Near-field 3D imaging approach combining MJSR and FGG-NUFFT

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Abstract: A near-field three-dimensional (3D) imaging method combining multichannel joint sparse recovery (MJSR) and fast Gaussian gridding nonuniform fast Fourier transform (FGG-NUFFT) is proposed, based on a perfect combination of the compressed sensing (CS) theory and the matched filtering (MF) technique. The approach has the advantages of high precision and high efficiency: multichannel joint sparse constraint is adopted to improve the problem that the images recovered by the single channel imaging algorithms do not necessarily share the same positions of the scattering centers; the CS dictionary is constructed by combining MF and FGG-NUFFT, so as to improve the imaging efficiency and memory requirement. Firstly, a near-field 3D imaging model of joint sparse recovery is constructed by combining the MF-based imaging method. Secondly, FGG-NUFFT and reverse FGG-NUFFT are used to replace the interpolation and Fourier transform in MF-based imaging methods, and a sensing matrix with high precision and high efficiency is constructed according to the traditional imaging process. Thirdly, a fast imaging recovery is performed by using the improved separable surrogate functionals (SSF) optimization algorithm, only with matrix and vector multiplication. Finally, a 3D imagery of the near-field target is obtained by using both the horizontal and the pitching interferometric phase information. This paper contains two imaging models, the only difference is the sub-aperture method used in inverse synthetic aperture radar (ISAR) imaging. Compared to traditional CS-based imaging methods, the proposed method includes both forward transform and inverse transform in each iteration, which improves the quality of reconstruction. The experimental results show that, the proposed method improves the imaging accuracy by about $O(10)$, accelerates the imaging speed by five times and reduces the memory usage by about $O(10^2)$.

Keywords: interference imaging, joint sparse recovery, compressed sensing (CS), matching filtering (MF), fast Gaussian gridding, nonuniform fast Fourier transform (NUFFT), near-field 3D imaging.

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1. Introduction

Near-field microwave imaging systems have been successfully developed for applications in the fields of security check, concealed weapon detection, nondestructive testing (NDT), through-wall and inner wall imaging, etc [1–6]. These systems employ microwave probes to scan targets, and two-dimensional/three-dimensional (2D/3D) images are reconstructed from the measurements via synthetic aperture radar (SAR) transform or inverse SAR (ISAR) transform. The near-field microwave imaging system has attracted more and more attention because of the high resolution and wide applications. So far, a large number of near-field imaging algorithms have emerged, such as range migration algorithm (or $\omega - k$ imaging algorithm) [7], polar format imaging [8], back-projection algorithm [9], space-time beamforming imaging [10], nonuniform FFT (NUFFT)-based imaging algorithm [11], and compressed sensing (CS)-based imaging [12].

Since the interference imaging system is easy to implement, this paper focuses on the interference near-field imaging. For the interferometric synthetic aperture radar (InSAR) system [13,14], a 3D image of a target is obtained by proposing the interference phase information of multi-antenna. The key to the interferometric imaging technology is the acquisition of high resolution 2D images. Traditional matched filtering (MF)-based near-field imaging methods have some limitations. (i) The images are affected

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by the side lobes, which is not conducive to the extraction of real scatter point information. (ii) In order to achieve high azimuth resolution, a large azimuthal synthetic aperture (or azimuth accumulation angle) is required, which increases the complexity of the antenna motion. (iii) In order to get a higher range resolution, it is necessary to transmit a large bandwidth signal, which greatly increases the data volume.

Recently, the CS theory has been widely used to reduce the amount of data, reduce the sampling rate, and reconstruct with a high probability when the data is under-sampled [15,16]. The CS theory has several advantages in microwave imaging: enhanced imaging performance, simplified hardware design, and reduced data acquisition time. Since Baraniuk [17] applied CS to microwave imaging for the first time in 2007, the application of CS in microwave imaging has rapidly developed and become an important branch of high-resolution microwave imaging research. In [18], a 2D fast iterative shrinkage-thresholding algorithm (FISTA)-based CS near-field imaging approach was proposed. The method firstly compensates the spherical wave as a plane wave, and then separates the 2D data into two 1D data for imaging processing. In [19], two methods for the wide-angle 3D image were proposed. A sparsity-constrained regularized least-squares technique is used to form a 3D image in one method. The other one, the Tomo-SAR approach, is tailored to a particular sparse data collection.

The existing CS-based interferometric 3D imaging has the following problems. (i) Low imaging accuracy. Existing methods do not make full use of the correlation between multiple channels, resulting in errors in interference phase extraction. (ii) Low imaging efficiency. At present, the reconstruction is mainly performed by the echo vectorization into the single measurement vector model, which is very time consuming and takes up a lot of memory.

For the low imaging accuracy of single-channel processing imaging, this paper proposes a 3D imaging algorithm by using multichannel joint sparse recovery (MCJSR). The proposed method, which utilizes the correlation between multi-channel echo signals, improves the reconstruction accuracy, and effectively maintains the relative phase information between channels. A higher-precision interference phase information is obtained, and high-quality 3D imaging is realized.

The essence of the CS theory is to convert the pressure at the sampling to the signal processing, and its computational complexity is greatly increased. It is mainly reflected in the nonlinear massive operation of recovering from the multi-dimensional information of the sparsely signal. How to achieve fast imaging is the first problem that must be

solved. For the rapid reconstruction of the imaging scene, the current research ideas mainly have three directions. (i) Reduce the dimensions of the echo to be processed. In order to avoid the high complexity and large storage capacity brought by the vectorization operation, in [20] a separable perceptual operator framework was designed, which used two low-dimensional measurement matrices to obtain an equivalent vector matrix. In addition, the idea of segmented reconstruction was proposed in [21], which was to reconstruct a large scene after dividing it into many small scenes. However, this method will lose performance. (ii) Reduce the complexity of the algorithm. It mainly includes two aspects, one is to reduce the number of iterations during the reconstruction [22], and the other is to reduce the complexity of each iteration. For example, in [23], the matrix vector multiplication complexity was reduced by using the non-uniform FFT idea. (iii) Combined with the traditional imaging method, the traditional MF idea is used to improve the efficiency. For example, in [24], the MF was combined with CS to realize the efficient reconstruction of SAR images. In order to speed up the reconstruction, this paper takes the following two steps: firstly, combine fast Gaussian gridding-nonuniform FFT (FGG-NUFFT) and MF, construct the dictionary matrix according to the forward SAR/ISAR transform and the R-SAR/R-ISAR transform, and reduce the complexity of the algorithm itself; secondly, adopt the improved SSF algorithm to further accelerate the reconstruction.

We combine MCJSR and FGG-NUFFT, and propose a near-field imaging method, which is based on the advantages of CS, interferometric imaging, and FGG-NUFFT. The proposed method combines the CS theory with the MF-based imaging method, and the sensing matrix is constructed according to the traditional MF-based SAR/ISAR imaging process, with which the dictionary scale is reduced. The forward FGG-NUFFT and inverse FGG-NUFFT are correspondingly used in both forward SAR/ISAR and reverse SAR/ISAR in each iteration, which both improve the imaging efficiency and imaging accuracy. Numerical simulations and microwave anechoic chamber experiments show that, compared with the traditional CS-based interferometric imaging methods, the proposed method has the following advantages: (i) improve the recovery precision of strong centers, and preserve effectively the relative phase information between different channels; (ii) accelerate the imaging speed and reduce complexity; (iii) reduce memory usage.

2. Multi-channel near-field 3D imaging model

The multi-channel near-field imaging model based on FGG-NUFFT for both SAR and ISAR is established in this

section. It should be noted that in the large-angle ISAR imaging mode, in order to obtain better imaging quality, the entire imaging interval is generally divided into several sub-apertures with overlapping segments for processing, that is, sub-aperture synthesis.

2.1 Interferometric ISAR imaging model

Fig. 1 shows the geometric model of the near-field InSAR imaging system. y' is the line of sight of radar, x' and x are parallel, z' and z are parallel. The distance from the

origin of the antenna coordinates to the origin of the target coordinates is R_0 ($R_0 < \frac{4D^2}{\lambda}$, D is the maximum size of the target, when the distance R between the imaging observation point and the scattering target body is smaller than the target outer diameter size, it becomes near-field measurement/imaging). The target rotates around the origin of the coordinate, and the angular velocity of rotation is ω . The coordinate of any scattering point P on the target is (r, θ, z) . Then, at the moment of t , the distance from the transceiver l ($l \in \{A, B\}$) to the target P is

$$R_l(r, \theta; t) = \sqrt{(R_0 + r \cos(\theta + \omega t))^2 + (r \sin(\theta + \omega t))^2 + (R_0 \tan \alpha_i - z)^2} = \sqrt{(R_0 + y)^2 + x^2 + (R_0 \tan \alpha_i - z)^2} \quad (1)$$

where α_i represents the pitch angle of the i th antenna, (x, y, z) is the Cartesian coordinate position of the target.

Fig. 1 Geometry model for multi-channel near-field ISAR imaging

The echo signal obtained by antenna A (or B) is

$$S_l(f, \theta) = \iint_{(x,y) \in D} g_l(x, y) \exp\left(-j \frac{4\pi f R_l}{c}\right) dx dy \quad (2)$$

where D indicates the area where the imaging scene is located, $g_l(x, y)$ represents the scattering coefficient of the target $P(x, y)$.

We express (2) as a summation form:

$$S_l(f, \theta) = \sum_{x=1}^P \sum_{y=1}^Q g_l(x, y) \exp\left[-j \frac{4\pi}{\lambda} R_l(x, y)\right] \quad (3)$$

where P and Q represent the number of discretized grids along the x and y axes, respectively.

We discretize the frequency and azimuth samples, where the frequency sampling number is N and the azimuth sampling number is M . Then $f_n = f_0 + (n - 1)\Delta f$ ($n = 1, 2, \dots, N$), $\theta_m = (m - 1)\Delta\theta$, $m = 1, 2, \dots, M$. Equation (3) can be expressed as follows:

$$S_l(f_n, \theta_m) =$$

$$\sum_{x=1}^P \sum_{y=1}^Q g_l(x, y) \exp\left[-j \frac{4\pi f_n}{c} R_l(x, y; \theta_m)\right] \quad (4)$$

We consider the above ISAR imaging as a wide-angle imaging problem based on the geometric transformation relationships. In wide-angle imaging, the scattering coefficient varies with the angle, namely the anisotropy. We divide the angle equally by using the concept of sub-aperture for imaging. Then, the echo signal for each $\theta_{m'}$ ($\theta_{m'} = m'\theta_m$, $m = 1, 2, \dots, M$) angle is expressed as follows:

$$S_{l-\text{sub}}(x', k_r) = \sum_{x=1}^P \sum_{y=1}^Q g_l(x, y) \exp[-j 2k_r R_l] \quad (5)$$

where x' is the equivalent moving length of the antenna when the angle is $\theta_{m'}$, $k_r = \frac{2\pi f}{c}$ ($f = \sum_{m=0}^{M-1} f_m$) refers to the wave number.

2.2 Interferometric SAR imaging model

Fig. 2 shows the geometric model of the InSAR near-field imaging system. Transceiver A and transceiver B move along l_a and l_b respectively, with l_a and l_b parallel to the x' axis. The pitch angles of transceiver A and transceiver B with respect to the target center are both α . The antennas transmit a step frequency signal.

The echo signal obtained by antenna A (or B) is

$$S_l(x', k_r) = \iint_{(x,y) \in \Omega} g_l(x, y) \exp(-j 2k_r R_l) dx dy \quad (6)$$

where $l \in \{A, B\}$, $k_r = \frac{2\pi f}{c}$ ($f = \sum_{m=0}^{M-1} f_m$) refers to the wave number, and Ω indicates the area where the imaging

scene is located, $g_l(x, y)$ represents the scattering coefficient of the target $P(x, y)$, $R_l = \sqrt{(x - x')^2 + (y + R_0)^2}$ represents the distance from the l th antenna to the target.

The discretized expression of (6) is

$$S_l(x', k_r) = \sum_{x=1}^P \sum_{y=1}^Q g_l(x, y) \exp(-j2k_r R_l). \quad (7)$$

Fig. 2 Geometry model for multi-channel near-field SAR imaging

2.3 Unified multi-channel near-field imaging model based on FGG-NUFFT

In the near-field measurement, the target scattered wave is a spherical wave, and the spherical wave is first converted into a superposition of a plurality of plane waves. Solving for $g_l(x, y)$ in (4) and (7), we have

$$g_l(x, y) = \mathbf{F}_{2D}^{-1} \{ ST \{ \mathbf{F}_{1D} \{ S_l(x', k_r) \} e^{-j\sqrt{4k_r^2 - k_x^2} R_0} \} \} \quad (8)$$

where k_x is the Fourier transform variable corresponding to x' , R_0 is the minimum distance between the probes and targets, $\mathbf{F}_{2D}^{-1} \{ \cdot \}$ and $\mathbf{F}_{1D} \{ \cdot \}$ denote the 2D inverse FFT (IFFT) and the 1D FFT, respectively. $ST \{ \cdot \}$ denotes Stolt interpolation.

The frequency is uniformly sampled and the probe scans at the uniform spatial step size. Consequently, k_y is non-uniformly distributed and Stolt interpolation is usually used to achieve uniform k_y [25]. In (8), the role of $ST \{ \cdot \}$ is to correct the range migration in near-field imaging, while regularizing the spectrum to facilitate IFFT. This operation is not only time consuming, but also causes great imaging error. NUFFT is a common method for analyzing non-uniform sampling [26]. In [27], FGG-NUFFT was proposed for speeding up NUFFT transformation. In near-field measurements, the frequency samples are non-uniformly sampled, i.e., the samples for k_y are non-uniformly sampled, so we perform a 1D NUFFT or NUIFFT for k_y .

The calculation expression for the 1D NUFFT is

$$\mathbf{F}_\eta(k) \approx \sum_{m=0}^{M_r-1} \mathbf{f}_\eta \left(\frac{2\pi m}{M_r} \right) e^{-\frac{jk2\pi m}{M_r}} \quad (9)$$

where

$$\mathbf{f}_\eta \left(\frac{2\pi m}{M_r} \right) = \sum_{i=0}^{N-1} \mathbf{f}_i g_\eta \left(\frac{2\pi m}{M_r} - x_i \right) = \sum_{i=0}^{N-1} \mathbf{f}_i \sum_{l=-\infty}^{\infty} e^{-\frac{(x_i - \frac{2\pi m}{M_r} - 2l\pi)^2}{4\eta}} \quad (10)$$

$$g_\eta(x) = \sum_{l=-\infty}^{\infty} e^{-\frac{(x - 2l\pi)^2}{4\eta}}. \quad (11)$$

Details of this algorithm can be found in [27].

Therefore, (8) becomes

$$g_l(x, y) = \mathbf{F}_{1D, k_x}^{-1} \{ \mathbf{F}_{NU, k_y}^{-1} \{ \mathbf{F}_{1D, x'} \{ S_l(x', k_r) \} e^{-j\sqrt{4k_r^2 - k_x^2} R_0} \} \} \quad (12)$$

where $\mathbf{F}_{NU, k_y}^{-1} \{ \cdot \}$ is the one dimensional inverse NUFFT operator in the k_y domain, $\mathbf{F}_{1D, k_x}^{-1} \{ \cdot \}$ is the one dimensional inverse FFT operator in the k_x domain, $\mathbf{F}_{1D, x'}^{-1} \{ \cdot \}$ is the one dimensional FFT in the x' domain. We can get a 2D image of the imaging scene in the l th channel through (12).

3. Accelerating high-precision near-field 3D imaging with MCJSR

3.1 Imaging model of joint sparse constrained

Equation (12) can be described as the matrix form:

$$\mathbf{g}_l = \mathbf{F}_{1D, k_x}^{-1} \{ \mathbf{F}_{NU, k_y}^{-1} \{ \mathbf{F}_{1D, x'} \{ S_l \} \cdot \mathbf{E} \} \} = \mathbf{A}^{-1} S_l \quad (13)$$

where S_l is the observation signal, $\mathbf{A}$ is the sensing matrix, and $\mathbf{g}_l$ is made up of the reflection coefficient of the scene.

Matrix $\mathbf{E}$ represents the matched filtering item, and it is defined as follows:

$$\mathbf{E} = \begin{bmatrix} e_{(1,1)} & e_{(1,2)} & \cdots & e_{(1,l)} & \cdots & e_{(1,N)} \\ \vdots & & \ddots & & \ddots & \vdots \\ e_{(M,1)} & e_{(M,2)} & \cdots & e_{(M,l)} & \cdots & e_{(M,N)} \end{bmatrix}. \quad (14)$$

The expression of $e_{(i,j)}$ is

$$e_{(i,j)} = [e^{-j\sqrt{4k_{ri}^2 - k_{xj}^2} R_0}], \quad 1 < i < M; 1 < j < N. \quad (15)$$

Equation (13) represents the forward SAR transform in imaging based on matched filtering, and the reverse SAR transform is formulated as follows:

$$S_l = \mathbf{F}_{1D, x'}^{-1} \{ \mathbf{F}_{NU, k_y} \{ \mathbf{F}_{1D, k_x} (\mathbf{g}_l) \} \cdot \mathbf{E}^* \} = \mathbf{A} \mathbf{g}_l. \quad (16)$$

In interference imaging, the echo signals received by the two antennas can be represented as an overall signal:

$$\mathbf{S} = \begin{bmatrix} \mathbf{S}_1 \\ \mathbf{S}_2 \end{bmatrix} = \mathbf{A}_0 \mathbf{g} + \mathbf{e} = \begin{bmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{0} & \mathbf{A} \end{bmatrix} \begin{bmatrix} \mathbf{g}_1 \\ \mathbf{g}_2 \end{bmatrix} + \begin{bmatrix} \mathbf{e}_1 \\ \mathbf{e}_2 \end{bmatrix} \quad (17)$$

where $\mathbf{S}$ and $\mathbf{A}_0$ correspond with the overall echo signal and composite dictionary, respectively, $\mathbf{g}$ represents the composite scattering coefficient, and $\mathbf{e}$ represents composite noise. Since the processing of the echo signals is consistent, the dictionary is also consistent in the interference channel.

When the Nyquist sampling theorem is satisfied, the number of frequency samples is N , and the number of azimuth samples is M . After sparse sampling (or compressed sampling), the $M'(M' \leq M)$ and $N'(N' \leq N)$ group echo data are randomly selected in M and N respectively. The signal model is

$$\mathbf{S}' = \Phi \mathbf{S} = \begin{bmatrix} \Phi_1 & \mathbf{0} \\ \mathbf{0} & \Phi_2 \end{bmatrix} \mathbf{S} = \Phi \mathbf{A} \mathbf{g} + \Phi \mathbf{e} = \mathbf{A}' \mathbf{g} + \mathbf{e}' \quad (18)$$

where $\mathbf{S}'$ represents a sparse interference signal with the size of $2M' \times N'$, $\Phi_i = \Phi_i^a \otimes \Phi_i^r$ represents the sparse sampling matrix of the two channels, $\otimes$ refers to the Kronecker product, $\mathbf{A}'$ represents a composite sensing matrix.

Solving (18) is an NP-hard problem. When the sensing matrix $\mathbf{A}'$ satisfies the restricted isometry property (RIP) [28], we can reconstruct the original image with high probability through the optimization technique.

The traditional CS reconstruction method is to vectorized $\mathbf{S}$ and $\mathbf{g}$. Different from this method, this paper directly processes the 2D echo signal and imaging. Based on the joint sparse reconstruction model constructed in (18), we will describe in detail the dictionary construction, reconstruction algorithm.

3.2 Dictionary design combining MF-based imaging technique and FGG-NUFFT

The combination of the CS theory and the traditional imaging approach will improve the imaging efficiency and accuracy. Based on the description of (13) and (16), we will present a dictionary design process based on the MF-based imaging process and FGG-NUFFT.

According to (13) and (16), the expression of $\mathbf{A}$ and $\mathbf{A}^{-1}$ can be expressed as matrix multiplication:

$$\begin{cases} \mathbf{A} = \mathbf{F}_{1D,x'}^{-1} \times \mathbf{F}_{NU,k_y} \times (\mathbf{F}_{1D,k_x} \circ \mathbf{E}^*) \\ \mathbf{A}^{-1} = \mathbf{F}_{1D,k_x}^{-1} \times \mathbf{F}_{NU,k_y}^{-1} \times (\mathbf{F}_{1D,x'} \circ \mathbf{E}) \end{cases} \quad (19)$$

where $\mathbf{A}^{-1}$ and $\mathbf{A}$ respectively represent the forward transform and the inverse transform processes of SAR imaging

based on matched filtering techniques, $\times$ denotes the matrix product, $\circ$ denotes the Hadamard product, $\mathbf{E}^*$ is the complex conjugate of $\mathbf{E}$.

$\mathbf{F}_{1D,k_x}$ represents 1D FFT along k_x domain, and is defined as follows:

$$\mathbf{F}_{1D,k_x} = \frac{1}{\sqrt{M}} \begin{bmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & \psi & \psi^2 & \cdots & \psi^{(M-1)} \\ 1 & \psi^2 & \psi^4 & \cdots & \psi^{2(M-1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \psi^{(M-1)} & \psi^{2(M-1)} & \cdots & \psi^{(M-1)(M-1)} \end{bmatrix}, \quad (20)$$

with $\psi = e^{-j\frac{2\pi}{M}}$.

$\mathbf{F}_{NU,k_y}$ is the one dimensional NUFFT along k_r domain, and is defined as follows:

$$\mathbf{F}_{NU,k_y} = \frac{1}{\sqrt{N}} \begin{bmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & \omega & \omega^2 & \cdots & \omega^{(N-1)} \\ 1 & \omega^2 & \omega^4 & \cdots & \omega^{2(N-1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \omega^{(N-1)} & \omega^{2(N-1)} & \cdots & \omega^{(N-1)(N-1)} \end{bmatrix} \quad (21)$$

where $\omega = e^{-jk_x}$.

In order to solve $\mathbf{g}_l$ by (13) with high probability, the dictionary $\mathbf{A}$ constructed shall satisfy orthogonality requirements. Since $\mathbf{F}_{1D,x'}$, $\mathbf{F}_{1D,k_x}^{-1}$ and $\mathbf{F}_{NU,k_y}$ respectively refer to 1D FFT, 1D IFFT, and 1D NUFFT, then

$$\begin{cases} \mathbf{F}_{1D,x'} \mathbf{F}_{1D,k_x}^{-1} = \mathbf{I} \\ \mathbf{F}_{NU,k_y} \mathbf{F}_{NU,k_y}^{-1} = \mathbf{I} \end{cases} \quad (22)$$

$\mathbf{E}\mathbf{E}^{-1}$ refers to a complex diagonal matrix:

$$\mathbf{E}\mathbf{E}^{-1} = \text{diag}(e_1, e_2, \dots, e_{MN}) \quad (23)$$

then

$$\begin{aligned} \mathbf{A}\mathbf{A}^{-1} &= \mathbf{F}_{1D,k_x}^{-1} \mathbf{F}_{NU,k_y} \mathbf{E} \mathbf{F}_{1D,x'} \\ &= (\mathbf{F}_{1D,k_x}^{-1} \mathbf{F}_{NU,k_y} \mathbf{E} \mathbf{F}_{1D,x'})^{-1} = \\ &= \mathbf{F}_{1D,k_x}^{-1} \mathbf{F}_{NU,k_y} \mathbf{E} (\mathbf{F}_{1D,x'} \mathbf{F}_{1D,k_x}^{-1}) \mathbf{E}^{-1} \\ &= \mathbf{F}_{NU,k_y}^{-1} \mathbf{F}_{1D,x'} = \text{diag}(e_1, e_2, \dots, e_{MN}). \end{aligned} \quad (24)$$

Thus, dictionary $\mathbf{A}$ is orthogonal, and thus $\Phi \mathbf{A}$ satisfies the RIP property.

$\mathbf{A}^{-1}$ and $\mathbf{A}$ represent the forward SAR transform matrix and R-SAR transform matrix, respectively, and their construction processes are shown in Fig. 3.

Fig. 3 Imaging flow chart for joint CS and FGG-NUFFT

3.3 Joint sparse constrained reconstruction algorithm

In the interferometric imaging system, the observation targets are identical, so the images of each channel have the same target support area, that is, the scattering points on the target are aligned in the respective channel images. The single-channel independent processing imaging method fails to utilize this prior information, so the number and position of scattering points in the reconstructed image of each channel cannot be guaranteed. That is to say, it is impossible to ensure that all scattering points are located in the same pixel of two images. Based on the correlation between multiple channels, we establish a joint sparse solution model:

$$\|\mathbf{g}\|_{2,0} = \|(|\mathbf{g}_1|^2 + |\mathbf{g}_2|^2)^{\frac{1}{2}}\|_0. \quad (25)$$

Based on the joint sparse model constructed in Section 3.1 and (25), we transform near-field interference imaging into joint sparse constraint solving:

$$\min_{\mathbf{g}_1, \mathbf{g}_2} \|\mathbf{g}\|_{2,0} \quad \text{s.t.} \quad \begin{cases} \|\mathbf{s}'_1 - \mathbf{A}\mathbf{g}_1\|_2^2 \leq \xi \\ \|\mathbf{s}'_2 - \mathbf{A}\mathbf{g}_2\|_2^2 \leq \xi \end{cases}. \quad (26)$$

According to the Bayesian CS theory, using the maximum posterior probability estimation method, $\mathbf{g}_l$ can be solved by the following sparse constrained optimization problem [13]:

$$\min_{\mathbf{g}_1, \mathbf{g}_2} \|\mathbf{g}\|_{2,0} \quad \text{s.t.} \quad \begin{cases} \mathbf{g}_1 = \arg \min \left\{ \frac{1}{2} \|\mathbf{S}'_1 - \mathbf{A}\mathbf{g}_1\|_2^2 + \lambda \|\mathbf{g}_1\|_1 \right\} \\ \mathbf{g}_2 = \arg \min \left\{ \frac{1}{2} \|\mathbf{S}'_2 - \mathbf{A}\mathbf{g}_2\|_2^2 + \lambda \|\mathbf{g}_2\|_1 \right\} \end{cases}. \quad (27)$$

Currently, there are many algorithms to solve the minimization problem of (27), for example, steepest-descent and conjugate-gradient. However, these methods are often found inefficient, requiring too many iterations and too many computations to reach their destination.

Rewrite (27) and express it as a functional form:

$$f(\mathbf{g}) = \frac{1}{2} \|\mathbf{S} - \mathbf{A}\mathbf{g}\|_2^2 + \lambda \|\mathbf{g}\|_1. \quad (28)$$

We adopt the SSF method based on the proximal point to solve it. Denoting $\mathbf{g}_0 = \mathbf{A}^{-1}\mathbf{S}$, we get

$$f(\mathbf{g}) = \frac{1}{2} \|\mathbf{S} - \mathbf{A}\mathbf{g}\|_2^2 + \lambda \|\mathbf{g}\|_1 = \sum_{k=1}^m \left[\frac{1}{2} (\mathbf{g}_0(k) - \mathbf{g}(k))^2 + \lambda |\mathbf{g}(k)| \right]. \quad (29)$$

Construct the scalar function from (29), $\eta(\tau) = \lambda|\tau| + 0.5(\tau_0 - \tau)^2$, and its solution is

$$\tau = \begin{cases} 0, & |\tau_0| \leq \lambda \\ \tau_0 - \text{sign}(\tau_0)\lambda, & \text{otherwise} \end{cases}. \quad (30)$$

Add the following to (30):

$$d(\mathbf{g}, \mathbf{g}_0) = \frac{c}{2} \|\mathbf{g} - \mathbf{g}_0\|_2^2 - \frac{1}{2} \|\mathbf{A}\mathbf{g} - \mathbf{A}\mathbf{g}_0\|_2^2 \quad (31)$$

where $c > \|\mathbf{A}^{-1}\mathbf{A}\|_2 = \lambda_{\max}(\mathbf{A}^{-1}\mathbf{A})$, which is used to ensure that the function is a strictly convex function. This new objective function is

$$\begin{aligned} \tilde{f}(\mathbf{g}) &= \frac{1}{2} \|\mathbf{S} - \mathbf{A}\mathbf{g}\|_2^2 + \lambda \|\mathbf{g}\|_1 + \\ &\quad \frac{c}{2} \|\mathbf{g} - \mathbf{g}_0\|_2^2 - \frac{1}{2} \|\mathbf{A}\mathbf{g} - \mathbf{A}\mathbf{g}_0\|_2^2. \end{aligned} \quad (32)$$

Equation (32) is the separable cost function to be used in the proposed algorithm. We expand and recombine (32):

$$\begin{aligned}\tilde{f}(\mathbf{g}) &= \frac{1}{2}\|\mathbf{S} - \mathbf{A}\mathbf{g}\|_2^2 + \lambda\|\mathbf{g}\|_1 + \frac{c}{2}\|\mathbf{g} - \mathbf{g}_0\|_2^2 - \\ &\quad \frac{1}{2}\|\mathbf{A}\mathbf{g} - \mathbf{A}\mathbf{g}_0\|_2^2 = \\ &\quad \frac{1}{2}\|\mathbf{g}\|_2^2 + \frac{1}{2}\|\mathbf{A}\mathbf{g}_0\|_2^2 + \frac{c}{2}\|\mathbf{g}_0\|_2^2 - \mathbf{S}^{-1}\mathbf{A}\mathbf{g} + \lambda\|\mathbf{g}\|_1 + \\ &\quad \frac{c}{2}\|\mathbf{g}\|_2^2 - c\mathbf{g}^{-1}\mathbf{g}_0 + \mathbf{g}^{-1}\mathbf{A}^{-1}\mathbf{A}\mathbf{g}_0 = \\ \text{Const} - \mathbf{g}^{-1}[\mathbf{A}^{-1}(\mathbf{S} - \mathbf{A}\mathbf{g}_0) + c\mathbf{g}_0] + \lambda\|\mathbf{g}\|_1 + \frac{1}{2}\|\mathbf{g}\|_2^2.\end{aligned}\quad (33)$$

The constant in the equation are determined by $\mathbf{S}$ and $\mathbf{g}_0$. We define an intermediate expression:

$$\mathbf{V}_0 = \frac{1}{c}\mathbf{A}^{-1}(\mathbf{S} - \mathbf{A}\mathbf{g}_0) + \mathbf{g}_0. \quad (34)$$

Now we can rewrite $\tilde{f}(\mathbf{g})$ as follows:

$$\begin{aligned}\tilde{f}(\mathbf{g}) &= \text{Const} - \mathbf{g}^{-1}\mathbf{V}_0 + \frac{\lambda}{c}\|\mathbf{g}\|_1 + \frac{1}{2}\|\mathbf{g}\|_2^2 = \\ &\quad \text{Const} + \frac{\lambda}{c}\|\mathbf{g}\|_1 + \frac{1}{2}\|\mathbf{g} - \mathbf{V}_0\|_2^2.\end{aligned}\quad (35)$$

This penalty function is exactly the one we minimized for the unitary case, and the solution is given as follows:

$$\mathbf{g}_{\text{out}} = \zeta_{\lambda/c}(\mathbf{V}_0) = \zeta_{\lambda/c}\left(\frac{1}{c}\mathbf{A}^{-1}(\mathbf{S} - \mathbf{A}\mathbf{g}_0) + \mathbf{g}_0\right). \quad (36)$$

Equation (36) is a global minimizer of the function $\tilde{f}(\mathbf{g})$ in (32).

So far we manage to convert the original function f to a new function $\tilde{f}$, for which we are able to get a closed-form expression for its global minimizer. Thus, the proposed algorithm is simply an iterative application of (36) in the form:

$$\mathbf{g}_{k+1} = \zeta_{\lambda/c}\left(\frac{1}{c}\mathbf{A}^{-1}(\mathbf{S} - \mathbf{A}\mathbf{g}_k) + \mathbf{g}_k\right). \quad (37)$$

Equations (28) to (37) describe the solution process for $\mathbf{g}$ in a signal channel. Below we present a joint sparse solution flow for (32).

Task: Find $\mathbf{g}$ that meets (26).

Initialization: Initialize $k = 0$, $\mathbf{g}_{i,0} = 0$, $\mathbf{r}_{i,0} = \mathbf{S}_i - \mathbf{A}\mathbf{g}_{i,k} = \mathbf{S}_i$.

Iteration: k adds 1 to each cycle, and apply these steps:

(i) Back-projection: compute

$$\mathbf{e}_k = \sum_{i=1}^2 (|\langle \mathbf{r}_{i,k-1}, \mathbf{A}^{-1} \rangle|^2)^{\frac{1}{2}}.$$

(ii) Shrinkage: compute $\mathbf{e}_{i,k}^* = \text{Shrink}(\mathbf{g}_{i,k-1} + \frac{\mathbf{e}_k}{c})$ with λ .

(iii) Line search: choose μ to minimize the real valued function $f(\mathbf{g}_{i,k-1} + \mu(\mathbf{e}_{i,k}^* - \mathbf{g}_{i,k-1}))$.

(iv) Update solution: compute $\mathbf{g}_{i,k} = \mathbf{g}_{i,k-1} + \mu(\mathbf{e}_{i,k}^* - \mathbf{g}_{i,k-1})$.

(v) Update residual: compute $\mathbf{r}_{i,k} = \mathbf{S}_i - \mathbf{A}\mathbf{g}_{i,k}$.

(vi) Stopping rule: if $\|\mathbf{g}_{i,k} - \mathbf{g}_{i,k-1}\|_2^2$ is smaller than some predetermined threshold, stop. Otherwise, apply another iteration.

Output: The result is $\mathbf{g}_{i,k}$.

3.4 Imaging process description

Fig. 4 shows the detailed and complete flow of the proposed imaging method. The proposed method is suitable for near-field SAR imaging and ISAR imaging. In the imaging process, we equal the near-field ISAR imaging to wide-angle SAR imaging. Therefore, the ISAR imaging is divided into several sub-apertures for imaging processing. In Fig. 4, the dashed box indicates the sub-aperture processing in ISAR imaging.

4. Experiments and analysis

In this section, we verify the validity of the proposed method, including the imaging accuracy, imaging efficiency, imaging performance under different sparsities, and imaging performance with different noises. In order to better illustrate the imaging accuracy of the proposed approach, the experimental part adopts a simple target that can better reflect the position information of the scattering point.

4.1 Near-field InISAR imaging

Firstly, we validate the algorithm by using generic Backhoe data. Fig. 5 shows the computer aided-design (CAD) model of Backhoe. In the Backhoe data set, two sets of data with pitch angles of 42° and 42.07° are selected as the interference imaging raw data, and divide it into 17 sub-apertures. Table 1 shows the detailed parameters.

Table 1 Backhoe electromagnetic simulation parameters

Parameter	Value
Center frequency/GHz	10
Bandwidth/GHz	6
Sampling number of frequency	512
Azimuth accumulation angle/($^\circ$)	51
Sampling number of direction	71*17
Pitch angle/($^\circ$)	0.07

Fig. 4 Imaging flow of proposed method

Fig. 5 3D CAD electromagnetic simulation model of Backhoe

Fig. 6 is a comparison of the imaging method proposed with a traditional imaging method. Fig. 6(a), Fig. 6(c), and Fig. 6(e) show the results of imaging by using the single-channel independently processed CS imaging method proposed in [13]. It can be seen from Fig. 6 that the single-channel independent processing imaging method has a distorted position of the scattering point and cannot be prepared to describe the target geometric information. The imaging proposed in this paper can accurately reflect the target geometric information. The reason for the above results is that the single-channel independent processing imaging method fails to make full use of the correlation between the channels, resulting in the two images not being in the same imaging pixel unit.

(a) Complex images of channel-1 using traditional imaging processing

(b) Complex images of channel-1 using imaging processing of the proposed approach

(c) Complex images of channel-2 using traditional imaging processing

(d) Complex images of channel-2 using imaging processing of the proposed approach

(e) 3D imaging results of the traditional imaging method

(f) 3D imaging results of imaging processing of the proposed method

Fig. 6 InISAR imaging of Backhoe with complete data

The proposed imaging method achieves the unification of the position of scattering points through multi-channel joint constraint.

4.2 Near-field InSAR Imaging

The imaging system is shown in Fig. 7. Fig. 8 shows the observation target scene, consisting of five metal balls. The synthetic aperture is formed by sliding guide, and the two adjacent scanning paths create two interference trajectories. Imaging parameters are shown in Table 2.

Fig. 7 Near-field InSAR imaging system in anechoic chamber

(a) Optical picture of five balls

(b) Distribution of target spatial position

Fig. 8 Target position of five metal balls

Table 2 Parameters of InSAR imaging system in anechoic chamber

Parameter	Value
Center frequency/GHz	10
Bandwidth/GHz	4
Interval of frequency sampling/(MHz*M)	40 (Sparse sampling)
Length of aperture/m	1
Antenna scanning interval/(m*N)	0.02 (Sparse sampling)
Baseline length/m	0.02
Distance between antenna and target/m	2

It can be seen from Fig. 9 that the proposed method can accurately reflect the position information of the scattering points.

(a) Traditional imaging method

(b) Proposed imaging method

(c) X-Y plane projection

(d) X-Z plane projection

Fig. 9 Near-field InSAR imaging results of different methods

However, the traditional imaging approach in Fig. 9(a) causes the position of the scattering point to be seriously deviated due to insufficient use of the relevant information between the channels, so that the target scattering point is

scattered due to the position mismatch.

4.3 Performance analysis

4.3.1 Imaging accuracy

We select three typical scattering points from Fig. 6, compare their position information, and quantitatively analyze the imaging accuracy of the proposed method. Table 3 compares the original coordinates of the three scattering points, the coordinates of the conventional imaging method, and the coordinates of the proposed imaging method. It can be seen from Table 3 that the imaging accuracy of the proposed method is significantly better than the conventional imaging method. Compared with the imaging method based on single channel independent processing, the accuracy of the proposed method is improved by 90%. Table 4 is the comparison of scatter point position information extracted by the proposed approach and the traditional approach in Fig. 9.

Table 3 Comparison of positional information of typical scattering points

Approach	Target 1 (x, y, z)	Target 2 (x, y, z)	Target 3 (x, y, z)
Original coordinate	(0.012 5, 0.268 8, 0)	(0.143 8, 0.243 8, 0)	(0.118 8, 0.168 8, 0.046 7)
Traditional method	(0, 0.25, 0.65)	(0.119, 0.229, 0.15)	(0.12, 0.11, 0.15)
Proposed method	(0.012, 0.266, 0)	(0.141, 0.241, 0.02)	(0.117 3, 0.16, 0.046)

Table 4 Comparison of scatter point position information extracted by different imaging methods

Approach	Target 1	Target 2	Target 3	Target 4	Target 5
Theoretical coordinate	(-0.2, -0.2, -0.2)	(0.2, -0.2, -0.2)	(0, 0, 0)	(-0.2, 0.2, 0.2)	(0.2, 0.2, 0.2)
Proposed method	(-0.2, -0.2, -0.21)	(0.21, -0.2, -0.2)	(0, 0, 0)	(-0.2, 0.2, 0.2)	(0.2, 0.2, 0.19)
Traditional method	(-0.19, -0.2, 0.2)	(0.2, -0.18, -0.2)	(0.03, -0.01, 0.1)	(-0.2, 0.2, 0.19)	(0.25, 0.19, -0.2)
	(-0.19, -0.21, -0.2)	—	(0.03, 0.01, -0.1)	—	(0.25, 0.21, 0.2)

As can be seen from Table 4, the maximum deviation of the target position obtained by the traditional method is 0.4, the maximum deviation of the target position obtained by the proposed method is 0.01.

4.3.2 Interferometric phase

Fig. 10 and Fig. 11 are the interferometric phase information of the target scattering in Fig. 6 and Fig. 9, respectively.

Fig. 10 Target scattering phase distribution for near-field InSAR 3D imaging

It can be seen in Fig. 10 and Fig. 11 that, for the extraction of the target scattering phase, the performance of the proposed method is superior to the traditional imaging method, and its accuracy and precision are significantly higher.

Fig. 11 Target scattering phase distribution for near-field InSAR 3D imaging

4.3.3 Anti-noise performance

In order to verify the performance of the proposed method in the presence of noise, we add -15 dB to 20 dB of Gaussian white noise to the echo signal, and calculate the mean squared error (MSE) estimated on the basis of height. Fig. 12 is a comparison of imaging performance between the proposed imaging method and the traditional imaging method at different SNRs. It can be seen from Fig. 12 that the proposed approach has a better performance to noise suppression than the conventional approach, especially at low SNR, and the average MSE is increased by 0.114 .

Fig. 12 Comparison for imaging performance of the traditional approach and the proposed approach under different SNRs

4.3.4 Downsampling imaging performance

We compare the imaging performance of the proposed method with the traditional method at different sparsity levels. The SNR is fixed as 10 dB. Calculate the MES estimated on the basis of height. It can be seen from Fig. 13 that the proposed approach can still effectively image when it is more than 90% sparse.

Fig. 13 Imaging performance comparison between the proposed method and the traditional method at different sparse rates

4.3.5 Imaging computational complexity analysis

We define the computational complexity as the number of complex multiplications in each imaging iteration. In one-iteration, the computational complexity of the traditional method is $C = 2MN$, and the proposed method is $C' = 2 * 3M$, where M represents all the number of samples and N represents all the number of imaging pixels. At the same time, $\mathbf{A}$ and $\mathbf{A}^{-1}$ can be computed and stored beforehand in the proposed method. The complexity of the traditional imaging method varies with the signal samples and the size of the scene, however, the proposed method is only related to the signal samples. We use the actual calculation time of the computer to show that the proposed method is more efficient. The hardware configuration is CPU of Intel(R) Core(TM) i7-4770HQ CPU @ 2.2 GHz 2.19 GHz, and 8 GB memory.

Table 5 Comparison of time-consuming of proposed method with the traditional imaging method

Method	Imaging time/s
Traditional CS imaging method	12.805
Proposed method	2.02

The imaging time of the proposed approach is $\frac{1}{6}$ of that of the traditional approach. Taking near-field InSAR imaging as an example, we set the number of signal samples to 51×101 . Fig. 14 describes the computational complexity of the traditional imaging method and the proposed method.

Fig. 14 Comparison of computational complexity of the proposed method with the traditional method

4.3.6 Analysis of memory requirements

The size of the sensing matrix in the traditional imaging method is $L \times M \times l \times m$, the size of the sensing matrix in the proposed method is $L \times M$, where $L \times M$ represents the size of signal sampling, $l \times m$ represents the size of the discrete target scene. The memory space required by the traditional imaging method and the proposed imaging method are $2 \times (L \times M) \times (l \times m) \times 4/1024/10^6$ GB and $2 \times (L \times M) \times 4/1024/10^6$ GB.

5. Conclusions

Focusing on the near-field interferometric imaging, a 3D imaging approach combining multichannel joint sparse recovery and FGG-NUFFT is presented. Firstly, based on the sparsity of interferometric images, a joint sparse constrained optimal imaging model is established, which effectively utilizes the correlation between multi-channel echo signals, and improves the reconstruction accuracy of scattering points in the images. Secondly, combining the MF technique, SAR transform, R-SAR transform and FGG-NUFFT, a sensing matrix with fast reconstruction performance is constructed. In addition, the improved FSS reconstruction method is used to further accelerate the imaging.

Meeting the near-field interferometric measurement conditions: $R_0 < \frac{4D^2}{\lambda}$ (near-field); $d \leq \frac{\lambda R_0}{2Z_0}$ (interferometric condition), where λ is the frequency, R_0 is the distance from the antenna to the target, Z_0 is the maximum height of the target, and d represents the distance between the two antennas, the imaging method proposed in this paper can effectively work.

This article combines the conventional SAR imaging

and sparse theory. The ideas of the constructed dictionary matrix can be widely used in the other mode of SAR imaging. Based on this, we will carry out more experimental experiments, such as security targets, stealth target analysis, etc., while carrying out cylindrical scanning imaging and circular SAR imaging.

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