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An efficient data compression technique based on BPDN for scattered fields from complex targets

Xiangyin QUAN[1*], Bingchen ZHANG[1], Zhengdao WANG[2], Chao GAO[3] & Yirong WU[1]

[1]*Institute of Electronics, Chinese Academy of Sciences, Beijing* 100190*, China;*
[2]*Department of Electrical and Computer Engineering, Iowa State University, Ames IA* 50011*, USA;*
[3]*Beijing Institute of Environmental Features, China Aerospace Science and Industry Corporation, Beijing* 100854*, China*

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Dear editor,

For complex targets, the scattered fields vary rapidly with frequency or aspect angle owing to diverse scattering mechanisms [1]. To comprehensively learn the characteristics of a target's signature, a large number of radar cross section (RCS) samples need to be collected and stored, which results in a heavy burden on the measurement equipment and the storage devices [2]. Since the scattering process of an electrically large target exhibits highly localized behavior related to the scattering mechanisms, its scattering physics can be modeled by a set of scattering centers [3]. In general, the scattering center model provides a sparse abstraction of radar targets. And it is insensitive to the variance of frequency and aspect angle. Compared with RCS samples, the number of corresponding scattering centers is far less. Thus, data compression can be achieved by transforming scattered fields into scattering centers and storing the backscattering coefficients and spatial positions of the extracted scattering centers.

In this letter, the extraction of scattering centers from RCS samples is performed using basis pursuit denoising (BPDN) [4, 5]. By means of the sparse distribution of scattering centers, the valid backscattering coefficients can be obtained with the undersampled measurements. It saves the time for measuring echo signals. However, the great computation load and memory cost caused by matrix-vector products always limit the application of sparse reconstruction algorithms in the data compression of RCS samples. To solve this problem, we derive efficient operators on the basis of support set and filtered backprojection. By combining the sparse solver SPGL1 with the operators, the new algorithm not only reduces consumption of system resources, but also estimates the backscattering coefficients accurately. In addition, the experimental results and analysis demonstrate that the proposed technique possesses high data compression ratio and small RCS reconstruction error.

Principles of data compression technique based on BPDN for scattered fields. As one of the equivalent optimization models to compressed sensing, BPDN makes use of a priori information of sparsity to approximately fit the underdetermined least-squares problem in the presence of noisy data [5]. In the research of radar targets, their distributions of scattering centers are mostly sparse in the high-frequency optics region [3]. Therefore, we apply

* Corresponding author (email: heavenmoonqxy@163.com)
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the BPDN to the transformation from scattered fields to scattering centers. The model used for data compression of RCS samples is described by

$$\min_{\boldsymbol{x}} \|\boldsymbol{x}\|_1 \quad \text{s.t.} \quad \|\boldsymbol{A}\boldsymbol{x}-\boldsymbol{y}\|_2 \leqslant \sigma, \tag{1}$$

where $\boldsymbol{x}$ is the backscattering coefficients of an observed region; $\boldsymbol{y}$ is the RCS samples of a radar target; $\boldsymbol{A}$ is the measurement matrix deduced from system parameters and observation geometry; σ is the additive noise level; $\|\cdot\|_1$ and $\|\cdot\|_2$ represent the l_1-norm and l_2-norm of a vector, respectively.

Generally, the computational complexity and memory usage of the sparse reconstruction algorithms for solving (1) both reach $O\left(n^2\right)$ due to the matrix-vector products. When a large number of RCS samples need to be transformed into 3-D scattering centers, the great computation load and memory cost make data processors fail to realize the data compression via limited time and memory. Thus, we derive efficient operators to replace these computationally expensive steps. Since the number of the nonzero backscattering coefficients is far less than the pixels in the observed region, $\boldsymbol{A}\boldsymbol{x}$ can be calculated only by the elements in the support set of $\boldsymbol{x}$. In light of this fact, the operator for generating RCS samples is expressed as

$$\begin{aligned}\mathcal{G}(\boldsymbol{x}) = & \Big\{ y_{l,m} \in \mathbb{C} \Big| y_{l,m} = \\ & \sum_{x_n \neq 0} x_n \exp\left(-jk_l R_{n,m}\right) \Big\},\end{aligned} \tag{2}$$

where x_n is the nth element of $\boldsymbol{x} \in \mathbb{C}^N$, whose space coordinate is (u_n, v_n, w_n); $k_l = \frac{4\pi f_l}{c}$ is the wavenumber with respect to the carrier frequency of the lth pulse, $f_l = f_1 + (l-1)\Delta f,\ l = 1, \ldots, L$, Δf is the frequency step size, L is the number of range pulses, and c is the speed of light; $R_{n,m}$ is the projected range of the nth scattering center at the mth aspect angle (φ_m, θ_m), $m = 1, \ldots, M$, $\varphi_m \in (-\pi, \pi]$ and $\theta_m \in [-\pi/2, \pi/2]$ are the azimuth and elevation angles, and M is the number of the aspect angles. In the case of far fields, the projected range is specifically written as

$$\begin{aligned}R_{n,m} = & u_n \sin\varphi_m \cos\theta_m + v_n \cos\varphi_m \cos\theta_m \\ & + w_n \sin\theta_m.\end{aligned}$$

The geometric relationship between the target and the radar is shown in Figure A1(a). To further reduce the computation load and memory cost, we construct the operator for estimating backscattering coefficients according to the principles of filtered backprojection [6]. And it is expressed as

$$\mathcal{I}(\boldsymbol{y}) = \mathcal{S}\left(\boldsymbol{\Psi}_{\text{aft}} \odot \mathcal{C}\left(\boldsymbol{\Psi}_{\text{bef}} \odot \mathcal{F}_{\text{r}}^{-1}\left(\boldsymbol{J} \odot \mathcal{R}_{\text{sf}}(\boldsymbol{y})\right)\right)\right), \tag{3}$$

where $\mathcal{R}_{\text{sf}}(\cdot)$ represents reshaping the vector $\boldsymbol{y} \in \mathbb{C}^{LM\times 1}$ to the matrix $\boldsymbol{Y} \in \mathbb{C}^{L\times M}$, whose mth column denotes the range RCS samples measured at (φ_m, θ_m); $\boldsymbol{J} \in \mathbb{R}^{L\times M}$ is the matrix obtained from the Jacobian for spherical coordinate transformation, whose (l, m)-th element $J_{l,m}$ is $k_l^2 \cos\theta_m$; $\odot$ denotes the Hadamard product; $\mathcal{F}_{\text{r}}^{-1}(\cdot)$ represents the inverse discrete Fourier transform in range; $\mathcal{C}(\cdot)$ represents the sinc interpolation from the range profile to the pixels in the observed region; $\boldsymbol{\Psi}_{\text{bef}} \in \mathbb{C}^{L\times M}$ and $\boldsymbol{\Psi}_{\text{aft}} \in \mathbb{C}^{N\times M}$ are the matrices for compensating the additive phase before and after the interpolation, the lth element in every column of $\boldsymbol{\Psi}_{\text{bef}}$ is $\psi_l^{\text{bef}} = \exp(-j\frac{\pi(L-1)l}{L})$ and $\boldsymbol{\Psi}_{\text{aft}}$ is composed of $\psi_{n,m}^{\text{aft}} = \exp(j\frac{4\pi f_c R_{n,m}}{c})$, f_c is the center frequency of the pulse sequence in range; $\mathcal{S}(\cdot)$ represents coherently summating the subimages acquired at different aspect angles. By replacing $\boldsymbol{A}^{\text{H}}\boldsymbol{y}$ with $\mathcal{I}(\boldsymbol{y})$, the computation load is reduced from $O\left(n^2\right)$ to $O\left(n^{3/2}\right)$, and the memory cost is reduced from $O\left(n^2\right)$ to $O(n)$(see [7]).

SPGL1 is a fast and accurate solver of BPDN, and does not require explicit access to the measurement matrix [5]. As such, we can incorporate the efficient operators into it. The new algorithm is given in Algorithm 1. In the inner iterations (Steps 11–32), the LASSO subproblem about the regularization parameter τ^p is approximately solved by the spectral projected-gradient algorithm, which mainly consists of the projected gradient path search (Steps 16–24) and the spectral step length update (Steps 26–30). In Step 12, $\delta_{\tau^p}\left(\tilde{\boldsymbol{r}}^{q-1}\right)$ is the duality gap, which provides a bound on the iteration error. It is defined as

$$\delta_\tau(\boldsymbol{r}) = \|\boldsymbol{r}\|_2 - \left(\boldsymbol{y}^{\text{H}}\boldsymbol{r} - \tau\|\mathcal{I}(\boldsymbol{r})\|_\infty\right)/\|\boldsymbol{r}\|_2, \tag{4}$$

where $\|\cdot\|_\infty$ represents the infinity norm of a vector. In Step 17, the operator $\mathcal{P}_\tau(\boldsymbol{\beta})$ represents projecting a vector $\boldsymbol{\beta} \in \mathbb{C}^N$ onto the one-norm ball with radius τ, which is briefly expressed as

$$\mathcal{P}_\tau(\boldsymbol{\beta}) = \arg\min_{\boldsymbol{z}} \|\boldsymbol{\beta} - \boldsymbol{z}\|_2 \quad \text{s.t.} \ \|\boldsymbol{z}\|_1 \leqslant \tau. \tag{5}$$

Its implementation is detailedly explained in [5]. In the outer iterations (Steps 1–34), the proposed technique uses the Newton's method to update τ^p in accordance with the Pareto frontier, so that the results of the LASSO subproblems can converge to the desired solution of BPDN gradually. To exclude the false scattering centers caused by the additive noise, the thresholding operation for selecting valid backscattering coefficients is placed in Step 35. The output threshold T_{v} is determined by the practical noise level.

Algorithm 1 RCS data compression based on BPDN

Input: RCS samples $\boldsymbol{y}$, additive noise level $\sigma \in [0, \|\boldsymbol{y}\|_2)$, optimality tolerance $T_{\rm op} \geqslant 0$, sufficient descent parameter $\eta \in (0,1)$, maximum and minimum step lengths $\alpha_{\max} > \alpha_{\min} > 0$, output threshold $T_{\rm v} < 0\,$dB;
Output: valid backscattering coefficients $\hat{\boldsymbol{x}}$;
Initialization: $\boldsymbol{x}^0 = \boldsymbol{0}$, $\boldsymbol{r}^0 = \boldsymbol{y}$, $\tau^0 = 0$, $\alpha^0 = \alpha_{\max}$;

for $p = 1$ to maxiter$_1$ **do**
  if $\left|\|\boldsymbol{r}^{p-1}\|_2 - \sigma\right| / \|\boldsymbol{r}^{p-1}\|_2 \leqslant T_{\rm op}$ **then**
    break;
  end if
  $\tau^p = \tau^{p-1} - \left(\sigma - \|\boldsymbol{r}^{p-1}\|_2\right) \frac{\|\boldsymbol{r}^{p-1}\|_2}{\|\mathcal{I}(\boldsymbol{r}^{p-1})\|_\infty}$;
  if $\tau^p < \tau^{p-1}$ **then**
    $\tilde{\boldsymbol{x}}^0 = \mathcal{P}_{\tau^p}(\boldsymbol{x}^{p-1})$, $\tilde{\boldsymbol{r}}^0 = \boldsymbol{y} - \mathcal{G}(\tilde{\boldsymbol{x}}^0)$, $\tilde{\boldsymbol{g}}^0 = -\mathcal{I}(\tilde{\boldsymbol{r}}^0)$;
  else
    $\tilde{\boldsymbol{x}}^0 = \boldsymbol{x}^{p-1}$, $\tilde{\boldsymbol{r}}^0 = \boldsymbol{r}^{p-1}$, $\tilde{\boldsymbol{g}}^0 = -\mathcal{I}(\tilde{\boldsymbol{r}}^0)$;
  end if
  for $q = 1$ to maxiter$_2$ **do**
    if $\delta_{\tau^p}(\tilde{\boldsymbol{r}}^{q-1}) \leqslant T_{\rm op}$ **then**
      break;
    end if
    $\alpha = \alpha^{q-1}$;
    for $h = 1$ to maxiter$_3$ **do**
      $\bar{\boldsymbol{x}} = \mathcal{P}_{\tau^p}(\tilde{\boldsymbol{x}}^{q-1} - \alpha\tilde{\boldsymbol{g}}^{q-1})$, $\bar{\boldsymbol{r}} = \boldsymbol{y} - \mathcal{G}(\bar{\boldsymbol{x}})$;
      if $\|\bar{\boldsymbol{r}}\|_2^2 \leqslant \|\tilde{\boldsymbol{r}}^{q-1}\|_2^2 + \eta(\bar{\boldsymbol{x}} - \tilde{\boldsymbol{x}}^{q-1})^H \tilde{\boldsymbol{g}}^{q-1}$ **then**
        break;
      else
        $\alpha = \alpha/2$;
      end if
      $h = h + 1$;
    end for
    $\tilde{\boldsymbol{x}}^q = \bar{\boldsymbol{x}}$, $\tilde{\boldsymbol{r}}^q = \bar{\boldsymbol{r}}$, $\tilde{\boldsymbol{g}}^q = -\mathcal{I}(\tilde{\boldsymbol{r}}^q)$, $\Delta\boldsymbol{x} = \tilde{\boldsymbol{x}}^q - \tilde{\boldsymbol{x}}^{q-1}$, $\Delta\boldsymbol{g} = \tilde{\boldsymbol{g}}^q - \tilde{\boldsymbol{g}}^{q-1}$;
    if $\Delta\boldsymbol{x}^{\rm H}\Delta\boldsymbol{g} \leqslant 0$ **then**
      $\alpha^q = \alpha_{\max}$;
    else
      $\alpha^q = \min\left(\alpha_{\max}, \max\left(\alpha_{\min}, \frac{\|\Delta\boldsymbol{x}\|_2^2}{\Delta\boldsymbol{x}^H\Delta\boldsymbol{g}}\right)\right)$;
    end if
    $q = q + 1$;
  end for
  $\boldsymbol{x}^p = \tilde{\boldsymbol{x}}^{q-1}$, $\boldsymbol{r}^p = \tilde{\boldsymbol{r}}^{q-1}$, $p = p + 1$;
end for
return $\hat{\boldsymbol{x}} = \left\{ x_n^{p-1} \in \boldsymbol{x}^{p-1} \,\middle|\, 20\lg\left(\frac{|x_n^{p-1}|}{\max(|\boldsymbol{x}^{p-1}|)}\right) \geqslant T_{\rm v} \right\}$;

Experimental results and analysis. To test the capability of data compression, we use the iterative shrinkage thresholding algorithm (IST), the iterative hard thresholding algorithm (IHT) and our method to extract the scattering centers. The far-field RCS samples of a typical warhead are generated with the high-frequency electromagnetic code. The primary parameters of the simulated data are listed in Table A1. Since there exists additive noise in the samples, the output threshold is set as −35 dB. By randomly selecting 90% of the azimuth angles and 90% of the elevation angles from the fullsampled data, 81% samples are used for estimating the distribution of scattering centers (Figures A1 (b)–(d)). The assessment of RCS recovery precision is based on the relative mean square error (rMSE). The data compression ratio and RCS reconstruction error of these algorithms are given in Table A2. The experimental results show that the proposed technique possesses higher data compression ratio and smaller RCS reconstruction error in comparison with IST and IHT. To evaluate its robustness to additive noise, we utilize the scattering centers in Figure A1(d) to reconstruct the RCS samples, and compare them with the noiseless simulated data. Figures A1(e) and (f) show that the reconstructed samples well resemble the noiseless data in different dimensions.

Conclusion. This letter applies BPDN to the data compression of RCS samples and proposes an efficient algorithm for extracting scattering centers. With the help of the prior knowledge of sparsity, the scattering center model of complex target can be built using the undersampled RCS samples in azimuth and elevation. It significantly reduces the time for measuring echo signals, which promotes the efficiency of radar systems. Additionally, experimental results and analysis verify that the proposed technique possesses high data compression ratio and small RCS reconstruction error.

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Supporting information Tables A1, A2, Figure A1. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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