Reduction of the Reconstruction Error With Lower and Upper Bounds in Synthetic Aperture Imaging Radiometers

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ABSTRACT Synthetic aperture imaging radiometers (SAIRs) are powerful instruments for high-resolution Earth observation by use of small-aperture antennas sparsely arranged to achieve a large-aperture antenna. High-precision reconstruction algorithm is one of the key contents of SAIRs. Owing to the ill-posed problem and band-limited physical characteristic, there is a still large residual error for traditional regularization methods. It should be noted that the prior information like the lower and upper bounds of the brightness temperature distributions has not been utilized in the reconstruction procedure, especially for the open ocean with relatively small brightness temperature difference. In order to reduce the reconstruction error in SAIRs, a reconstruction method based on active set algorithm is presented by solving the least squares problems with lower and upper bounds. The simulation experiment results show that the proposed method can more effectively reduce the reconstruction error and better improve the accuracy of retrieved brightness temperature distributions in SAIRs than the band-limited regularization method, demonstrating the effectiveness of the proposed method.

INDEX TERMS Imaging radiometry, synthetic aperture, inverse problem, reconstruction error.

I. INTRODUCTION Synthetic aperture imaging radiometers (SAIRs) are passive microwave sensors by use of synthetic aperture technique. For real aperture radiometers, increasing the antenna aperture is the only way to improve the spatial resolution. However, large aperture antenna brings the difficulties of mechanical scanning, the weight as well as the bulky volume. In order to overcome the above shortcomings of real aperture radiometers, SAIRs improve the spatial resolution by sparsely arranging small antennas. With the deepening of theoretical and systematic research, SAIRs have entered practical applications [1] and researchers have developed some instruments such as Soil Moisture and Ocean Salinity (SMOS) [2], the Geostationary Synthetic Thinned Array Radiometer (GeoSTAR) [3], and Geostationary Interferometric Microwave Sounder (GIMS) [4], [5].

It has been demonstrated that the inverse problem of SAIRs is mathematically ill-posed so that the solution is neither unique nor stable [6]. Therefore, the inverse problem needs to be regularized in order to provide a stable and unique solution. Currently, regularization methods have become the dominant methods to solve the inverse problem of SAIRs and get excellent results [7]–[9]. The direct regularizations, such as Tikhonov regularization and truncated singular value decomposition (TSVD), overcome the ill-conditioned property of the inverse problem by use of numerical methods, but they need to choose the suitable regularization parameter. Band-limited regularization proposed by [6] cures the ill-posed property of the inverse problem by considering the physical characteristic of limited bandwidth for SAIRs. However, owing to the ill-posed property and band-limited
physical characteristic, there is still a large residual error after reconstructing [10], [11].

An important application of SAIRs is to detect Sea Surface Salinity (SSS), which requires that the measurement accuracy of the ocean brightness temperature is within 0.1 K. Residual error for traditional reconstruction methods needs to be effectively reduced to meet the detection needs of geophysical parameters such as SSS. It should be noted that the three regularization methods mentioned above do not make use of any prior information about brightness temperature images of the observed scene in the spatial domain. Actually, it is easy to obtain some prior information such as the upper and lower bounds, especially for the observed scene like the open ocean with relatively small dynamic range of the brightness temperatures.

The principle of SSS remote sensing is based on the salinity sensitivity of sea surface brightness temperatures at microwave frequencies [12]. The dielectric constant models have been widely used to study the sensitivity of microwave radiation to the water salinity. It has been shown that the Ellison model proposed by [13] can be well consistent with radiation to the water salinity. It has been shown that the dielectric constant models have been widely used to study the sensitivity of microwave frequencies [12]. The dielectric constant models have been widely used to study the sensitivity of microwave frequencies [12].

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which shows stable range of the brightness temperatures compatible with global salinity maps. From Figure 1, we can find that the upper and lower bounds of the brightness temperature distributions in the open oceans are 85K and 95K, respectively. Therefore, the brightness temperature distribution in the open oceans is relatively stable and has upper and lower limits.

By considering the bounded property of the brightness temperature distribution, a reconstruction method based on active set algorithm is proposed. The optimization problem can be expressed as

$$\min \| V - GT \|^2 \quad \text{s.t.} \beta_1 \leq T \leq \beta_2$$

(6)

where $\beta_1$ is the constant vector with the lower bound $\beta_1$ and $\beta_2$ is the constant vector with the upper bound $\beta_2$. The least-squares problem can be transformed into a quadratic programming problem

$$\min T^TGT - 2(G^TV)^T T$$

s.t. $\beta_1 \leq T \leq \beta_2$

(7)

The bounded constraints can be converted into

$$\begin{pmatrix} I & -I \end{pmatrix} T \geq \begin{pmatrix} \beta_1 \\ -\beta_2 \end{pmatrix}$$

(8)

where $I$ is the identity matrix. If we define

$$A^T = \begin{pmatrix} I \\ -I \end{pmatrix}, \quad B = \begin{pmatrix} \beta_1 \\ -\beta_2 \end{pmatrix}$$

(9)

the constraints are written as follows:

$$A^T T \geq B$$

(10)

Thus, (6) can be given by standard form of the quadratic programming problem [16]

$$\min \frac{1}{2} T^TDT + C^T T \quad \text{s.t.} A^T T \geq B$$

(11)

where $D = 2G^TG$ is the symmetric matrix, $C = -2G^TV$, $A = (a_1, a_2, \ldots, a_m)$, $B = (b_1, b_2, \ldots, b_m)^T$.

When $D$ is a positive semidefinite matrix, the objective function in (11) is convex. If the feasible region of the quadratic programming problem is not empty, it must be a convex set. In consequence, (11) is the convex quadratic programming problem. Under the circumstance, the local optimal solutions are the global optimal solutions [17], [20]. In addition, when $D$ is a positive definite matrix, the global optimal solution is unique.

Under general circumstances, the quadratic programming problem with inequality constraints needs to be transformed into the equality constraint problem. In order to solve the quadratic programming problem with the equality constraints, Lagrange multipliers $\gamma = (\gamma_1, \gamma_2, \ldots, \gamma_m)^T$ are introduced

$$La(T, \gamma) = \frac{1}{2} T^TDT + C^T T - \gamma^T(A_2^T T - B_2)$$

(12)

where $A_2 = (a_1, a_2, \ldots, a_i)$, $B_2 = (b_1, b_2, \ldots, b_i)^T$, $i \in w'$, $w'$ represents the set including all the effective constraints.

The equality constraint problem can be solved by finding the stationary point of the Lagrange function. Hence, the $T$ and $\gamma$ satisfy:

$$\nabla_T La(T, \gamma) = DT - A_2 \gamma + C = 0$$

$$\nabla_\gamma La(T, \gamma) = -A_2^T T + B = 0$$

(13)

We can get $T'$ and $\gamma'$ by solving (13). If $T'$ satisfies the Kuhn-Tucker rules, $T'$ is also the optimal point. In this situation, $\gamma'$ should satisfy

$$\sum_{i \in w'} a_i \gamma'_i = DT' + C$$

$$\gamma'_i \geq 0$$

(14)

For the active set algorithm, it is assumed that after $k$ iterations, we can get the feasible point $T_k$ and the working set $w_k$. Then check whether the current iteration point is optimal under the current working set. If not, we define a step $q$ [17]

$$q = T - T_k$$

(15)

$$h_k = DT_k + C$$

By substituting (15) into (11), we get

$$\min h_k^T q + \frac{1}{2} q^T D q \quad \text{s.t.} a_i^T q = 0, \quad i \in w_k$$

(16)

The solution of (16) is given by $q_k$. Consequently, the iteration point is updated by

$$T_{k+1} = T_k + s_k q_k$$

(17)

where $s_k \in [0,1]$ is the step-length parameter. In order to ensure that the new iteration point meets the original constraints, $s_k$ needs to satisfy [17]

$$s_k = \min \left\{ 1, \min \frac{b_i - a_i^T T_k}{a_i^T q_k} \right\}$$

(18)

If $s_k < 1$, it means the step $q_k$ is blocked by the constraint that is not in the working set. So we construct a new working set $w_{k+1}$ by adding this constraint that satisfies

$$a_j^T (T_k + s_k q_k) = b_j.$$
The algorithm procedure is summarized as follows in Table 1. In this paper, for purpose of speeding up the convergence, the constant vector with the mean value of the upper and lower limits is selected as the initial solution $T_0$.

IV. RESULTS AND DISCUSSION

Numerical simulation experiments have been performed in order to verify the effectiveness and performance of the above inverse method. The experiments are based on the L-band FPIR system [21] and the specific parameters of the system are listed in Table 2. Antenna array configuration of the system is shown in Figure 2, where the antennas elements $n_1, n_2, \ldots, n_{16}$ are arranged at different positions with the shortest baseline set to $\Delta d = 0.589\lambda_0$. After applying the hermiticity property, there are 241 visibility function samples in total. The antenna has been simulated with nonisotropic antenna voltage patterns, shown in Figure 3. In Figure 3, the horizontal axes $\xi$ is the direction cosines in the Cartesian coordinates, and $n_1, n_2, \ldots, n_{16}$ denote the element antennas in sequence. In addition, the fringe-washing function is set to $\text{sinc}(Bt)$ for modeling the operator $G$.

As shown in Figure 4, the initial distribution used in the simulations derives from the observed ocean brightness temperature of H polarization in the 1.4 GHz channel for the SMAP satellite. In Figure 4, the horizontal axes $\xi$ is the direction cosines in the Cartesian coordinates. When the matrix size of the brightness temperature distribution is $500 \times 1$, the size of the matrices $G$ is $241 \times 500$. The complex

| TABLE 1. The algorithm procedure. |
|-----------------------------------|
| 1. Initialize a solution $T_0$ and a working set $w_0$. |
| 2. Get $q_k$ by solving (16). If $q_k = 0$ and the Lagrange multiplier $\lambda'_i \geq 0$, stop the program with solution $T' = T_k$. If $q_k = 0$ and $\lambda'_i < 0$, remove the constraint $i$ corresponding to the minimum value of $\lambda'_i$. And then update $w_{k+1}, T_{k+1} = T_k$ and jump to the fourth step. If $q_k \neq 0$, jump to the third step. |
| 3. Compute $s_k$ by solving (18) and update the iteration solution $T_{k+1} = T_k - s_k q_k$. If $s_k = 1$, jump to the fourth step. If $s_k < 1$ (there are blocking constraints), construct a new working set $w_{k+1}$ by adding this constraint from (18). |
| 4. Modify the working set and the number of iterations. Return to the second step and continue to iterate until the optimal solution. |

| TABLE 2. The system parameters. |
|-----------------------------------|
| Array parameters | parameters |
| Antenna number | 16 |
| The shortest baseline | $\Delta d = 0.589\lambda_0$ |
| The longest baseline | $90\Delta d$ |
| Receiver parameters | |
| Central frequency | $f_c=1.4$ GHz |
| Bandwidth | $B=20$MHz |
| Integration time | $\tau = 1s$ |

| FIGURE 2. Array configuration. |
|----------------------------------|

| FIGURE 3. The voltage patterns of 16 antennas. |
|-----------------------------------------------|

| FIGURE 4. The original brightness temperature distribution of the observed ocean. |
visibilities are obtained by simulating the test distribution based on the above FPIR system. In actual measurement, the measurement error or noise interference is generally unavoidable. Gaussian white noises with zero mean and the variance \( \sigma^2 \) are added to the complex visibilities to mimic measurement error and noise interference.

When the variance of the added noise is \( \sigma^2 = 0.1 \max(V_i) \), the retrieved distributions in the alias-free field of view by active set method and band-limited regularization method are shown in Figure 5. For active set method, the upper and lower bounds of the brightness temperature distribution are separately set to 105K and 85K according to the Ellison model, and the initial solution \( T_0 \) is the constant vector with the value 95. As can be seen from Figure 5, reconstruction result of the band-limited regularization has obvious oscillation ripples especially at the edge of the brightness temperature distribution, which is the Gibbs effect owing to limited bandwidth coverage in the frequency domain for SAIR system. In addition, compared with the band-limited regularization, the active set method produces better result, which has weaker ripples and exhibits better suppression of oscillation ripples, demonstrating the effectiveness of the active set method. The RMSE and PSNR are calculated for quantitative analysis on the reconstruction error. In Figure 5, the RMSE and PSNR for band-limited method are respectively 5.51K and 33.30dB, and the RMSE and PSNR for active set method are respectively 4.19K and 35.68dB.

In order to analyze quantitatively the impact of noises on the retrieved distributions, the Gaussian white noises of different levels are added to the complex visibilities and then reconstructed to obtain the brightness temperature distribution. The performance comparison of the two inverse methods in different noise level is shown in Figure 6, where the upper and lower bounds and the initial distribution for active set method are the same as those in Figure 5.

Figure 6(a) indicates that the RMSE for the active set method is lower obviously than the RMSE for the band-limited regularization in the case of high-intensity noises such as \( \sigma^2 = 0.1 \max(V_i) \) and the two RMSE values gradually approach when the variance \( \sigma^2 \) decreases from 0.1 \max(V_i) to 0.01 \max(V_i). It should be noted that in the case of low variance, the RMSE absolute values for the two methods are small so that the relative difference between the two RMSE becomes very small. For example, when the variance \( \sigma^2 = 0.01 \max(V_i) \), the RMSE for the band-limit regularization and active set method are 1.86K and 1.63K, respectively. From Figure 6(b), we can find that whether the noise level is high or low, the PSNR for the active set method is 1.8dB higher than that for the band-limited regularization. Therefore, the results show that the active set method is more robust to the noise interference than the band-limit regularization, proving that it can better improve the accuracy of the retrieved brightness temperature distributions.

In addition, the convergence performance of active set method in different level noises is presented in Figure 7. As shown in Figure 7, when the iteration steps increase, the fitness function decreases rapidly until a stable value, demonstrating the convergence of the active set method. In Figure 7, when the number of iterations is about 10, the fitness function converges to a stable value.
For the active set method, the upper and lower bounds of the brightness temperature distribution in the open oceans are predicted according to the Ellison model combined with the influence of other error sources. However, there may be the errors of a few kelvin or even more than a dozen kelvin between the estimated results and the actual results. Simulations have been performed to quantitatively analyze the impact of different upper and lower bounds on the reconstruction results. The original distribution, where the minimum and maximum brightness temperatures are respectively $T_{\text{min}} = 89.05\text{K}$ and $T_{\text{max}} = 101.73\text{K}$, is shown in Figure 4.

In an ideal situation, the lower and upper limits for the active set method are $T_{\text{min}}$ and $T_{\text{max}}$. The boundary error of the brightness temperature distribution $\epsilon$ is defined as the difference of the minimum $T_{\text{min}}$ and the lower bound $\beta_1$. For convenience, it is assumed to $\epsilon = T_{\text{min}} - \beta_1 = \beta_2 - T_{\text{max}}$. When the measured visibility function samples are corrupted by Gaussian white noise with the variance $\sigma^2 = 0.1 \max(V_i)$, the retrieved distributions in the alias-free field of view for different boundary errors are shown in Figure 8. The results show that the boundary error has an impact on the retrieved distribution. The greater the boundary error is, the poorer quality of the retrieved distribution is, particularly on the edge of the distribution.

In order to determine the impact of the boundary error on the retrieved distributions for the active set method, the RMSE and PSNR are calculated. The relation between the boundary error and the performance (RMSE or PSNR) of the retrieved distribution is presented in Figure 9. From Figure 9, we can find that when the boundary error increases, the RMSE gradually increases and the PSNR gradually decreases. Moreover, compared with the band-limit regularization method, the active set method has a lower RMSE and a higher PSNR even when the boundary error is 20K, that is, the upper and lower limits of the brightness temperatures are set to $121.73\text{K}$ and $79.05\text{K}$, respectively. Therefore, although the boundary error has an impact on the performance of the reconstruction results, the active set method can in general produce better reconstruction results compared to the band-limit regularization.

Compared with the band-limited regularization method, the computation time of the active set method as an iterative
High-precision reconstruction algorithm is one of the key contents of SAIRs. Different from real aperture radiometers, the output of SAIRs is the sampled data of the visibility function. The purpose of the reconstruction algorithm is to transform the visibility function samples in the frequency domain into the brightness temperature distribution in the spatial domain. Due to the ill-posed property and band-limited physical characteristic, there is still a large residual error for the reconstruction result of the traditional reconstruction algorithm. However, the prior information has not been utilized in the restructuring procedure. A novel reconstruction method, which makes use of the lower and upper bounds of the brightness temperature distributions, is proposed to reduce the reconstruction error. The proposed method is based on active set algorithm, which solves sparse least squares problems with lower and upper bounds. The simulation experiment results show that the proposed method can more effectively reduce the reconstruction error, especially in the case of high-intensity noise, compared to the band-limited regularization. In addition, the upper and lower bounds should be set as close as possible to the minimum and maximum values of the original brightness temperature distribution.

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