best resolution enhancement, and our method has less noise amplification.

To further investigate resolution quantitatively, the profiles of the horizontal (azimuth direction) cut of values extracted from Fig. 5 across the top row of spots are analyzed, as shown in Fig. 6 [Figure 6: see original paper]. For clarification, Fig. 6(a) shows a comparison between the proposed method and three scatterometer image reconstruction methods (SIR, AART, and MART), while Fig. 6(b) presents the comparison between our method and three regularization methods (TR, TV, and L1). From Fig. 6(a), it is apparent that except for the SIR method, the other methods achieve 2 km resolution. Our method recovers the true signal with the highest accuracy. In Fig. 6(b), all methods achieve 2 km resolution, and both our proposed and L1 methods have better amplitude recovery than the other two. Overall, the proposed method shows good performance in resolution enhancement compared to other methods except for the L1 method.

B. DFPSCAT Reconstruction Framework

To illustrate the application of the proposed deconvolution method for DFPSCAT measurements of SWE, simulation is initially used. Fig. 7 [Figure 7: see original paper] shows the simulation flow chart of DFPSCAT reconstruction. In the process, the DMRT-QCA model [24] is adopted as the snow forward model to obtain the surface original backscattering coefficient _t . The DMRT-QCA model takes incidence angle, frequency, polarization, snow parameters (density, depth, and grain size), and surface soil parameters (here assumed to be frozen ground) as input parameters. The observation system outputs the measured backscattering coefficient _m based on the echo signal model described in Section II. Then, the reconstructed backscattering coefficient _s is obtained after super-resolution algorithms.

Existing SWE spatial distribution data includes AMSR-E/Aqua L3, ESA Globe Snow products, Snow Data Assimilation System (SNODAS) Data Products [25], and some airborne and snow pit databases. Since AMSR-E/Aqua L3 and ESA SWE products have low spatial resolution of 25 km, and observations from airborne and ground pits have limited spatial distribution, the SNODAS SWE dataset becomes the optimal alternative for our application. The SNODAS SWE dataset assimilates satellite-derived, airborne, and ground-based observations of snow-covered area and snow water equivalent, outputting SWE gridded data for the continental United States with 1 km spatial resolution and 24-hour temporal resolution [25].

In this paper, the state of Montana in the United States is chosen as the study domain to investigate algorithm performance across different SWE distributions.

In the study domain, the western part is flat (referred to as Coastal Plain), the middle part includes gentle hills and valleys (Foothill region), whereas the southern part is characterized by mountain ridges (Mountain region). We choose two days of SWE data (February 28 in 2014 and 2015, respectively) as input SWE distribution. Since actual SWE values are less than 700 mm, SWE values above 700 mm are removed. The SWE distributions are shown in Fig. 8 [Figure 8: see original paper].

C. Algorithm Comparison

To investigate the performance of the proposed method, an algorithm comparison is conducted among the proposed method and existing resolution enhancement methods. Based on the DFPSCAT reconstruction framework, we take Ku-band VV polarization on Feb. 28, 2015 as a test image, in which three different areas corresponding to the Coastal Plain, Foothill region, and Mountain region of Montana are chosen as study regions. Fig. 9 [Figure 9: see original paper] illustrates the test image and three study regions marked with red rectangles.

Fig. 10 [Figure 10: see original paper] shows the reconstructed results of the three study regions through various reconstruction methods for a particular noise realization with Kp = 0.08. It can be seen that SIR, AART, MART, and TV methods produce smoother images than the other three. For TR, L1, and our proposed results, L1 shows the best resolution enhancement but with the largest noise amplification; TR has the least noise amplification but sacrifices resolution; the proposed method shows comparable resolution enhancement as L1 while having less noise.

Besides, quantitative assessment of these super-resolution results is conducted. Two evaluation indices, correlation coefficient and relative error, are computed from the difference between the "truth" and estimated images, where the relative error is defined as $\|\sigma_s^0 - \sigma_t^0\|_2 / \|\sigma_t^0\|_2$. The quantitative experimental results are shown in Table 3 and Table 4 .

From Table 3, it is obvious that with increasing Kp, the correlation coefficient of reconstructed results gradually decreases. When Kp is less than 5%, the proposed method has the highest correlation coefficient. For various Kp values, the proposed method has higher correlation coefficient than the L1 method, whereas lower than TR, which is caused by noise amplification.

Table 4 shows the relative error results of different methods. It is noted that SIR, AART, MART, TR, and TV methods have similar relative errors for the same Kp. The L1 method has the largest relative errors for different Kp values. Compared with L1, the proposed method shows significant error reduction. Moreover, the relative error of the proposed method does not increase much compared with the others.

D. SWE Backscattering Coefficient Reconstruction

Since the goal of our improved adaptive regularization method is to obtain high-resolution for SWE retrieval application, processing accuracy is crucial. In this section, the processing accuracy of the proposed method is investigated to validate its feasibility for SWE retrieval. Fig. 11 [Figure 11: see original paper] shows images over Montana State using one-day data from February 28, 2015, for DFPSCAT. The figures from left to right in each row respectively represent original, observed, and reconstructed images. The figures from top to bottom in each column represent X-band VV-pol, X-band HV-pol, Ku-band VV-pol, and Ku-band HV-pol, respectively. It is obvious that the reconstructed images have significant resolution improvement compared with the observed ones.

To further verify algorithm performance, another similar experiment is conducted using data from the same day but for different years. Fig. 12 [Figure 12: see original paper] exhibits the original, observed, and reconstructed images of Montana State for the year 2014. The same results are obtained as for 2015.

The relative error and correlation coefficient of measured and reconstructed images for different Kp values are shown in Table 5 . For each Kp, the first row shows relative error in decibels, and the second row shows correlation coefficient. For the day in 2015, the relative errors of reconstructed images are about 0.30 dB for X-band VV-pol, 0.42 dB for X-band HV-pol, 0.27 dB for Ku-band VV-pol, and 0.33 dB for Ku-band HV-pol across various Kp values. They all satisfy the accuracy requirement for SWE retrieval except for the X-band HV-pol case. The reason is that the Coastal Plain has the highest SWE and relatively larger variation compared with other regions. The corresponding relative errors are about 0.36 dB, 0.34 dB, 0.22 dB, and 0.31 dB for 2014, and they all satisfy the accuracy requirement.

In addition, compared with observed results, the relative errors of reconstructed images decrease by more than 0.03 dB for Ku-band in both years. For X-band, the relative errors decrease by more than 0.06 dB in both years. The correlation coefficient of reconstructed results for both years shows significant improvement over that of observations.

Based on this analysis, the proposed reconstruction method satisfies the accuracy requirement of 0.5 dB for SWE retrieval and produces high-correlation reconstructed images with the original ones. The results also indicate that the proposed method is insensitive to measurement noise and has stable performance.

V. Real Data Validation

The previous analysis is based on simulation processing. In this section, we illustrate the feasibility of the deconvolution framework and the effectiveness of the deconvolution algorithm with actual scatterometer data. For existing pencil-beam scatterometer data like SeaWinds, the azimuth sampling interval is more than ten kilometers, which does not satisfy the high azimuth sampling rate requirement in our framework. Therefore, fan-beam scatterometer data become the optimal alternative.

ASCAT (Advanced Scatterometer on Metop) is a C-band fan-beam scatterometer with two swaths and three beams on each side, as shown in Fig. 13 [Figure 13: see original paper]. Each beam is split into 256 nodes through range processing, and the corresponding measurement values (radar backscatter, incidence angle, azimuth angle) along with location (latitude and longitude) are reported in the "full resolution"product (SZF) [26]. We take the right middle beam measurement as an example and combine its multiple measurements for azimuth resolution enhancement. In this case, the measurements are 5.6 km apart, and the "slice" measurements have an aperture function with an effective size of approximately 6 km $\times$ 35 km.

The coastline of Mogadishu centered at 45°E, 1°N is chosen as the study region. Both observed and reconstructed images created from scatterometer measurements are shown in Fig. 14 [Figure 14: see original paper]. Through comparison of the observed and reconstructed images, it is apparent that the reconstructed image discriminates the coastline clearly and preserves more detailed information. It should be noted that noise enhancement in the reconstructed image is not obvious, mainly due to the lower noise level of ASCAT measurements.

VI. Conclusions

This paper introduces an improved adaptive regularization deconvolution method with gradient histogram preservation constraint to enhance azimuth resolution and successfully applies it to the DFPSCAT forward-looking case. Compared with the oversmoothness of the adaptive regularization method, the proposed method can recover more details. To illustrate the feasibility of the deconvolution framework and the effectiveness of the proposed algorithm, both simulation and real scatterometer data processing are implemented.

In the simulation, synthetic field reconstruction and SWE reconstruction are carried out to quantitatively evaluate resolution enhancement and algorithm processing accuracy. Meanwhile, the proposed method is compared with existing resolution enhancement methods. The results show that the proposed method can obtain comparable resolution enhancement as the L1 method. From quantitative analysis of processing accuracy, the proposed method has the highest correlation coefficient and least relative error when Kp is less than 5%, and shows higher accuracy than the L1 method with higher correlation coefficient and lower relative errors.

Taking SWE distributions over Montana State on two different days as examples to judge the effectiveness of the proposed method for SWE retrieval application, our proposed method satisfies the accuracy requirement of 0.5 dB for SWE retrieval and produces high-correlation reconstructed images with the truth.

Compared with observation results, the relative errors of reconstructed images decrease by more than 0.03 dB for Ku-band in both polarizations and by 0.06 dB for X-band.

In addition, we use ASCAT "full resolution" product (SZF) for further validation. Compared with observation, the reconstructed image discriminates the coastline clearly and shows better performance.

Acknowledgment

The work of this paper is supported by the Strategic Priority Program on Space Science from the Chinese Academy of Sciences, under the project of intensive study of candidate mission of Water Cycle Observation Mission (WCOM) (Grant Number: XDA04061202).

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