Fast Monostatic Scattering Analysis Based on Bayesian Compressive Sensing

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Abstract **─** The Bayesian compressive sensing algorithm is utilized together with the method of moments to fast analyze the monostatic electromagnetic scattering problem. Different from the traditional compressive sensing based fast monostatic scattering analysis method which cannot determine the required measurement times, the proposed method adopts the Bayesian framework to recover the underlying signal. Error bars of the signal can be obtained in the recovery procedure, which provides a means to adaptively determine the number of compressive-sensing measurements. Numerical results are given to demonstrate the accuracy and effectiveness of proposed method.

Index Terms **─** Bayesian compressive sensing, method of moments, monostatic, scattering.

I. INTRODUCTION

Electromagnetic scattering simulation has been widely applied to the area of non-cooperative radar target identification and radar imaging to get the echo signal of radar target without measurement. Among various electromagnetic scattering analysis methods, the method of moments (MoM) has drawn great interests in the past several decades [1-3]. The MoM is particularly advantageous for the analysis of exterior open-region scattering problems duo to its inherent capability for simulating unbounded domains.

When utilizing MoM to acquire echo signals from a large amount of aspect angles, one has to run the simulation code equal times with the number of aspect angles to obtain all the echo signals. For instance, to obtain the inverse synthetic aperture radar (ISAR) image of the B2 model as shown in Fig. 1, one has to get the wideband scattered field data from 720 aspect angles of the model. Actually, it takes much time to analyze the electrically large objects only once, let alone many times. So there is an urgent demand to accelerate the simulation process of monostatic scattering.

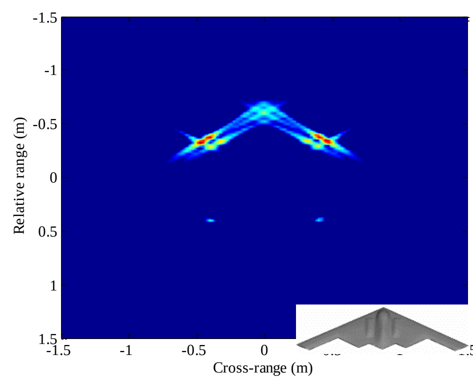

Fig. 1. Inverse synthetic aperture radar (ISAR) image of the B2 model based on the wideband scattered field data from 720 aspect angles of the target.

Two kinds of effort have been done to achieve this goal. One is to speed up the single simulation by using fast algorithms to accelerate the method of moments. The existing fast algorithms can mainly be classified into three categories: fast multipole method (FMM) [4-6], FFT-based methods [7-9], and low rank matrix based methods [10-12]. The alternative way is to reduce the total number of simulations using algorithms like asymptotic waveform evaluation (AWE) [13, 14], model-based parameter estimation (MBPE) [15], excitation matrix compression methods [16, 17], etc. But these algorithms show some shortcomings. For AWE and MBPE, a multi-point expansion or interpolation is needed for wide-angle problems. The major technical challenge is to adaptively choose the expansion points or interpolation points. The excitation matrix compression methods compress the excitation matrix and remove redundancies in the initial excitation assembly. The considered full right-hand-side (RHS) matrix has to be stored explicitly. Moreover, a SVD-based compression is restricted to comparatively small matrices due to the high computational complexity.

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Compressive sensing (CS) is a rapidly emerging signal processing technique and has already been applied to electromagnetics [18-20]. A CS based method is proposed in [20] for fast analysis of wide-angle monostatic scattering problems, which falls into the second category fast algorithm described above. This method uses CS to construct a new set of right-hand-side vectors for MoM, where the number of constructed right-hand-side vectors is much less than the original ones. But it is found that orthogonal matching pursuit (OMP) algorithm [21] is adopted to solve the CS optimization problem and the number of measurement cannot be determined adaptively, just like that the number of expansion or interpolation points is unknown in [13-15]. This sets up a limit for the practical applications of this technique.

Recently, more and more researchers focus on the study of Bayesian compressive sensing (BCS) method [22-25], which adopts the Bayesian framework to recover the underlying signals. Error bars of the signal can be obtained in the recovery procedure, leading to an effective strategy for adaptively determining the number of compressive-sensing measurements. The BCS method is used for coherent fusion of multi-band radar data from multiple spatially collocated radars in [24]. In [25], the BCS method is applied for estimation of the directions of arrival (DoAs) of narrow-band signals impinging on a linear antenna array. In this paper, we utilize the BCS for fast monostatic scattering calculation. Numerical results show the proposed method can determine the number of compressive-sensing measurements in an adaptive manner.

The rest of this paper is organized as follows. Section II describes the detailed theory and formulation of the proposed Bayesian compressive sensing based fast monostatic scattering analysis method. Section III demonstrates the accuracy and effectiveness of the proposed method through several numerical results. Section IV presents our conclusions.

II. THEORY AND FORMULATION

A. Review of MoM for electromagnetic scattering problems

For the analysis of electromagnetic scattering from perfect electrical conductor (PEC), the Maxwell's equations can be recast in the form of surface integral equations, including electric field integral equation (EFIE), magnetic field integral equation (MFIE) and combined field integral equations (CFIE). Take the following EFIE as an example:

$$\int_S \hat{t}\cdot[j\omega\mu J_s(\mathbf{r}')G(\mathbf{r},\mathbf{r}') - \frac{j}{\omega\varepsilon}(\nabla'\cdot J_s(\mathbf{r}'))(\nabla' G(\mathbf{r},\mathbf{r}'))]dS' = \hat{t}\cdot\mathbf{E}^i(\mathbf{r}). \tag{1}$$

Here, $G(\mathbf{r},\mathbf{r}')$ refers to the Green's function in free space. $\mathbf{r}$ and $\mathbf{r}'$ denote the observation and source point locations. $\mathbf{E}^i(\mathbf{r})$ is the incident excitation plane wave. ε and μ are the permittivity and permeability, respectively. ω is the angular frequency. $J_s(\mathbf{r}')$ is the unknown surface current. $\hat{t}$ refers to the tangential direction of the surface.

Equation (1) can be discretized by using MoM with planar Rao-Wilton-Glisson (RWG) basis functions [26]. The linear system of equations after Galerkin's testing is briefly outlined as follows:

$$\sum_{n=1}^{N} Z_{mn} I_n = V_m, \qquad \mathrm{m} = 1,2,...,N, \tag{2}$$

where

$$Z_{mn} = \int_s \Lambda_m(\mathbf{r})\cdot\int_{s'} j\omega\mu\Lambda_n(\mathbf{r}')G(\mathbf{r},\mathbf{r}')dS'dS - \int_s \frac{j}{\omega\varepsilon}\nabla\cdot\Lambda_m(\mathbf{r})\int_{s'}\nabla'\cdot\Lambda_n(\mathbf{r}')G(\mathbf{r},\mathbf{r}')dS'dS, \tag{3}$$

$$V_m = \int_s \Lambda_m(\mathbf{r})\cdot\mathbf{E}^i(\mathbf{r})dS. \tag{4}$$

Here, I_n represents the unknown current coefficients. Equation (2) can be written as:

$$\mathbf{ZI}(\theta) = \mathbf{V}(\theta), \tag{5}$$

where $\mathbf{Z}$ is the impedance matrix with its elements given in (3), $\mathbf{V}(\theta)$ is the right-hand-side vector related to the (4), $\mathbf{I}(\theta)$ is a vector containing the unknown current coefficients. Both the right-hand-side vector and the unknown current coefficients will change with the incident angle θ.

B. Basic principle of using CS for fast monostatic scattering analysis

Suppose that multiple monostatic scattering problem with the incident angles $\theta_1,\theta_2,\cdots\theta_M$ is analyzed, then the following M matrix equations need to be solved:

$$\mathbf{ZI}(\theta_i) = \mathbf{V}(\theta_i),\ i = 1,2,\cdots,M. \tag{6}$$

Use $\mathrm{I}_n(\theta_i)$ to represent the current coefficient of the n-th element in $\mathbf{I}(\theta_i)$ and $n = 1,2,\cdots,N$. Based on the CS theory, a measurement matrix $\boldsymbol{\phi} = \left[c_{ij}\middle| i = 1,2,\cdots,M';\ j = 1,2,\cdots,M\right]$ with its elements i.i.d. Gaussian can be constructed. The measurement value of $\{I_n(\theta_1),\ I_n(\theta_2),\cdots,\ I_n(\theta_M)\}$ can be written as:

$$\begin{pmatrix} I_{n1}^{CS} \\ I_{n2}^{CS} \\ \vdots \\ I_{nM'}^{CS} \end{pmatrix} = \begin{pmatrix} c_{11} & c_{12} & c_{13} & \cdots & c_{1M} \\ c_{21} & c_{22} & c_{23} & \cdots & c_{2M} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ c_{M'1} & c_{M'2} & c_{M'3} & \cdots & c_{M'M} \end{pmatrix} \begin{pmatrix} I_n(\theta_1) \\ I_n(\theta_2) \\ \vdots \\ \vdots \\ I_n(\theta_M) \end{pmatrix}. \tag{7}$$

It is worth mentioning that the number of measurement values M' is much less than M. Obviously, the m-th measurement can be expressed as:

$$I_{nm}^{CS} = \sum_{i=1}^{M} c_{mi} I_n(\theta_i). \tag{8}$$

Let $\mathbf{I}_m^{CS} = \{I_{1m}^{CS}, I_{2m}^{CS}, \cdots, I_{Nm}^{CS}\}$, then we have:

$$\mathbf{Z}\mathbf{I}_m^{CS} = \mathbf{Z}\begin{pmatrix} \mathrm{I}_{1m}^{CS} \\ \mathrm{I}_{2m}^{CS} \\ \vdots \\ \mathrm{I}_{Nm}^{CS} \end{pmatrix} = \mathbf{Z}\begin{pmatrix} \sum_{i=1}^{M} c_{mi} I_1(\theta_i) \\ \sum_{i=1}^{M} c_{mi} I_2(\theta_i) \\ \vdots \\ \sum_{i=1}^{M} c_{mi} I_N(\theta_i) \end{pmatrix} = \sum_{i=1}^{M} c_{mi} \mathbf{Z}\mathbf{I}(\theta_i) = \sum_{i=1}^{M} c_{mi} \mathbf{V}(\theta_i). \tag{9}$$

The right hand side of (9) is a random superposition of M right-hand-side vectors related to different incident angles and the weights are the m-th row elements of $\boldsymbol{\phi}$. So the M' measurement values of each current coefficient can be obtained by changing the subscript m in (9) from 1 to M'. In such a manner, the number of equations to be solved can be greatly reduced.

According to the theory of CS [27], if the unknown vector $\{I_n(\theta_1),\ I_n(\theta_2), \cdots,\ I_n(\theta_M)\}$ is compressible in terms of a orthonormal basis $\boldsymbol{\Psi}$, i.e.,

$$\begin{pmatrix} I_n(\theta_1) \\ I_n(\theta_2) \\ \vdots \\ \vdots \\ I_n(\theta_M) \end{pmatrix} = \boldsymbol{\Psi}\boldsymbol{\omega}, \tag{10}$$

where $\boldsymbol{\Psi}$ is a $M \times M$ matrix, $\boldsymbol{\omega} = \{\omega_1, \omega_2, \cdots, \omega_M\}$ has just a few of large coefficients and many small coefficients. Substitute (10) into (7), $\boldsymbol{\omega}$ can be obtained by solving the following matrix equation:

$$\begin{pmatrix} I_{n1}^{CS} \\ I_{n2}^{CS} \\ \vdots \\ I_{nM'}^{CS} \end{pmatrix} = \boldsymbol{\phi}\boldsymbol{\Psi}\boldsymbol{\omega} = \boldsymbol{\Phi}\boldsymbol{\omega}, \tag{11}$$

where $\boldsymbol{\Phi} = \boldsymbol{\phi}\boldsymbol{\Psi}$ is a $M \times M$ sensing matrix. M' is much smaller than M. Hence, (11) is an underdetermined equation which is a nondeterministic polynomial time (NP)-hard problem. A reconstruction algorithm is required to recover $\boldsymbol{\omega}$ from M' measurements. After $\boldsymbol{\omega}$ is solved, we can adopt (10) to obtain the original current coefficient vector.

C. Bayesian compressive sensing method

To solve (11), the reconstruction algorithm in [20] is the orthogonal matching pursuit (OMP) algorithm [21]. However, the OMP algorithm is a greedy algorithm and it frequently converges to local optimal. Moreover, the number of measurement cannot be predefined adaptively and one has to try several times to find the optimized values for the number of measurements.

In the Bayesian compressive sensing method, the solution of the NP-hard problem in (11) can be rewritten into the following form:

$$\mathbf{t} = \boldsymbol{\Phi}\boldsymbol{\omega} + \boldsymbol{\varepsilon}, \tag{12}$$

where $\mathbf{t}$ is the vector of measurement values, $\boldsymbol{\varepsilon}$ is the expansion error and it is assumed to be zero-mean Gaussian distribution with variance σ^2. Then the vector $\mathbf{t}$ obeys a multivariate Gaussian distribution,

$$p(\mathbf{t}|\boldsymbol{\omega}, \sigma^2) = (2\pi\sigma^2)^{-\frac{M'}{2}} \exp(-\frac{1}{2\sigma^2}\|\mathbf{t} - \boldsymbol{\Phi}\boldsymbol{\omega}\|^2). \tag{13}$$

A zero-mean Gaussian prior is defined over $\boldsymbol{\omega}$:

$$p(\boldsymbol{\omega}|\mathbf{a}) = \prod_{i=1}^{M} N(\omega_i|0, a_i^{-1}), \tag{14}$$

where $\mathbf{a} = [a_1, a_2, \cdots, a_M]^T$ is a vector of M independent hyperparameters and a_i is the precision (reciprocal of variance) of a Gaussian distribution.

For the fixed values of hyperparameters controlling the prior, the posterior probability density of the weights can be obtained:

$$p(\boldsymbol{\omega}|\mathbf{t}; \mathbf{a}, \sigma^2) = N(\boldsymbol{\omega}|\boldsymbol{\mu}, \boldsymbol{\Sigma}), \tag{15}$$

where its mean and covariance are:

$$\boldsymbol{\mu} = \sigma^{-2}\boldsymbol{\Sigma}\boldsymbol{\Phi}^T\mathbf{t}, \tag{16}$$

$$\boldsymbol{\Sigma} = (\mathbf{A} + \sigma^{-2}\boldsymbol{\Phi}^T\boldsymbol{\Phi})^{-1}, \tag{17}$$

with $\mathbf{A} = diag(a_1, a_2, \cdots, a_M)$.

According to (13) and (14), the marginal distribution of $\mathbf{t}$ can be computed as:

$$p(\mathbf{t}|\mathbf{a}, \sigma^2) = (2\pi)^{-M'/2}|\mathbf{C}|^{-1/2}\exp\left(-\frac{1}{2}\mathbf{t}^{\mathrm{T}}\mathbf{C}^{-1}\mathbf{t}\right), \tag{18}$$

where

$$\mathbf{C} = \sigma^2\mathbf{I} + \boldsymbol{\Phi}\mathbf{A}^{-1}\boldsymbol{\Phi}^T. \tag{19}$$

In the sparse Bayesian learning method, the maximization of $p(\mathbf{t}|\mathbf{a}, \sigma^2)$ is termed as type-II maximum likelihood method. The hyperparameters $\mathbf{a}$ and σ^{-2} are estimated through computing the derivatives of (18) with respect to $\mathbf{a}$ and σ^{-2}:

$$a_i^{new} = \frac{\gamma_i}{\mu_i^2}, \tag{20}$$

$$(\sigma^2)^{new} = \frac{\|\mathbf{t} - \boldsymbol{\Phi}\boldsymbol{\mu}\|^2}{M' - \sum_{i=1}^{M}\gamma_i}, \tag{21}$$

where $\gamma_i = 1 - a_i \Sigma_{ii}$, Σ_{ii} is the i th diagonal element of the covariance in (17).

The formulas (16) and (17) coupled with (20) and (21) lead to an iterative learning process, which updates the corresponding quantity until a convergence criterion is satisfied. Many elements of $\mathbf{a}$ tend to infinity during the iteration with the consequence that $\boldsymbol{\mu}$ contains very few non-zero elements. After the convergence of the iterative learning process, $\boldsymbol{\mu}$ is used to approximate $\boldsymbol{\omega}$.

Since the diagonal elements of the covariance matrix $\boldsymbol{\Sigma}$ correspond to the variance of each element in $\boldsymbol{\omega}$, they provide error bars on the accuracy of $\boldsymbol{\omega}$. When the number of measurement is sufficiently large, the variance of each element in $\boldsymbol{\omega}$ should be small. If the diagonal elements of the covariance matrix $\boldsymbol{\Sigma}$ is $\Sigma_{ii}, i = 1, 2, \cdots, M$, the number of measurement times M' is enough when,

$$\frac{\Sigma_{11} + \Sigma_{22} + \cdots + \Sigma_{MM}}{M} < \delta, \tag{22}$$

where δ is a small value and $\delta = 10^{-3}$ in this paper. If (22) is not satisfied, more measurement will be added. In such a manner, the proposed method can adaptively determine the number of measurement.

III. NUMERICAL RESULTS

The effectiveness and accuracy of the proposed method are demonstrated through several numerical results. All results are generated on a personal PC with 2.83 GHz CPU and 8 GHz RAM. The flexible general minimal residual (FGMRES) algorithm is adopted to solve the matrix equation and the iteration process is terminated when the 2-norm residual error is reduced by 10^{-3}. Multilevel fast multipole method (MLFMM) is utilized to accelerate the matrix vector product process.

A. Almond

The NASA almond model is analyzed as the first example as shown in Fig. 2 [28]. It is discretized with 3290 triangular patches with 4935 unknowns. The tip of the almond points to the x-axis. The elevation angle of the incident wave is fixed to be 90°, while the aspect angle ranges from 0° to 63° with a 1° increment. Since the basis matrix $\boldsymbol{\Psi}$ has an important effect on the measurement number, we compare three different bases in this example including Hermite basis, discrete cosine transformation (DCT) basis and Haar wavelet basis. All these basis are adopted to analyze the monostatic scattering problem and their results are compared with the result of MLFMM. The real parts of current coefficients at a randomly chosen edge under different incident angles are shown in Fig. 3. It can be observed that the results obtained by Hermite and DCT basis agree well with that of MLFMM. The result obtained by using Haar basis is comparable to that of MLFMM. The numbers in the brackets means the corresponding measurement times. Note that the measurement number corresponds to the number of MoM solutions. Obviously, the measurement times after adopting Hermite basis achieve its minimum. So the basis function is fixed to be the Hermite basis in the following two examples. Figure 4 demonstrates the current magnitude distributions obtained by MLFMM and the proposed method with different basis. Good agreement can be achieved.

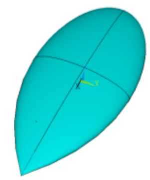

Fig. 2. Almond model.

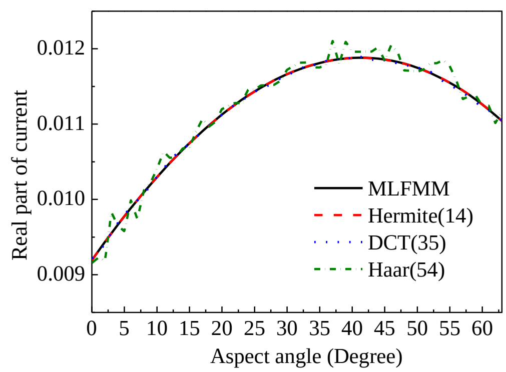

Fig. 3. Real parts of current coefficients at a randomly chosen edge under different incident angles obtained by using three kinds of basis. The numbers in the brackets represent the number of measurement.

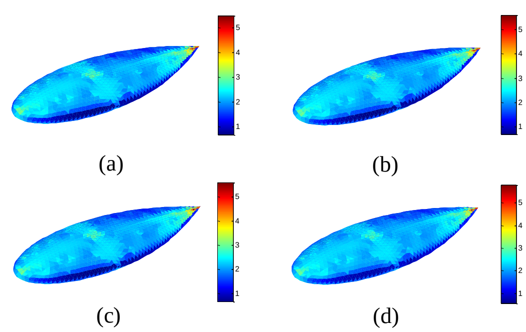

Fig. 4. The current magnitude distributions obtained by MLFMM and the proposed method with different basis when the aspect angle is 0°: (a) MLFMM, (b) Hermite, (c) DCT, and (d) Haar.

B. Missile model

A PEC missile model as shown in Fig. 5 is analyzed as the second example. The model is created based on the picture of Tomahawk missile in Wikipedia [29]. The maximum size in the x, y and z directions are 1.4 m, 0.62 m and 0.25 m. It is discretized into 6792 unknowns at 1.5 GHz. The warhead is towards the positive direction of x-axis. The elevation angle of the incident wave is fixed to be 90° while the aspect angle ranges from 0° to 180° with 0.5° increment. Both the proposed method (BCS) and the method in [20] (CS_OMP) are adopted to analyze the monostatic scattering problem and their results are compared with that of MLFMM as shown in Fig. 6. Table 1 lists the measurement number and CPU time for different methods. The number of measurement of the proposed method is determined to be 63 adaptively, and the result match well with that of MLFMM. Since the CS_OMP method cannot determine the number of measurement, we try several different measurement number and select the smallest one giving the similar level of accuracy with the proposed method. The measurement number determined in such a manner for CS_OMP method is 71. Although the measurement time of the proposed method is less than the CS_OMP method, their CPU time is similar since the computational cost of BCS algorithm is larger than OMP algorithm.

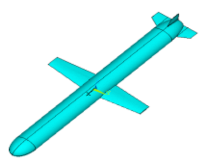

Fig. 5. Missile model.

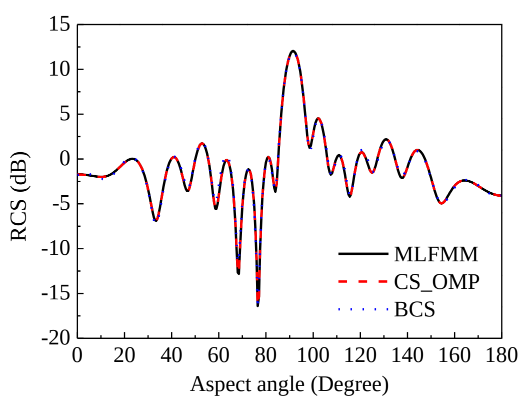

Fig. 6. Monostatic RCS of the missile model obtained by MLFMM, CS_OMP and BCS.

Table 1: Measurement number and CPU time of three kinds of methods for the missile model

Method	Measurement Number	CPU Time (s)
MLFMM	360	5527
CS_OMP	71	1272
BCS	63	1295

C. Aircraft model

A scaled aircraft model shown in Fig. 7 is analyzed as the third example. The model is created based on the picture of F15 fighter plane in Wikipedia [30]. The maximum size in the x, y and z directions are 1.9 m, 1.2 m and 0.4 m. It is discretized into 6741 unknowns at 600 MHz. The nose of the aircraft is towards the positive direction of x-axis. The elevation angle of the incident wave is fixed to be 90° while the aspect angle ranges from 0° to 360° with 1° increment. Figure 8 demonstrates the monostatic RCS computed by the MLFMM, CS_OMP and BCS method. Table 2 lists the measurement number and CPU time for different methods. Similar conclusions can be drawn with the second numerical example.

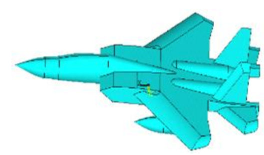

Fig. 7. Aircraft model.

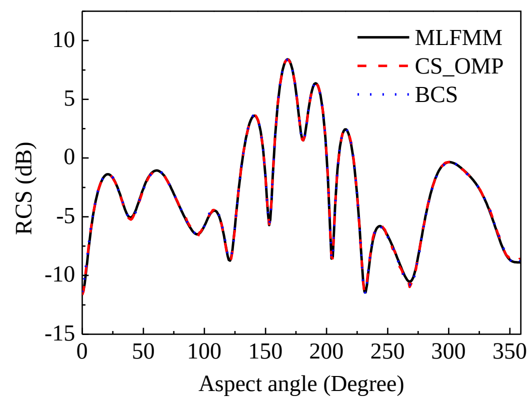

Fig. 8. Monostatic RCS of the aircraft model obtained by MLFMM, CS_OMP and BCS.

Table 2: Measurement number and CPU time of three kinds of methods for the aircraft model

Method	Measurement Number	CPU Time (s)
MLFMM	360	15817
CS_OMP	80	3534
BCS	69	3505

IV. CONCLUSION

The Bayesian compressive sensing method is applied to the fast monostatic scattering analysis. Compared with the traditional CS based method, the proposed method adopts the Bayesian framework and can adaptively determine the number of compressive-sensing measurements. Moreover, the proposed method needs less measurements than OMP method with the similar level of accuracy.

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