The Journal of Engineering

IET International Radar Conference (IRC 2018)

BSBL-based multiband fusion ISAR imaging
eISSN 2051-3305
Received on 20th February 2019
Accepted on 03rd May 2019
E-First on 30th July 2019
doi: 10.1049/joe.2019.0369
www.ietdl.org

Di Xiong1,2, Junling Wang1, Lizhi Zhao3, Meiguo Gao1

1School of Information and Electronics, Beijing Institute of Technology, Beijing, People’s Republic of China
2Science and Technology on Metrology and Calibration Laboratory, Beijing Institute of Radio Metrology and Measurement, Beijing 100854, People’s Republic of China
3School of Information Engineering, Minzu University of China, Beijing, People’s Republic of China
E-mail: emailwjd@gmail.com

Abstract: Multiband fusion imaging can effectively improve the range resolution of inverse synthetic aperture radar (ISAR) imaging. In this study, the block sparse Bayesian learning (BSBL) method is applied to multiband fusion imaging to achieve high-resolution ISAR imaging of a block-structured target. The BSBL method is suitable for the ISAR imaging of numerous and continuous scatterers because it considers the block structure characteristics of the signal. The validity of the proposed method is verified by the simulation and real-data experimental results.

1 Introduction

A high-resolution inverse synthetic aperture radar (ISAR) image can provide detailed structure information that can improve the efficiency of target identification and classification in space surveillance [1]. The high cross-range resolution can be achieved by increasing the accumulation angle of ISAR imaging, while increasing range resolution should increase the transmit signal bandwidth. Multiband fusion imaging technology can effectively improve the radar range resolution by fusing the target frequency responses, which are measured by multiple radars with different frequency bands at the same view angle, to a higher bandwidth frequency response in the signal level without changing the existing radar configuration, and thus attracts many researchers to study this technology [1, 2].

The traditional multiband radar signal fusion technology is mainly based on the modern spectral estimation methods [3, 4]. Even though these methods have high estimation accuracy, they need to know the number of target scatterers, which is difficult to accurately estimate in a practical scenario. In recent years, sparse reconstruction theory has developed rapidly, and it has been successfully applied in ISAR imaging [5]. Compared with traditional ISAR imaging methods, the sparse representation-based methods can effectively reconstruct the target image. The existing sparse representation methods for ISAR imaging are based on the reality that the target scatterers are discretely distributed in the imaging region. Moreover, the target of ISAR imaging usually has some block structural characteristics, i.e. nonzero scattering coefficients occur in blocks in the imaging scene, such as aircrafts and satellites with complex structures. Thus, the block sparse representation method is more suitable for ISAR imaging of these numerous and continuous scatterers because it considers the block structure characteristics of the signal [6].

Compared with the traditional sparse representation algorithm, the block sparse signal recovery algorithm can remove the irrelevant components and obtain higher recovery performance [6]. The existing block sparse reconstruction methods are mainly based on the lp (0 < p ≤ 1) regularisation [7] and sparse Bayesian learning (SBL) [8]. The SBL-based methods automatically estimate the signal parameters by Bayesian inference, which have much less local minimum than the lp regularisation method. Zhang Zhilin studied the characteristics of the block sparse Bayesian learning (BSBL) recovery algorithm in detail; the results showed that the BSBL algorithm had a better effect than the conventional SBL algorithm in recovering the block structure target [9].

In this paper, the BSBL algorithm is applied to multiband signal fusion ISAR imaging to get a high-resolution image of the target. Both the range dimension and cross-range dimension of the target image have the block structural characteristic, so the multiband fusion ISAR imaging based on the BSBL method can be achieved through a cross-range decoupled sparse reconstruction. Simulation and real-data experiments will be used to verify the effectiveness of the method.

2 Multiband fusion ISAR imaging echo model

The radars for multiband fusion ISAR imaging discussed in this paper are adjacent configured, and the target response of each sub-band is reflected by ideal scatterers. We should note here that when the radars with multiple different frequency bands observe the target simultaneously, the echoes measured by radars are incoherent due to the difference of the radar positions, the signal transmission time, and the initial phases of the radar systems. The incoherence will affect the performance of multiband fusion, so the echo data are pre-processed according to the approach proposed in [10]. In a later discussion, we focus on the fusion process of the pre-processed data.

The fusion of radar echo signals in two different sub-bands is considered in this paper. Suppose the radars transmit chirp signals. The carrier frequency and the bandwidth of sub-band 1 are f1 and B1, respectively. The carrier frequency and the bandwidth of sub-band 2 are f2 and B2, respectively. After translational motion compensation, the echo signals can be equivalent to the turntable model, as shown in Fig. 1. The pulse-compressed echo spectra of the two sub-bands are given by

\[
s(f_i) = \sum_{k=1}^{K} \sigma_k \text{rect} \left( \frac{f_i}{f_s} \right) \exp \left( -\frac{i\pi}{c} (f_{i1} + f_{i2}) R_k \right), \quad i = 1, 2 \quad (1)
\]

where K is the number of scatterers, \( \sigma_k \) is the scattering coefficient of the arbitrary scatterer k on the target, \( R_k \) is the range between the scatterer k and the radar. For sub-band 1, \( i = 1 \), \( f_{i1} \) is the fast time frequency of the baseband signal; \( f_{i1} + f_{i2} = f_0 + n_i \Delta f, f_0 = f_{i1} - B_i/2 \) is the starting frequency of the full band; \( \Delta f \) is the frequency sampling interval; \( n_i = 0, 1, ..., N_i - 1 \); \( N_i = B_i/\Delta f \) is the number of samples in sub-band 1. For sub-band 2, \( i = 2 \), \( f_{i2} \) is the fast time frequency; \( f_{i2} + f_{i2} = f_0 + n_2 \Delta f, n_2 = N - N_2, N = N_1 + 1, ..., N - 1 \);
\(N_t = B_t / \Delta f\) is the number of samples in sub-band 2; \(N\) is the number of samples in the full band, \(N_1 + N_2 \leq N\). Let \(R_b\) be the range between the target centroid and the radar; then

\[
R_b = [R_b^2 + r^2 - 2R_b r \cos(\pi/2 + \theta_b + \Delta \theta)]^{1/2}
\]

(2)

where \((x_k, y_k)\) is the coordinate of the scatterer \(k\) in the target coordinate system, \(x_k = r_k \cos \theta_k, y_k = r_k \sin \theta_k\), and \(r_k\) is the distance between the scatterer \(k\) and the target centroid. \(\Delta \theta\) is the accumulative rotation angle of the target relative to the radar within \(m\) pulses; \(m = 0, 1, \ldots, M - 1\); \(M\) is the total number of echo pulses. Substituting (2) into (1) and ignoring the constant phase, (1) can be written as

\[
s(f_0, m) = \sum_{k=1}^{K_0} \sigma_k \text{rect}(f_0 - B_k) \cdot \exp(-j\frac{4\pi}{c}(f_0 + n_\alpha f_0) y_k)
\]

(3)

Since \(\Delta \theta\) is small during the imaging process, \(\cos \Delta \theta \approx 1, \sin \Delta \theta \approx \Delta \theta\). It is considered that the target is constantly rotating at the rotation velocity of \(\omega_s\) during the imaging time. \(\Delta \theta_m = \omega_s t_m, t_m = mT_r\) is the slow time, and \(T_r\) is the pulse repetition time (PRT). Then (3) can be further written as

\[
s(n, m) = \sum_{k=1}^{K_0} \sigma_k \exp\left(-j\frac{4\pi}{c}(f_0 + n_\alpha f_0) y_k\right) \cdot \exp(-j\frac{4\pi}{c}f_0 y_k + x_k \omega_s t_m), \quad i = 1, 2
\]

(4)

Considering the high range resolution after multiband fusion processing, the migration through resolution cell (MTRC) effect of scatterers is negligible even with a small cumulative angle during the imaging time. Therefore, in this paper, the keystone transform of each sub-band is applied to correct the MTRC before the fusion processing. The keystone transformation of the two sub-bands based on the same frequency \(f_0\) through variable substitution and sinc interpolation can eliminate the time-frequency coupling of the last term on the right side of (4):

\[
(f_0 + n_\alpha f_0) t_m = f_0 t_m, \quad i = 1, 2
\]

(5)

After the keystone transformation, the signals can be expressed as

\[
s(n, m) = \sum_{k=1}^{K_0} \sigma_k \exp\left(-j\frac{4\pi}{c}y_k f_0 + x_k \omega_s t_m\right), \quad i = 1, 2
\]

(6)

\section{3 BSBL-based multiband fusion ISAR}

\subsection{3.1 Multiband signal sparse reconstruction in range dimension}

\subsubsection{3.1.1 Sparse representation of a multiband signal:}

Firstly, we analyse the sparse representation of multiband signals in the range dimension. For simplicity, we let

\[
\sigma_m = \sigma_k \exp\left(-j\frac{4\pi}{c}f_0 y_k + x_k \omega_s t_m\right)
\]

(7)

which is constant for the \(m\)th pulse. Then (6) can be written as

\[
s(n, m) = \sum_{k=1}^{K_0} \sigma_m \exp\left(-j\frac{4\pi}{c}n_\alpha f_0 y_k\right), \quad i = 1, 2
\]

(8)

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{image1.png}
\caption{Turntable imaging geometry}
\end{figure}

Let \(\omega_0 = 2\Delta f y_k/c, \quad \omega_k \in [0, 1]\). Denote \(\omega_0\) as \(\omega_0 = p/P, \quad p = 0, 1, \ldots, P - 1, \quad P \geq N\). The sparse representation of the fusion signal of the \(m\)th pulse can be written as

\[
s_m = [s_1, \ldots, s_N]^T = H\Psi_m = \Psi_m \alpha_m
\]

(9)

where

\[
\begin{bmatrix}
  s_1 \\
  \vdots \\
  s_N
\end{bmatrix} = \begin{bmatrix}
  s(0, m) \\
  s(1, m) \\
  \vdots \\
  s(N - 1, m)
\end{bmatrix}^T
\]

\[
\begin{bmatrix}
  \alpha_m \\
  \vdots \\
  \alpha_m
\end{bmatrix} = \begin{bmatrix}
  \alpha_{m,1} \\
  \vdots \\
  \alpha_{m,N}
\end{bmatrix}
\]

(10)

This is an open access article published by the IET under the Creative Commons Attribution License (http://creativecommons.org/licenses/by/3.0/)

\subsection{3.1.2 Reconstruction based on BSBL:}

Considering the block structure of the target in range dimension, the BSBL method is used to reconstruct the range profile \(\alpha_m\) in (9). The signal model with noise can be rewritten as

\[
s_n = \Psi_m \alpha_m + \nu
\]

(13)

The most common block structure is that the vector \(\alpha_m\) contains \(g\) blocks, and the size of each block is \(d\):

\[
\begin{bmatrix}
  \alpha_{m,1} \\
  \vdots \\
  \alpha_{m,g}
\end{bmatrix}
\]

(14)
Therefore, \( P = dg \). Only \( g_{d|\omega_s} \propto g \) signal blocks are nonzero in signal \( \alpha_m \). The BSBL algorithm \cite{9} assumes that the \( i \)th \((i = 1, 2, \ldots, g)\) signal block follows the Gaussian distribution, and the blocks are mutually uncorrelated. Then the signal model can be given as

\[
p(\alpha_m|\{\gamma_i, B_i\}) = \mathcal{N}(\alpha_m; 0, \Gamma)
\]

where \( \Gamma = \text{diag}\{\gamma_1 B_1, \ldots, \gamma_g B_g\} \), \( \gamma_i \) denotes the correlation of the \( i \)th block signal, and \( \gamma_i B_i \) is the covariance matrix. The matrix \( B_i \in \mathbb{C}^{d \times d} \) represents the correlation structure information within the \( i \)th signal block. \( \mathcal{N}() \) denotes the complex Gaussian distribution.

For the measurement vector \( s_{m} \), it satisfies the following probability density function:

\[
p(s_{m}|\beta) = \mathcal{N}(s_{m}; \Psi \alpha_m, \beta^{-1} I)
\]

where the noise \( \nu \) is independent and identically distributed, and it satisfies \( p(\nu) = \mathcal{N}(0, \beta^{-1} I) \). \( \beta^{-1} \) is the noise power.

According to (15) and (16), we can obtain the posterior probability density function and likelihood function

\[
p(\alpha_m|s_m, \{\gamma_i, B_i\}, \beta) = \mathcal{N}(\alpha_m|\mu, \Sigma)
\]

\[
p(s_{m}|\{\gamma_i, B_i\}, \beta) = \mathcal{N}(s_{m}|0, C)
\]

where

\[
\mu = \beta \Sigma f_{m}^{\dagger} s_{m}, \quad \Sigma = \left( \Gamma^{-1} + \Psi_{f}^{\dagger} \beta \Psi_{f} \right)^{-1}
\]

\[
C = \beta^{-1} I + \Psi_{f} \Gamma \Psi_{f}^{\dagger}
\]

In order to estimate the parameters \( \{\gamma_i, B_i\} \) and \( \beta \), the cost function \( \mathcal{L} \) can be obtained by the Type II likelihood maximisation method \cite{9}:

\[
\mathcal{L}(\{\gamma_i, B_i\}, \beta) \equiv -2 \log p(s_{m}|\{\gamma_i, B_i\}, \beta) = \log |C| + n_s \beta \Sigma f_{m}^{\dagger} s_{m}.
\]

After obtaining the estimated values of the parameters \( \{\gamma_i, B_i\} \) and \( \beta \), the maximum posterior estimation of \( \alpha_m \) equals the mean of the posterior probability:

\[
\hat{\alpha}_m = \mu
\]

So we can obtain the estimated range profile matrix \( \hat{\alpha}_{p,s_{\theta}} \) from multiband signals via the BSBL sparse reconstruction pulse by pulse.

### 3.2 Sparse reconstruction in cross-range dimension

Considering that the scatterers of target are also distributed in blocks in the cross-range direction, a high-quality ISAR image can be obtained by using the BSBL reconstruction method in the cross-range dimension of the target's range profiles.

According to (7), let \( \omega_{d} = 2 f_{s} \omega_{M} \omega_{f} / c_{t} \), \( t_{i} = t_{\omega_{d}} / m \), \( \omega_{d} \in [0, 1] \), and it can be denoted as \( \omega_{d} = q / Q \), \( q = 0, 1, \ldots, Q - 1, Q \geq M \). The range profile matrix \( \alpha_{p,s_{\theta}} \) in the \( p \)th range cell can be written as the following sparse representation:

\[
\alpha(p,:) = A \sigma(p,:)^{T}
\]

where \( \sigma_{p,Q} \) is the ISAR image matrix and \( A_{M,s_{\theta}} \) is the Fourier basis matrix:

\[
A_{M,s_{\theta}} = [A_{0}, A_{1}, \ldots, A_{Q - 1}]
\]

so we can obtain the estimated range profile matrix \( \hat{\alpha}_{p,s_{\theta}} \) from multiband signals via the BSBL sparse reconstruction pulse by pulse.

### 4 Simulation and real-data experimental results

The effectiveness of BSBL reconstruction algorithm for multiband fusion ISAR imaging is verified by simulation and measured data experiments.

#### 4.1 Simulation of the scatterer model

The simulation parameters are as follows: the frequency of sub-band 1 is 10–10.5 GHz, the frequency of sub-band 2 is 11.5–12 GHz, and the frequency sampling interval \( \Delta f \) is 10 MHz. The target scatterer model is shown in Fig. 2. The target includes 4 discrete scatterers and 32 continuous block scatterers, the target centroid is located at \((0, 0)\). The interval of continuous block scatterers is 0.3 m in range dimension, and the amplitudes of the scatterers are all 1. The target rotates constantly at a distance of 3,000 m away from radars during the imaging time, and the accumulated rotation angle is 1.72°. In the simulation, Gaussian white noise is added and the SNR is 20 dB after the pulse compression.

Fig. 3 shows the two-sub-band fusion ISAR imaging results of the scatterer target. Figs. 3a and 3b are the ISAR images reconstructed by the traditional SBL method and the proposed BSBL method, respectively. In Fig. 3a, it can be seen that the image of the block structure target is defocused and blurred. The positions of the continuous block scatterers are incorrectly reconstructed by the SBL method, although the discrete scatterers are correctly reconstructed. While Fig. 3b shows the high-quality ISAR image of the target, both the discrete scatterers and the continuous block scatterers are correctly reconstructed by the

---

\( J. \) Eng., 2019, Vol. 2019 Iss. 19, pp. 6039-6042

This is an open access article published by the IET under the Creative Commons Attribution License (http://creativecommons.org/licenses/by/3.0/)

---
proposed BSBL method. The position and structure of the target in the image are consistent with the model. Therefore, the BSBL method outperforms the SBL method in multiband fusion ISAR imaging of block structure targets.

4.2 Experiment of Yak-42 real data

The measured Yak-42 aircraft data are also used to verify that a better quality ISAR image can be reconstructed using the BSBL method than using the SBL method. The radar system parameters are consistent with those in [11]. A total 128 echo pulses are used for imaging. The first 64 and the last 64 sampling points of full band are selected as the data of sub-band 1 and sub-band 2 for decoupled fusion imaging, respectively.

Fig. 4a shows the result of range doppler (RD) imaging of the full-band data. It can be seen that defocus exists in the cross-range direction. Fig. 4b shows the result of the BSBL reconstruction using the data of sub-band 1. Due to the narrow bandwidth, the resolution is low and the outline of the aircraft are very blurry. Fig. 4c shows the result of multiband fusion imaging using the SBL method. After the fusion imaging, the resolution of the image is obviously improved, but the image is still defocused, as shown by the circle mark. Fig. 4d shows the result of multiband fusion imaging using the proposed BSBL method. Compared with the first three images, Fig. 4d provides more complete outline of the aircraft, especially the nose and wings, and the image quality is better. Fig. 4 indicates that the fusion ISAR image reconstructed with the BSBL method is better than the SBL method.

5 Conclusions

This paper proposes to apply the BSBL method to multiband fusion ISAR imaging. With the exploitation of the block structure characteristic of targets in multiband fusion ISAR imaging, the BSBL-based method can obtain a better fusion ISAR image than the traditional SBL-based method. Simulation and real-data experiment results show that the proposed method can reconstruct high-quality images in multiband fusion ISAR imaging.

6 Acknowledgments

This work is supported by the National Natural Science Foundation of China under grant nos. 61401024 and 61701554, Beijing Institute of Technology Foundation under grant nos. 20140542001 and 20150542012.

7 References

[1] Cuomo, K.M., Pio, J.E., Mayhan, J.T.: ‘Ultrawide-band coherent processing’, IEEE Trans. Antennas Propag., 1999, 47, (6), pp. 1094-1107
[2] Tian, J., Sun, J., Wang, G., et al.: ‘Multiband radar signal coherent fusion processing with IAA and apFFT’, IEEE Signal Process. Lett., 2013, 20, (5), pp. 463-466
[3] Tian, B., Chen, Z., Xu, S.: ‘Sparse subband fusion imaging based on parameter estimation of geometrical theory of diffraction model’, Radar Sonar Navig. Lett., 2013, 8, (4), pp. 318-326
[4] Naishadham, K., Pio, J. E.: ‘State-space spectral estimation of characteristic electromagnetic responses in wideband data’, IEEE Antennas Wirel. Propag. Lett., 2005, 4, (1), pp. 406-409
[5] Zhang, X., Bai, T., Meng, H., et al.: ‘Compressive sensing based ISAR imaging via the combination of the sparsity and nonlocal total variation’, IEEE Geosci. Remote Sens. Lett., 2014, 11, (5), pp. 990-994
[6] Zou, Y., Gao, X., Li, X.: ‘A block sparse Bayesian learning based ISAR imaging method’, IEEE Geosci. Remote Sens. Symp., Beijing, China, July 2016, pp. 1011-1014
[7] Stojnic, M.: ‘L2/L1-optimization in block-sparse compressed sensing and its strong thresholds’, IEEE J. Sel. Top. Signal Process., 2010, 4, (2), pp. 350-357
[8] Liu, H., Bo, J., Liu, H., et al.: ‘Super resolution ISAR imaging based on sparse Bayesian learning’, IEEE Trans. Geosci. Remote Sens., 2014, 52, (8), pp. 5005-5013
[9] Zhang, Z., Rao, B. D.: ‘Extension of SBL algorithms for the recovery of block sparse signals with intra-block correlation’, IEEE Trans. Signal Process., 2013, 61, (8), pp. 2009-2015
[10] Xiong, D., Wang, J., Qi, X., et al.: ‘A coherent compensation method for multiband fusion imaging’, IEEE Radar Conf., Seattle, WA, USA, May 2017, pp. 1024-1027
[11] ‘ISAR.rar’, Available http://www.junfang-uestc.net/codes/ISAR.rar, accessed 27 November 2017

Fig. 4 Fusion ISAR imaging of Yak-42
(a) RD image of the full band. (b) BSBL reconstruction of sub-band 1. (c) SBL reconstruction of multiband. (d) BSBL reconstruction of multiband