Coherent compensation and high-resolution technology of multi-band inverse synthetic aperture radar fusion imaging

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Abstract

Multi-band inverse synthetic aperture radar (ISAR) fusion imaging technology can effectively improve the range resolution without incurring high hardware cost. The coherent phase between sub-bands is a prerequisite to achieve multi-band ISAR fusion imaging. Here, a joint approach of coherent compensation and high-resolution imaging is proposed to compensate the incoherent phase and obtain high-resolution ISAR fusion images. First, an incoherent phase estimation model based on sparse representation is established, and the phase estimation accuracy is improved by a modified coherent dictionary in case of off-grid. Then, a multi-band ISAR fusion imaging model based on sparse representation is established. The complex Gaussian scale mixture priors and the complex Gaussian priors are imposed on the scatterers and noise, respectively. The solution is derived in the complex domain based on the variational Bayesian expectation maximization framework. The proposed method can not only achieve better incoherent phase compensation in the case of off-grid, but also obtain high-quality ISAR fusion images under low signal-to-noise ratio and low bandwidth sampling ratio. Experimental results verify the effectiveness and robustness of the proposed method based on both numerical simulations and real data.

1 | INTRODUCTION

High-resolution inverse synthetic aperture radar (ISAR) images can provide more detail structure information of targets, which is conducive to target identification and classification [1–3]. The range resolution can be improved by increasing the bandwidth directly. However, it incurs high hardware complexity and manufacturing cost. Multi-band ISAR fusion imaging technology can fuse the echo data measured by multiple radars with different frequency bands at the same view angle into an equivalent wider band one. It can improve the range resolution and overcome the problems caused by directly increasing the transmitting signal bandwidth in a single radar system [4–6].

The coherent compensation is a prerequisite for multi-band fusion imaging. Traditional incoherent phase estimate methods can be divided into two categories. The first one is based on the minimum mean square error (MSE) criterion [7], the minimum entropy criterion [8], or the distance profile correlation [9] to estimate the incoherent phase by extrapolating the spectrum of each sub-band to obtain the overlapping frequency band. However, the extrapolation error is easily affected by noise and the extrapolation length, and traditional optimization methods are easily falling into a local minimum. Another approach is based on an all-pole model. A coherent method based on valid poles and phase auto-focusing is proposed to compensate the incoherent phase between sub-bands in Ref. [10]. The unitary estimation of signal parameter via rotational invariance techniques (U-ESPRIT) method is proposed to further improve the performance of signal pole estimation in Ref. [11]. This method is feasible when all poles are estimated accurately and matched correctly. However, the poles are difficult to be estimated correctly with low signal-to-noise ratio (SNR), which inhibits the robustness in real scenarios.

The available multi-band fusion imaging methods can be mainly divided into two categories, which are based on spectral analysis and sparse representation, respectively. Spectral analysis-based methods transform the multi-band fusion imaging problem into a spectral estimation problem, and the
typical methods include the modified root–multiple signal classification (Root-MUSIC) method [12], estimation of signal parameter via rotational invariance techniques (ESPRIT) method [13], and gapped data amplitude and phase estimation (GAPES) [14]. The model order which is difficult to be estimated accurately has a significant impact on the performance of the spectral analysis-based methods. Most of the spectral estimation methods are sensitive to noise. Hence, the order selection and model mismatch will degrade the performance seriously in low SNR scenarios.

Sparse representation-based methods exploit the sparsity of ISAR imaging signal to convert the multi-band fusion imaging problem into a sparse signal reconstruction problem. Sparse reconstruction algorithms mainly include greedy algorithms represented by orthogonal matching pursuit (OMP) algorithm [15], \( l_p \)-norm optimization algorithms represented by \( l_1 \)-norm algorithm [16] and Bayesian framework-based algorithms represented by sparse Bayesian learning (SBL) algorithm [17]. Although the greedy algorithms are simple and easy to implement, the reconstruction performance is sensitive to noise and the accuracy is limited. \( l_p \)-norm optimization algorithms have a higher reconstruction accuracy. However, they are easy to fall into a local minimum and require manual adjustments of the regularization parameters. In contrast, the Bayesian framework-based algorithms can automatically learn the unknown parameters to improve the adaptability while ensuring reconstruction accuracy. However, the prior model of SBL algorithm is not flexible enough due to the Gaussian priors. To improve the model flexibility, a sparse sub-band imaging method based on hierarchical Gaussian-Gamma priors model is proposed in Ref. [18]. However, the solution is derived in the real domain, and the complex-valued signal model need be converted to a real one. It not only increases the computational complexity and the memory storage space, but also destroys the correlation and the same support set of the real part and imaginary part of the complex signal.

To tackle the above-mentioned problems, a joint approach of coherent compensation and high-resolution imaging is proposed for multi-band ISAR fusion imaging. First, a sparse representation-based model is established and solved by the OMP algorithm to estimate the incoherent phase between sub-bands, and a modified coherent dictionary is proposed to further improve the estimation accuracy in case of off-grid. Then, complex Gaussian scale mixture (CGSM) priors and complex Gaussian priors are imposed on the scatterers and the noise, respectively. The hierarchical priors can enhance the model flexibility and exploit the statistical characteristics of both scatterers and noise to improve the robustness with low SNR. To exploit the same support set characteristics and correlation between the real and imaginary parts of the complex signal, the variational Bayesian expectation maximization (VB-EM) framework is utilized to estimate the parameters and reconstruct the target image directly in the complex domain.

The remainder is organized as follows. Section 2 discusses the coherent compensation process based on sparse representation. The multi-band ISAR fusion high-resolution imaging method based on CGSM priors is described in detail in Section 3. Section 4 evaluates the performance of the proposed method via numerical simulations. Finally, a conclusion is presented in Section 5.

## 2 | COHERENT COMPENSATION PROCESS

Multiple radars for multi-band ISAR fusion imaging are adjacently configured with the same view angle and share the same scattering model. Since the bandwidths of sub-bands are usually narrow, the target response of each sub-band with high frequency and narrowband in the far-field condition can be regarded as the reflection of ideal scatterers. The target scattering is assumed to be point-scattering, which is independent on the frequency. The fusion imaging of two radars in different frequency bands is performed in a later discussion.

### 2.1 | Incoherent phase between sub-bands

Suppose that the radars transmit chirp signals with \( M \) pulses. The pulse repetition time is \( T_r \) and the slow time can be expressed as \( t_m = mT_r (m = 0,1,2,\cdots, M-1) \). The carrier frequency of sub-band 1 and sub-band 2 are \( f_{1c} \) and \( f_{2c} \) respectively, and the bandwidth of sub-band 1 and sub-band 2 are \( B_1 \) and \( B_2 \) respectively. The signal model is consistent with the model in Ref. [19]. Due to the different initial system phases of the two radars and the different time delays from the target to the radars, the echoes of sub-bands are usually incoherent. Considering the incoherent phase between sub-bands, after translation compensation and pulse compression, the echo signals of two sub-bands in the range frequency-slow time domain can be expressed as

\[
s_i(f_i, t_m) = \sum_{p=1}^{P} a_p \text{rect}\left( \frac{f_i - f_{pc}}{B_p} \right) \exp \left( -j4\pi f_i \frac{\Delta R_p(t_m)}{c} \right) \exp \left( -j2\pi f_i \tau_i + j\varphi_i \right)
\]

where \( P \) is the number of scatterers, \( a_p \) is the scattering coefficient of the \( p \)-th scatterer, \( c \) is the speed of electromagnetic waves, \( \Delta R_p(t_m) \) is the instantaneous slant range between the \( p \)-th scatterer and the reference point, \( \tau_i \) and \( \varphi_i \) are the time delay and initial phase caused by the hardware differences in the sub-bands, respectively. \( \text{rect}(x) \) is a rectangular window function. \( \text{rect}(x) = 1 \) when \( |x| \leq 0.5 \) and \( \text{rect}(x) = 0 \) when \( |x| > 0.5 \).

For sub-band 1, \( i = 1, f_1 = f_{1c} + n_1\Delta f \), where \( f_{1c} = f_{1c} - B_1/2 \) is the starting frequency of sub-band 1 and the full-band, \( \Delta f \) is the frequency sampling interval, \( n_1 \) is the range frequency index in sub-band 1. The index of \( n_1 = 0,1,\cdots, N_1-1 \), where \( N_1 = B_1/\Delta f \) is the frequency sampling number of sub-band 1. For sub-band 2, \( i = 2, f_2 = f_{2c} + n_2\Delta f \), \( n_2 \) is the range frequency index of sub-band 2. The index value of \( n_2 = N-N_2, N - N_2 + 1,\cdots, N-1 \), where \( N \) is the frequency sampling number of the full-band, \( N_2 = B_2/\Delta f \) is the frequency sampling number
of sub-band 2 and \( N \geq N_1 + N_2 \). When \( N_1 = N_2 \), we have \( n_2 = n_1 + N - N_2, f_2 = f_0 + n_1 \Delta f + \Delta B = f_0 + \Delta B \) and \( \Delta B = (N-N_2) \Delta f \). Let the echo of sub-band 1 \( s_1 \) be the reference signal, refer to [4], the echo of sub-band 2 can be written as

\[
s_2(n_1, m) = s_1(n_1, m)\exp(jn_1\alpha + jm\eta) \tag{2}
\]

where \( \alpha \) and \( \eta \) are the linear phase term and the fixed phase term, respectively. It can be seen from (2) that the incoherent phase between sub-bands can be regarded as consisting of a linear phase term and a fixed phase term. The purpose of the coherent processing is to estimate and compensate the incoherent phase to ensure the coherence between sub-bands. It should be pointed out that the above-mentioned derivation is based on the premise that \( N_1 = N_2 \). If \( N_1 \neq N_2 \), \( N_C \) echoes taken from sub-bands are exploited for the coherent processing, where \( N_C = \min(N_1, N_2) \).

### 2.2 Incoherent phase estimation

According to (2), the echo data of the \( m \)-th pulse can be expressed as

\[
s_2(n_1, m) = \tilde{a} \cdot s_1(n_1, m)\exp(jm\alpha) \tag{3}
\]

where \( \tilde{a} = \exp(j\eta) \). Since \( \alpha \in [0, 2\pi) \), it can be discretized as \( \alpha = 2\pi k/K = 0, 1, \cdots, K-1 \) and \( K > N_1 \). Hence, (3) can be converted to a sparse representation problem as \( s_2 = \tilde{F}a \). \( s_2 \) is the \( m \)-th pulse echo data of sub-band 2, which can be expressed as \( s_2 = [s_2(0, m), s_2(1, m), \cdots, s_2(N_1-1, m)]^T \). \( a \) is a vector of coefficients, which can be expressed as \( a = [a_m(0, m), a_m(1, m), \cdots, a_m(K-1, m)]^T \). \( \tilde{F} \) is a coherent processing dictionary, which can be expressed as \( \tilde{F} = [F_0, F_1, \cdots, F_{K-1}] \), and its column atom \( \tilde{F}_k \) is defined as

\[
\tilde{F}_k = \left[ s_1(0, m), s_1(1, m)e^{2\pi jk}, \cdots, s_1(N_1-1, m)e^{2\pi j(N_1-1)k} \right]^T.
\]

The grids in \( \tilde{F} \) are pre-defined by the parameter \( K \). The estimation accuracy is high when the linear phase term \( \alpha \) is exactly located on a grid. However, the linear phase term \( \alpha \) may not be located on a grid exactly in practice. It is the off-grid problem, which deteriorates the estimation accuracy of the incoherent phase. Refining the grid can reduce the off-grid effect [20]. However, it will increase the coherence of the dictionary, which is not conducive to reliable reconstruction. Moreover, increasing the dictionary dimension \( K \) directly to refine the grid will increase the computational burden due to the large dictionary dimension. In order to mitigate the off-grid influence, we choose to refine the grid by reducing the grid area without increasing the dictionary dimension \( K \). Assuming that the range of the linear phase term \( \alpha \) is reduced from \([0, 2\pi] \) to \([0, 2\pi/Q] \), where \( Q \geq 1 \). Consequently, the improved column atom \( \tilde{F}_k \) in the coherent processing dictionary can be expressed as

\[
\tilde{F}_k = \left[ s_1(0, m), s_1(1, m)e^{2\pi jk/Q}, \cdots, s_1(N_1-1, m)e^{2\pi j(N_1-1)k/Q} \right]^T
\]

(when \( Q = 1 \), the coherent processing dictionary is \( F \)). The sparse representation model of the coherent processing in multiband ISAR fusion imaging can be expressed as (see (4)), where \( \tilde{F} \) is the modified coherent processing dictionary. The parameter \( Q \) can be set reasonably according to the estimation result obtained by utilizing the coherent processing dictionary \( F \).

Since the incoherent phase between the sub-bands is unique, there is only one non-zero coefficient in \( a \). According to the relationship of (3) and (4), the value and the position of the only one non-zero coefficient in \( a \) are related to \( \tilde{a} \) and \( \alpha \), respectively. Assuming that the only one non-zero coefficient in \( a \) is the \( i \)-th element which can be expressed as \( a_m(i-1, m) \). Since \( \tilde{a} = \exp(j\eta) \) and \( \alpha = 2\pi k/QK \), the fixed phase \( \eta \) can be estimated by deriving the angle of \( \arg(a_m(i-1, m)) \), and the linear phase \( \alpha \) can be estimated as \( \arg(a_m(i-1, m)) = \arg(\tilde{a}) - \arg(a_m(i-1, m)) \).

Due to the sparsity, sparse reconstruction algorithms can be utilized to estimate the incoherent phase. We utilize the OMP algorithm [15] to solve (4) and derive the estimation of \( a \) as \( \hat{a} = [\hat{a}_m(0, m), \hat{a}_m(1, m), \cdots, \hat{a}_m(K-1, m)]^T \). Assuming that the only one non-zero coefficient in \( \hat{a} \) is the \( i \)-th element as \( \hat{a}_m(i-1, m) \). The estimations of the linear phase term and the fixed phase term are derived as \( \hat{\alpha} = 2\pi(i-1)/QK \) and \( \hat{\eta} = \angle(\hat{a}_m(i-1, m)) \), respectively, where \( \angle(x) \) represents the angle of \( x \). The phase compensation is performed on the echo data of sub-band 2 to obtain the compensated signal as \( \tilde{s}_2(n_2, m) = s_2(n_2, m)\exp(-jn_2\alpha - j\eta) \), which is coherent with the sub-band 1 echo data. The coherent sub-bands echoes can be obtained by performing

\[
s_2 = \tilde{F}a
\]
the above-mentioned coherent compensation on all pulse echoes in sequence.

3 | MULTI-BAND ISAR FUSION HIGH-RESOLUTION IMAGING BASED ON CGSM

Since the radar echo is a complex signal, we propose complex hierarchical Gaussian-Gamma priors to impose on the scatterers, which is different from the Gaussian priors in the traditional SBL method. The hierarchical Gaussian-Gamma priors can enhance the model flexibility, and the complex-valued model can be solved by a VB-EM method directly in the complex domain.

3.1 | Fusion imaging model based on sparse representation

After the incoherent phase compensation process, the coherent echoes of sub-bands can be expressed as

\[ s_i(n_i, m) = \sum_{p=1}^{P} \alpha_p \cdot \exp \left( -j4\pi \left( f_0 + n_i\Delta f \right) \frac{\Delta R_p(t_m)}{c} \right) \]  
\[ (i = 1, 2) \]  

(5)

where \( \Delta R_p(t_m) = y_p \cos \Delta \theta_m + x_p \sin \Delta \theta_m \), \((x_p, y_p)\) is the coordinate of the \( p \)-th scatterer and \( \Delta \theta_m \) is the accumulative rotation angle of the target relative to the radar within \( m \) pulses.

For a target with small size that rotates a small angle during the imaging interval, the migration through resolution cells (MTRC) can be ignored. However, MTRC may be induced for a large complex target, which will lead to defocusing of the ISAR image [18]. Hence, it is necessary to conduct MTRC correction before multi-band fusion ISAR imaging to attain well-focused images. Since the \( \Delta \theta_m \) is small during the imaging interval, we have \( \sin \Delta \theta_m \approx \Delta \theta_m \), and (5) can be written as

\[ s_i(n_i, m) = \sum_{p=1}^{P} \alpha_p \cdot \exp \left[ -j4\pi \left( f_0 + n_i\Delta f \right) y_p \cos \Delta \theta_m \right] \] \[ \cdot \exp \left[ -j4\pi \left( f_0 + n_i\Delta f \right) x_p \Delta \theta_m \right] \] \[ (i = 1, 2) \]  

(6)

The effect of the first exponential term on the slant-range MTRC can be negligible, however, the second exponential term may result in slant-range MTRC for a large target or a long observation time [21]. After translation compensation, the target is regarded as a turntable model rotating at an angular rotation velocity \( \omega \), and \( \Delta \theta_m = \omega t_m \). To correct the slant-range MTRC, let \((f_0 + n_i\Delta f)t_m = f_d t_m\), where \( t_m \) is the new slow time and ignore the effect of \( \cos \Delta \theta_m \) on the pulse compression. Equation (6) can be expressed as

\[ s_i(n_i, m) = \sum_{p=1}^{P} \alpha_p \cdot \exp \left( -j4\pi \frac{n_i \Delta f y_p}{c} \right) \] \[ \cdot \exp \left( -j4\pi \frac{f_0 x_p \omega t_m}{c} \right) \] \[ \cdot \exp \left( -j4\pi \frac{f_0 y_p \cos \Delta \theta_m}{2c} \right) \] \[ (i = 1, 2) \]  

(7)

Although the effect of \( \cos \Delta \theta_m \) on the envelope of the range profiles obtained by pulse compression is negligible, the effect on the phase of the scatterers in the range profiles cannot be ignored. The phase compensation term should be constructed as \( \Phi_{\text{com}} = \exp (j \frac{\pi}{4} f_0 y_p \cos \Delta \theta_m) \) to correct the cross-range MTRC [21]. After correcting the MTRC, Equation (7) can be expressed as

\[ s_i(n_i, m) = \sum_{p=1}^{P} \alpha_p \cdot \exp \left( -j4\pi \frac{n_i \Delta f y_p}{c} \right) \] \[ \cdot \exp \left( -j4\pi \frac{f_0 x_p \omega t_m}{c} \right) \] \[ (i = 1, 2) \]  

(8)

We first perform azimuth compression to the sub-band echoes, and then obtain the two-dimensional ISAR image by the multi-band fusion imaging [22]. The azimuth-compressed echoes satisfy

\[ s_i(n_i, m) = \sum_{p=1}^{P} A_p \exp \left( -j4\pi \frac{n_i \Delta f y_p}{c} \right) \] \[ (i = 1, 2) \] \[ \cdot \exp \left( -j4\pi \frac{f_0 x_p \omega t_m}{c} \right) \]  

(9)

where \( A_p = \alpha_p \cdot \sin c \left( f_d - \frac{\pi}{2} f_0 x_p \omega \right) \), \( f_d \) is the Doppler frequency. Let \( \omega_p = 2\Delta f \frac{f_d}{c} \in (0, 1] \), \( \omega_p \) can be discretized as \( \omega_p = l/L \), \( l = 0, 1, \ldots, L-1 \) and \( L \geq N \).

Denote \( S_1 \) as the echo data of sub-band 1 with the dimension of \( N_1 \times M \), \( S_2 \) is the echo data of sub-band 2 with the dimension of \( N_2 \times M \), and \( S = \begin{bmatrix} S_1 \\ S_2 \end{bmatrix} \) is measurement echo data of the multi-band with the dimension of \( (N_1+N_2) \times M \). According to (9), the sparse representation model of multi-band fusion ISAR imaging with noise can be expressed as

\[ S = \Phi \Psi A + \epsilon = \Theta A + \epsilon \]  

(10)
the dimension of \((N_1+N_2) \times L\), \(\varepsilon\) is the noise matrix with the dimension of \((N_1+N_2) \times M\), \(A\) is the scattering coefficients matrix with the dimension of \(L \times M\), which also represents the fused ISAR image. The measurement matrix \(\Phi\) and the dictionary matrix \(\Psi\) can be expressed as

\[
\Phi = \begin{bmatrix}
I_{N_1 \times N_1} & 0_{N_1 \times (N-N_1)} \\
0_{N_2 \times (N-N_2)} & I_{N_2 \times N_2}
\end{bmatrix}_{(N_1+N_2) \times N}
\]

\[
\Psi = \begin{bmatrix}
\psi_0, \psi_1, \cdots, \psi_{L-1}
\end{bmatrix}_{N \times L}
\]

\[
\psi_l = [\exp\left(-j2\pi \frac{l}{L}\right), \cdots, \exp\left(-j2\pi \frac{(N-1)f}{L}\right)]^T
\]

where \(I\) and \(O\) are the identity matrix and the zero matrix, respectively. According to (10), the multi-band fusion imaging model of the \(m\)-th pulse echo can be written as

\[
S_m = \begin{bmatrix}
s_1 \\
s_2
\end{bmatrix} = \Theta A_m + \varepsilon
\]

where \(A_m\) is the fusion image result corresponding to the \(m\)-th pulse echo data, \(s_1\) and \(s_2\) are the \(m\)-th pulse echo data of sub-band 1 and sub-band 2, respectively. According to (9), we have

\[
s_1 = [s_1(0, m), s_1(1, m), \cdots, s_1(N_1-1, m)]^T
\]

\[
s_2 = [s_2(N-N_2, m), s_2(N-N_2+1, m), \cdots, s_2(N-1, m)]^T
\]

where \(\Gamma(a) = \int_0^\infty \varepsilon^{a-1} e^{-\varepsilon} d\varepsilon\). To ensure the prior non-informative, the scale parameters \(a\) and \(b\) are generally fixed to small values, such as \(a = b = 10^{-4}\) [23]. The likelihood function of the echo \(S\) also follows a complex Gaussian distribution, which can be written as

\[
P(S | \Theta A, \beta^{-1}I) = \prod_{m=1}^M \text{CN}(S_m | \Theta A_m, \beta^{-1}I)
\]

\[
= \pi^{-M} \beta^M \exp\left(-\beta \|S - \Theta A\|_F^2\right)
\]

where \(\|\cdot\|_F\) denotes the Frobenius norm. Assuming that the coefficients \(A_{lm}\) in \(A\) are independent and follow CGSM priors, which consist of a complex Gaussian prior and a Gamma prior. First, \(A_{lm}\) is assumed to follow a complex Gaussian distribution with a mean of zero and a variance of \(\lambda_{lm}^{-1}\). The conditional probability density function of \(A\) is

\[
p(A | \lambda) = \prod_{l=1}^L \prod_{m=1}^M \text{CN}(A_{lm} | \lambda_{lm})
\]

\[
= \prod_{l=1}^L \prod_{m=1}^M \pi^{-1} \lambda_{lm} \exp\left(-\lambda_{lm} A_{lm}^2\right)
\]

Then, the hyperparameter \(\lambda_m\) corresponding to \(A_m\) is assumed to follow an independent Gamma distribution, and the probability density function of \(\lambda_m\) is

\[
p(\lambda_m; c, d) = \prod_{l=1}^L \text{Gamma}(\lambda_{lm} | c, d)
\]

To ensure the prior non-informative, the scale parameters \(c\) and \(d\) are generally fixed to small values, such as \(c = d = 10^{-4}\). The probability graphical model is shown in Figure 1. The filled circle denotes the observation echo data, the open circles represent the unknown variables and open squares indicate the hyperparameters. The scattering coefficients obey hierarchical priors composed of complex Gaussian priors and Gamma priors. Such a hierarchical complex Gaussian-Gamma prior model has a better model flexibility and can derive a sparser solution than a simple Gaussian distribution in SBL algorithm.

### 3.2 Graphical model

Reference [17] theoretically proves the effectiveness of SBL algorithm to achieve multi-band fusion imaging. The SBL algorithm is generally based on the Gaussian prior model and estimate the parameters by Bayesian inference. It can learn the parameters automatically to avoid the manual adjustment, and have high accuracy of parameters estimation. To enhance the flexibility of the model and exploit the statistical characteristics of both noise and scatterers to improve reconstruction performance and the robustness, hierarchical complex Gaussian-Gamma priors are introduced to be imposed on the scattering coefficients and noise. To exploit the same support set characteristics and correlation between the real and imaginary parts of the complex signal, we directly establish the prior model in the complex domain.

Suppose the noise \(\varepsilon\) follows a complex Gaussian distribution with mean of zero and covariance of \(\beta^{-1}I\). The parameter \(\beta\) follows a Gamma distribution as

\[
p(\beta) = \text{Gamma}(\beta | a, b) = \Gamma(a)^{-1} \beta^{a-1} e^{-\beta b}
\]

3.3 VB-EM solution

The VB-EM method is a full Bayesian method, which can avoid the local minimum and structural errors and analytically achieve the posterior of the sparse signal. Hence, the VB-EM method is adopted to derive the sparse reconstruction of high-resolution multi-band fusion images.

Since each column \(A_{mj}\) is independent in \(A\), it can be reconstructed separately with the \(m\)-th pulse echo data \(S_{mj}\). Assuming that the posterior probabilities of unknown variables are independent, and the associated posterior probability can be approximately factored as
\[ p(A_m, \lambda_m, \beta | S_m) \approx q(A_m) q(\lambda_m) q(\beta) \] (19)

where \( q(\cdot) \) is the approximate posterior probability density.

The maximum a posterior (MAP) estimate of \( A_m \) can be derived as [24].

\[ A_m^{MAP} = \langle \beta \rangle \left( \langle \beta \rangle \Theta^H \Theta + \frac{1}{2} A_m \right)^{-1} \Theta^H S_m \] (20)

where \( \langle \cdot \rangle \) represents the expectation, \( A_m = \text{diag}(\lambda_1, \lambda_2, \ldots, \lambda_L) \) represents a diagonal matrix composed of the expectations of the hyperparameters, \( \lambda_i(l = 1, 2, \ldots, L) \). \( q(A_m) \) can be regarded as following a complex Gaussian distribution with mean of \( \mu_m \) and covariance of \( \Sigma_m \), where

\[ \mu_m = A_m^{MAP} = \langle \beta \rangle \Sigma_m \Theta^H S_m \] (21)

\[ \Sigma_m = \langle \langle \beta \rangle \Theta^H \Theta + A_m \rangle^{-1} \] (22)

where \( \mu_m \) also represents the reconstructed fusion image \( A_m \) corresponding to the \( m \)-th pulse echo data \( S_m \). The multiband fusion image can be obtained through the stitching of image results corresponding to each pulse as \( A = [\mu_1 \mu_2 \cdots \mu_M] \).

To obtain the fused image \( A \), it is necessary to estimate the scale parameter \( \lambda \) and noise parameter \( \beta \). If the prior is conjugate to the likelihood, the posterior has the same form as the prior, which is convenient to solve the posterior analytically [25]. The hierarchical Gaussian-Gamma priors are conjugate to the likelihood function, and the specific estimation process can refer to Ref. [24].

From (18), we know that the prior of the scale parameter \( \lambda_m \) is the Gamma distribution, which is conjugate to the likelihood function of Gaussian distribution represented by (17). The posterior probability density \( q(\lambda_m) \) has the same form as the Gamma distribution, which can be expressed as

\[ q(\lambda_m) = \prod_{l=1}^{L} \text{Gamma} \left( \lambda_m | \tilde{c}, \tilde{d}_m \right) \] (23)

where \( \tilde{c} = c + 1, \tilde{d}_m = d + \langle A_m^H \rangle, \langle A_m^H \rangle = \mu_m \mu_m + \Sigma_m, \Sigma_{m,l} \) is the \( l \)-th element on the diagonal in \( \Sigma_m \).

Similarly, the prior of the noise parameter \( \beta \) is the Gamma prior, which is conjugate to the likelihood function of Gaussian distribution. The posterior probability density \( q(\beta) \) also follows the Gamma distribution as

\[ q(\beta) = \text{Gamma}(\beta | \tilde{a}, \tilde{b}) \] (24)

where \( \tilde{a} = a + M(N_1 + N_2), \tilde{b} = b + \langle \| S - \Theta A \|_F^2 \rangle \).

The expectation of the posterior probability is generally exploited as the estimate of the unknown variable in full Bayesian inference. The expectations of the posterior probabilities \( q(A_m), q(\lambda_m) \) and \( q(\beta) \) can be utilized to estimate the unknown variables. Since \( q(A_m) \) follows the complex Gaussian distribution, the mean of the complex Gaussian distribution is the expectation of \( A_m \). According to (21), \( \langle A_m \rangle \) can be derived as

\[ \langle A_m \rangle = \mu_m = \langle \beta \rangle \Sigma_m \Theta^H S_m \] (25)

Since \( q(\lambda_m) \) follow the Gamma distribution according to (23), the scaling parameters \( \tilde{c} \) and \( \tilde{d}_m \) can be utilized to derive the expectations of \( \lambda_m \) as

\[ \langle \lambda_m \rangle = \frac{\tilde{c}}{\tilde{d}_m} = \frac{c + 1}{d + \langle A_m^H \rangle} \] (26)

Since \( q(\beta) \) follow the Gamma distribution according to (24), the scaling parameters \( \tilde{a} \) and \( \tilde{b} \) can be utilized to derive the expectations of \( \beta \) as

\[ \langle \beta \rangle = \frac{\tilde{a}}{\tilde{b}} = \frac{a + M(N_1 + N_2)}{b + \langle \| S - \Theta A \|_F^2 \rangle} \] (27)

### 3.4 Computational complexity analysis

Furthermore, the computational complexity of the proposed algorithm is discussed. In the reconstruction process of the \( m \)-th pulse echo data, \( \Theta \in \mathbb{C}^{(N_1+N_2) \times L}, A_m \in \mathbb{C}^{L \times L}, \Sigma_m \in \mathbb{C}^{L \times L} \) and \( S_m \in \mathbb{C}^{(N_1+N_2) \times 1} \), where \( \mathbb{C} \) denotes the complex domain. The computational complexity of updating \( \Sigma_m \), \( A_m \) and \( \lambda_m \) according to (22), (25) and (26) are \( O(L^3 + (N_1+N_2)L^2), O((N_1+N_2)L^2+(N_1+N_2)L) \) and \( O(L \log L)^2 \), respectively. The computational complexity of updating the parameters of the \( M \) pulses is \( O(ML^3 + 2(N_1+N_2)L^2 + (N_1+N_2)L + L \log L)^2 \). Then, the computational complexity of updating \( \beta \) according to (27) is \( O((N_1+N_2)ML + (N_1+N_2)M) \). The total computational complexity of the proposed algorithm in one iteration is \( O((N_1+N_2)ML + 2(N_1+N_2)L^2 + 2(N_1+N_2)L + (N_1+N_2)L + (N_1+N_2)L \log L)^2) \). To reduce the computational burden introduced in (22), \( \Sigma_m \) can be written as
\( \Sigma_m = \Lambda_m^{-1} - \Lambda_m^{-1}\Theta (\beta I + \Theta \Lambda_m^{-1}\Theta^H)^{-1}\Theta \Lambda_m^{-1} \) in the form of the Woodbury formula.

The solution of the sparse sub-band imaging method with hierarchical priors proposed in [18] is derived in the real domain. In the reconstruction process of the \( m \)-th pulse echo data, the complex-valued signal model in (13) need be converted to a real one as

\[
\begin{bmatrix}
\text{Re}(S_m) \\
\text{Im}(S_m)
\end{bmatrix} = \begin{bmatrix}
\text{Re}(\Theta) & -\text{Im}(\Theta) \\
\text{Im}(\Theta) & \text{Re}(\Theta)
\end{bmatrix} \begin{bmatrix}
\text{Re}(A_m) \\
\text{Im}(A_m)
\end{bmatrix} + \begin{bmatrix}
\text{Re}(\varepsilon) \\
\text{Im}(\varepsilon)
\end{bmatrix}
\]

where \( \text{Re}(\cdot) \) and \( \text{Im}(\cdot) \) denote the real and imaginary parts, respectively. For the convenience of description, we re-define \( S'_m = \frac{\text{Re}(S_m)}{\text{Im}(S_m)}, \quad \Theta' = \begin{bmatrix}
\text{Re}(\Theta) & -\text{Im}(\Theta) \\
\text{Im}(\Theta) & \text{Re}(\Theta)
\end{bmatrix}, \quad A'_m = \frac{\text{Re}(A_m)}{\text{Im}(A_m)} \quad \text{and} \quad \varepsilon' = \begin{bmatrix}
\text{Re}(\varepsilon) \\
\text{Im}(\varepsilon)
\end{bmatrix}. \) We have \( S'_m \in \mathbb{R}^{2(N_1+N_2)L} \) and \( A'_m \in \mathbb{R}^{2L \times 1} \). Similar to the previous computational complexity analysis, if we adopt the real-domain processing mentioned in Ref. [18] to solve the problem in (13), the total computational complexity is

\[
O(M \left(8L^3 + 16(N_1 + N_2)L^2 + 8(N_1 + N_2)L \right) + 2(N_1 + N_2) + 2L \log L)^2)
\]

in one iteration. It shows that the computational complexity of the proposed method directly solved in the complex domain is much lower than that solved in the real domain.

4 | SIMULATION RESULTS AND DISCUSSION

In this section, we conduct the simulation experiments on the one-dimensional signal and two-dimensional ISAR imaging to verify the effectiveness and superiority of the proposed algorithm.

4.1 | Simulation experiments of the one-dimensional signal

Parameters of the radar system are shown in Table 1. Assuming that there are five scatterers along the range dimension, the ideal frequency response of each sub-band can be expressed as

\[
s_i(n_i) = \sum_{p=1}^{3} \sigma_p \exp \left[ -j 4\pi (f_0 + n_i \Delta f) \frac{\Delta r_p}{c} \right] (i = 1, 2)
\]

where \( \sigma_p \) is the scattering coefficient of the \( p \)-th scatterer, and \( \sigma_1 = 3, \sigma_2 = 4, \sigma_3 = 5, \sigma_4 = 6, \sigma_5 = 7, f_0 = 10 \text{GHz} \) is the initial frequency of sub-band 1 and the full-band, \( \Delta f = 5 \text{MHz} \) is the frequency sampling interval, \( \Delta r_p \) is the instantaneous slant range between the \( p \)-th scatterer and the reference point, and \( \Delta r_1 = 0.5 \text{m}, \Delta r_2 = 0.7 \text{m}, \Delta r_3 = 1 \text{m}, \Delta r_4 = 2 \text{m}, \Delta r_5 = 2.5 \text{m} \).

4.1.1 | Performance verification of coherent compensation method

To verify the performance of the proposed coherent compensation method, a linear phase term of \( \alpha = \pi/7 \) and a fixed phase term of \( \eta = \pi/6 \) are added to \( s_2 \). The range profiles of sub-band 1 and sub-band 2 are shown in Figure 2a. Due to the incoherent phase, the range profiles of the two sub-bands are misaligned. Let \( s_i \) be the reference echo, the frequency responses of sub-bands are exploited to perform the coherent compensation. The proposed coherent compensation algorithm is utilized to estimate the incoherent phase. If \( F \) is the coherent processing dictionary, the linear phase term can be discretized as \( \alpha = 2\pi k/K \). When the dictionary dimension \( K = 300 \), the column atom corresponding to \( \alpha \) is \( k = 150/7 \), which is not an integer. It indicates that only the column atom closest to \( k \) can be selected to estimate \( \alpha \). It is a problem with off-grid which affects the estimation accuracy of the incoherent phase. The modified coherent processing dictionary \( \tilde{F} \) is utilized to estimate the incoherent phase. Set the parameter \( Q \) to 1 and 10, respectively. The modified coherent processing dictionary \( \tilde{F} \) is the coherent processing dictionary \( F \) when \( Q = 1 \). The estimate results of the linear phase and the fixed phase are shown in Table 2.

It can be seen from the results that the relative errors of estimating the linear phase and the fixed phase with \( Q = 1 \) are higher than that with \( Q = 10 \). It indicates that the modified coherent processing dictionary \( \tilde{F} \) can improve the estimation accuracy of the incoherent phase than \( F \) with off-grid by

| Table 1 | Parameters of the radar system |
|---|---|---|
| Sub-band 1 | Sub-band 2 | Fusion Band |
| Frequency band/GHz | 10–10.5 | 11.5–12 | 10–12 |
| Signal bandwidth/GHz | 0.5 | 0.5 | 2 |
| Frequency sampling interval/MHz | 5 | 5 | 5 |
| Samples number | 100 | 100 | 400 |
| Range resolution/m | 0.3 | 0.3 | 0.075 |
coherent processing dictionary \( \hat{F} \) with \( Q = 1 \). The results indicate that the proposed coherent compensation method can reduce the impact of off-grid and compensate the incoherent phase between sub-bands effectively. After coherent compensation, the echoes of sub-bands are coherent to be fused.

Furthermore, the white Gaussian noise is added into the frequency responses of sub-bands to verify the anti-noise performance of the proposed coherent compensation method. SNR ranges from 0 to 30 dB, and setting the step size as 3 dB. The pole-based coherent compensation method \cite{14} and the proposed coherent compensation method are utilized to estimate the incoherent phases, respectively. The modified coherent processing dictionary \( \hat{F} \) in the proposed coherent compensation method is set as \( Q = 10 \). 100 independent Monte Carlo trials are performed at each fixed SNR. The root mean square errors (RMSE) of the linear phase and the fixed phase estimation versus SNRs are shown in Figure 4a and Figure 4b, respectively. It can be seen from Figure 4a that the RMSE of the linear phase estimated by the proposed method is very small and changes smoothly with the decrease of SNR. However, the RMSE of the linear phase estimated by the pole-based method is higher than the proposed method and increases obviously with the decrease of SNR. It indicates that the proposed method has better robustness in estimating the linear phase. It can be seen from Figure 4b that the RMSE of the fixed phase estimated by the proposed method is still much lower than the pole-based method. Moreover, the RMSE of the incoherent phase estimated by the pole-based method increases sharply especially when SNR is lower than 15 dB, and the incoherent phase can hardly be estimated correctly. The reason is that the pole-based method is sensitive to noise and cannot estimate the model order accurately with low SNR. However, the incoherent phase and the fixed phase can be estimated accurately by the proposed method even when SNR is 0 dB. The results reflect that the proposed method has a stronger robustness and higher anti-noise performance.

### 4.1.2 Validation of fusion method

After coherent compensation, the coherent signals of sub-bands are utilized to be fused based on the proposed fusion

**Figure 2** Comparison of range profiles with off-grid. (a) Incoherent range profiles; (b) Coherent compensation with \( Q = 1 \); (c) Coherent compensation with \( Q = 10 \).

| \( Q \) | \( Q = 1 \) | \( Q = 10 \) |
|---|---|---|
| The linear phase Estimate value | 0.4398 | 0.4482 |
| Relative error | 2.00% | 0.13% |
| The fixed phase Estimate value | 0.5531 | 0.5312 |
| Relative error | 5.63% | 1.45% |
method. The frequency responses of the full-band and the fusion band are shown in Figure 5a. It can be seen that the frequency response of the fusion band is aligned with the full-band. The results indicate that the proposed fusion method can effectively reconstruct the full-band signal. The range profile of the fusion band obtained by the proposed fusion method and the range profiles obtained by fast Fourier transform (FFT) of the sub-band 1 and the full-band are shown in Figure 5b. We cannot distinguish the five scatterers in the range profile of sub-band 1 due to the poor resolution caused by the narrow bandwidth. The five scatterers can be basically distinguished in the range profile of the full-band due to the improvement of the bandwidth. However, the main lobe broadening and energy leakage exist in the result due to the FFT. While the five scatterers can be completely distinguished in the range profile obtained by the proposed fusion method. The reason is that the proposed fusion method based on sparse representation can break through the Rayleigh limit in the methods based on the Fourier theory. Hence, it can achieve a better resolution than FFT. The fusion performance of the proposed method will be verified further in the simulation experiments of the two-dimensional ISAR imaging.

4.2 Simulation experiments of the two-dimensional ISAR imaging

In this section, the Yak-42 plane real dataset with a carrier frequency of 5.52 GHz and a bandwidth of 400 MHz is utilized to perform the multi-band ISAR fusion imaging experiments. The radar system parameters for the dataset are the same as those in Ref. [26]. The echo data contains 256 pulses and 256 range cells.

4.2.1 Validation of the proposed algorithm

The first 64 and the last 64 range cells of the full band are selected as the echo data of sub-band 1 and sub-band 2 for fusion imaging, respectively. To verify the performance of the proposed coherent compensation method, a linear phase term of \( \alpha = \pi /9 \) and a fixed phase term of \( \eta = \pi /8 \) are added to the echo data of sub-band 2. The white Gaussian noise is added into the echo data of sub-bands and set the SNR equal to 20 dB. The imaging results of sub-band 2 and the fusion band obtained by the range-Doppler (RD) algorithm are shown in Figure 6a and Figure 6b, respectively. It can be seen that the resolution in the imaging result of sub-band 2 is poor due to the narrow bandwidth, and the multi-band fusion imaging cannot be achieved due to the incoherent phase between sub-bands. The proposed coherent compensation method is utilized to estimate and compensate the incoherent phase of each pulse echo data. Figure 7 shows the spectrums before and after the coherent compensation between sub-bands corresponding to the echo data of the 128-th pulse. It can be seen from Figure 7a that the spectrum of sub-band 2 is misaligned with the full-band due to the incoherent phase. It can be seen from Figure 7b that the spectrum of sub-band 2 is aligned with the
full-band after coherent compensation by the proposed method. It indicates that the signals of two sub-bands after coherent compensation are coherent, which verifies the effectiveness of the proposed coherent compensation method.

After coherent compensation, the multi-band fusion imaging results obtained by the RD algorithm and the proposed CGSM method are shown in Figure 8. It can be seen from Figure 8a that large energy leakage and defocus occur in the RD image result due to the missing band data. Compared with Figure 8a, the fusion imaging result in Figure 8b has a better quality with a well-focused image. It indicates that the proposed CGSM method can obtain a high-resolution fusion image with clear outline, which verifies the effectiveness of the proposed fusion method.

4.2.2 | Performance verification of the proposed fusion method

We utilize the $l_1$-norm algorithm [16], SBL algorithm [17] and the proposed CGSM algorithm to achieve multi-band ISAR fusion imaging with the same convergence condition. The first 64 and the last 64 range cells of the full band are selected as the echo data of sub-band one and sub-band 2, respectively. The white Gaussian noise is added into the echo and SNR is set as 20 dB, 10 dB and 0 dB, respectively. The fusion image results obtained by the three algorithms are given in Figures 9–11. As can be seen from Figure 9, the performance of the $l_1$-norm algorithm deteriorates sharply with the decrease of SNR. The image background is not clear due to some artefacts under low

![Image 1](https://example.com/image1.png)

![Image 2](https://example.com/image2.png)

![Image 3](https://example.com/image3.png)
SNR. In particular, the contour of the target is not clear enough to distinguish the geometric structure due to the large number of artefacts when SNR is 0 dB. In comparison, the results of the SBL algorithm in Figure 10 are better than that of the $l_1$-norm algorithm under the same SNR. However, the quality of the results obtained by the SBL algorithm also deteriorates as the SNR decrease and the fusion image is not clear with some artefacts when SNR is 0 dB. Distinctively, as shown in Figure 11, the proposed CGSM algorithm can still obtain well-focused images with clear background even when SNR is 0 dB. It indicates that proposed fusion method has better anti-noise performance than the other two algorithms.

Furthermore, image entropy is utilized as the image quality evaluation indicator. The smaller the value, the better the image quality. The image entropy of imaging results under different SNRs are shown in Table 3. It can be seen that image entropy of the images obtained by CGSM algorithm is the smallest, followed by the SBL algorithm, and the $l_1$-norm algorithm is the highest under the same SNR. It can be seen that image entropy of the images obtained by CGSM algorithm is the
The multi-band imaging results of CGSM algorithm. (a) SNR = 20 dB; (b) SNR = 10 dB; (c) SNR = 0 dB

The multi-band imaging results with $\rho = 50\%$. (a) $l_1$-norm; (b) SBL; (c) CGSM

Image entropy of imaging results under different SNRs

| SNR/dB | 20 | 10 | 5 |
|--------|----|----|---|
| $l_1$-norm | 0.7531 | 0.8144 | 0.8859 |
| SBL | 0.7126 | 0.7407 | 0.7994 |
| CGSM | 0.6923 | 0.7014 | 0.7145 |

The smallest, followed by the SBL algorithm, and the $l_1$-norm algorithm is the highest under the same SNR. It indicates that the fusion image quality of the CGSM algorithm is better than the other two algorithms under the same SNR. Moreover, the image entropy of the CGSM algorithm changes smaller than the other two algorithms with the decrease of SNR. It further verifies the robust anti-noise performance of the proposed algorithm in ISAR fusion imaging.

To verify the fusion performance of the proposed algorithm with different bandwidths of sub-bands, we utilize different sampling numbers of sub-bands to achieve multi-band fusion imaging when SNR is 10 dB. The first $N_1$ and the last $N_2$ range cells of the full band are selected as the echo data of sub-band 1 and sub-band 2, respectively. Define the bandwidth sampling ratio as $\rho = (N_1 + N_2)/N$, where $N$ is the total range cells as 256. Set the sampling range cells of sub-bands to $N_1 = N_2 = 64$ ($\rho = 50\%$), $N_1 = N_2 = 32$ ($\rho = 25\%$) and $N_1 = N_2 = 20$ ($\rho = 15.6\%$), respectively. The fusion image results obtained by the $l_1$-norm algorithm [16], SBL algorithm [17] and the proposed CGSM algorithm are shown in Figures 12–14. As can be seen from Figure 12, the outline of the target can be reconstructed basically by the three algorithms when $\rho = 50\%$. However, a few artefacts exist in the background in the image result obtained by the $l_1$-norm algorithm which affects the image quality. As shown in Figure 13, the quality of the imaging results obtained by the $l_1$-norm algorithm and SBL algorithm have been deteriorated seriously when $\rho$ decreases. The results are defocused and the outline of the target is not clear due to a large number of artefacts, which result in the inability to distinguish the geometric structure of the target correctly. However, as shown in Figure 14, the proposed CGSM algorithm can still reconstruct the outline of the target basically even when $\rho = 15.6\%$. The results indicate that the proposed algorithm has strong robustness to achieve the multi-band fusion imaging with narrow bandwidth in sub-bands.

The image entropy of imaging results with different bandwidth sampling ratios are shown in Table 4. It can be seen from the table that image entropy of the results obtained by the CGSM algorithm is the lowest, followed by the SBL algorithm, and the results obtained by the $l_1$-norm algorithm have the highest image entropy with the same bandwidth sampling ratio.
The multi-band fusion imaging results with $\rho = 25\%$.(a) $\ell_1$ -norm; (b) SBL; (c) CGSM

The multi-band fusion imaging results with $\rho = 15.6\%$. (a) $\ell_1$ -norm; (b) SBL; (c) CGSM

| Image entropy of imaging results with different bandwidth sampling ratios |
|--------------------------------------------------------------------------|
| $\rho/\text{dB}$ | 50   | 25   | 15.6 |
| $\ell_1$ -norm   | 0.8144 | 6.2344 | 4.9521 |
| SBL            | 0.7407 | 7.4923 | 6.7108 |
| CGSM           | 0.7014 | 8.1412 | 7.8923 |

It indicates the CGSM algorithm can obtain better-quality fusion images than the other two algorithms.

5 | CONCLUSION

A joint approach of coherent compensation and high-resolution imaging is proposed for multi-band ISAR fusion imaging. The incoherent phase between sub-bands can be estimated based on sparse representation. Moreover, a modified coherent dictionary is utilized to reduce the estimate error with off-grid. The CGSM priors are developed to establish the ISAR fusion imaging model, which can enhance the model flexibility and exploit the statistic characteristics of noise and scatterers distribution. The parameters and the fusion image can be directly estimated in the complex domain by the VB-EM method, which can derive the parameters adaptively and ensure the reconstruction accuracy. The proposed multi-band ISAR fusion imaging algorithm not only improves the accuracy of coherent compensation with off-grid, but also can obtain high-resolution fusion images under low SNR and low bandwidth sampling ratio.

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