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Research on Computer Graphics Design and Visual Communication Design

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Abstract

From the perspective of computer graphics design model construction, computer graphics design model refers to the reconstruction of sparse signals from the observation matrix.$\mathrm{Y} = \mathrm{AX} + \mathrm{EX}$In the visual vector reconstruction model, the same cognitive matrix column is used to observe multiple visual vector structures through multiple unknown correlated signals. The position of the visual vector is part of the same wireless matrix, and the wireless unstructured signals show some characteristics.We can use the available information of the discrete signal to reconstruct the discrete signal better.

Keywords: *Computer, Graphic Design, Visual Communication, Algorithm Research*

1. Introduction

In visual communication design, the prior distribution of bayesian regularization method can use different flexible structure sparse signal reconstruction model, and can assess the error range of solutions, more than at the same time the parameters of the model can get the best value, through the adaptive learning more robust sparse observation vector signal reconstruction the vision has the potential application value to solve the problem, and at the same time, it also makes the analytic hierarchy process (ahp) and bayesian framework in more extensive attention.Stratified analysis and processing requires bayesian model to accurately locate unknown signals, reflect signal sparsely, and use appropriate prior distribution to represent the noise feature observation matrix, and further infer the actual observation effect of relevant parameters.

2. Computer graphics design model and reconstruction algorithm

2.1. Introduction to computer graphics design model

When there is no noise in the observation matrix, the identification set of non-zero row visual vectors of the signal matrix is expressed as, then the signal reconstruction model under the computer graphics design can be obtained by extending the reconstruction model under the single observation visual vector:

$$\mathrm{Y} = \mathrm{AX} + \mathrm{EX} supp(X) := \bigcup_{l} supp(X_l)$$
$$\min_{X \in R^{N \times L}} |supp(X)|, s.t. Y = AX \quad (1)$$

Further, by virtue of the mixed norm of the matrix, this model can be expressed as:

$$\min_{X \in R^{N \times L}} \|X\|_{0,q}, s.t. Y = AX \quad (2)$$

Where the norm of the matrix is defined as the visual vector representing the row 1.

$Xl_{p,q}\|X\|_{p,q} = \left(\sum_{n=1}^{N}\|X_n\|_p^q\right)^{1/q}, p, q > 0\ X_n$Xn For any sum, the number of non-zero rows in the representation is called row-pseudo-norm.

$$q > 0p = 0\|X\|_{0,q} = |supp(X)|Xl_0$$

At present, there are two models which are mainly used to study and analyze the observation vector structure problems: the model based on mixed mode and the Bayesian model.

2.2. Mixed norm model

To rebuild a consortium of the sparse signal reconstruction sparse visual vector joint sparse vector vision, normal model reconstruction demand solutions are usually based on signal matrix x this specification is used to measure the nonzero number of rows in the matrix x model reconstruction problems are generally considered to have three forms, one of the most representative is the first form.That is to minimize the norm under the constraint of the norm inequality of the residual matrix.Is a fidelity term for the data model used to ensure that the solution conforms to the loss function of the observation data error term, and regularization is a multiplicity of X-ray measurement features designed to ensure joint sparsity of the solution.However, because - norm is not continuous, row sparse solutions are usually difficult to find.$l_{0,\ q}$.

2.3. Bayesian Model

Structural sparsity is an extension of a standard sparsity model in which variables in the same set are often zero or zero at the same time. Therefore, the spatial connection structure mainly depends on the population dispersion model. In this structure, we use the potential variables that show the fracture model to capture the spatial compatibility of MMV.In fact, MMV is a special kind of structural signal.If we add X to a column of a visual vector, the visual vector is a discrete structural signal, and it has a known group model.However, unlike general discrete structural signals, the correlation of MMV is not only shown in the discrete fixed distribution of all measurements, but also in the temporal correlation between different measurements.A deeper exploration of temporal correlation is important for more effective recovery. In order to solve this problem, the time relation model of quantities related to the positive matrix is proposed.

We know that the Bayesian model can capture the temporal relationship between different sources and the spatial relationship between different sources.In this article, we combine the relationship between space and time in a unified Gulf framework. In particular, the preceding variables and hidden variables are used to collect temporal and spatial relationships. In this part, we will delve into the Bayesian model. As mentioned above, we separate learning from extensive learning. The corresponding Bayesian model is proposed:

$$Y = \Phi(\mathcal{W} \circ \mathcal{Z}) + E \qquad (3)$$

Bayesian algorithm takes fault recovery problem as the solution of Bayesian inference and applies statistical tools to solve it. In the former option, the split signal can be modeled as a continuous random variable with a spike in 0.A widely used precedent for signal vector models is the Laplace density function:

$$x \sim \left(\frac{\lambda}{2}\right)^N esp(-\lambda \textstyle\sum_{i=1}^{N} |x_i|)$$

(4)

Laplaciansparsity priors are not gauss likelihood conjugate, so it may not be possible to perform bayesian inference accurately.This problem has been solved in sparse Bayesian learning with automatic correlation determination (ARD)[3-8].The stratified priori has similar properties to Laplace Prior, but it is convenient to perform conjugate exponent analysis instead of applying Laplace prior to X.For this reason, the first choice is the zero-mean Gauss prior on each element of X. Wife et al. attempted to apply sparse Bayesian learning in signal measurement model (SMV) and extend it to the MMV model. In order to model time correlation, the Bayesian MMV model was extended as follows:

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$$x \sim \prod_{i=1}^{N} \mathcal{N}(x_i|0,\alpha_i^{-1})\ X_i \sim \mathcal{N}(X_i|0,\gamma_i^{-1}B)$$

$$W_i \sim \mathcal{N}(W_i|0,(\gamma_i B)^{-1}). \qquad (5)$$

γ_i Is a non-negative hyperparameter that controls sparsity.Following the traditional sparse Bayesian learning principle, we use the distribution as the prior distribution of accuracy: $Gamma\gamma_i$

$$\gamma_i \sim Gamma(\gamma_i|a,b) = \Gamma(a)^{-1} b^a \gamma_i^{a-1} exp(-b\gamma_i) \qquad (6)$$

In order to avoid over-fitting and improve adaptability, positive definite will be used to model all source covariance matrices:

$B \in \mathbb{R}^{L\times L}$ $\quad B \sim \mathcal{W}(B|\mathcal{V}_0, v_0) = \frac{1}{C}|B|^{(v_0-L-1)/2} exp\left(-\frac{1}{2}Tr(\mathcal{V}_0^{-1}B)\right). \qquad (7)$

Where is the normalized constant, is the number of degrees of freedom, is the proportional matrix.$Cv_0\mathcal{V}_0$ Here, we focus on bayesian models that emphasize not only Numbers but also sparse patterns.Therefore, the binary visual vector S is introduced to enhance the recovery and capture of spatial relationships.The standard choice for the binary visual vector S model is Bernoulli distribution:

$$s \sim \prod_{i=1}^{N} Bernoulli(S_i|\pi_i) \qquad (8)$$

With this model, we know that the collapse of standards leads only to simple master data structures. With more data structures in place, we focus on Markov dependencies between components and neighbors. For an element, if its neighbor is nonzero (0), then it is likely that the element is nonzero (0).

3. Reconstruction algorithm based on mixed norm model

Many structural algorithms are created by extending the structural algorithms that observe a single visual vector model.

3.1. SOMP algorithm

At the same time orthogonal matching tracing algorithm can be used to solve several different simultaneous sparse approximation problems.For different problems, just change the rules of the pause algorithm.

The detailed algorithm is as follows:

Input:

• A signal matrix$d \times KS$

• Stop condition.

Output:

• A set of indexes containing the number of iterations completed.$\boldsymbol{A}_T TT$

• An approximation matrix.$d \times K\boldsymbol{A}_T$

• A residual matrix.$d \times K\boldsymbol{R}_T$

When no end condition is met, repeat:

(1) Initialize the residual matrix, index set and iteration counter$\boldsymbol{R}_0 = \boldsymbol{S} A_0 = \emptyset t = 1$

(2) Find indexes that can solve simple optimization problemsλ_t

$$\max_{\omega\in\Omega} \sum_{k=1}^{K} |\langle \boldsymbol{R}_{t-1}\mathbf{e}_k, \varphi_\omega\rangle| \qquad (9)$$

The canonical base vector that we used to represent.$\mathbf{e}_k \mathbb{C}^K k$

(3) Update the index set

$$\Lambda_t = \Lambda_{t-1} \cup \{\lambda_t\} \qquad (10)$$

Determines the orthogonal projection onto the index set of atoms$\boldsymbol{P}_t \Lambda_t$

(5) Calculate new approximations and residuals:

$$\boldsymbol{A_t} = \boldsymbol{P_t S}, \boldsymbol{R_t} = \boldsymbol{S} - \boldsymbol{A_t} \qquad (11)$$

(6) Increase. Unless the stop condition is satisfied, return step 2.t

3.2. M - FOCUSS algorithm

M-focal Underdetermined System Solver (M-FocUSS) algorithm:

In the noiseless sparse signal reconstruction model, the FOCUSS algorithm applied to solve the -norm minimization problem is extended to obtain the M-FocUSS algorithm.l_q

It is a method based on mixed norm optimization, which can effectively solve the - norm minimization model.$l_{2,\ q}$

The M-FocUSS algorithm is summarized as follows:

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$$W_{k+1} = diag\left(c_k[i]^{1-p/2}\right) \tag{12}$$

Among them $c_k[i] = \|x_k[i]\| = \left(\sum_{l=1}^{L}\left(x_k^{(l)}[i]\right)^2\right)^{1/2}, p \in [0,1]$

$$Q_{k+1} = A_{k+1}^{\dagger}B \tag{13}$$

Among them$A_{k+1} = AW_{k+1}$

$$X_{k+1} = W_{k+1}Q_{k+1} \tag{14}$$

In order to stimulate sparsity, we make, once the convergence criteria are met:$p \in [0,1]$

$$\frac{\|X_{k+1}-X_k\|_F}{\|X_k\|_F} < \delta \tag{15}$$

(where is the parameter selected by the user)δ

3.3. Reconstruction algorithm based on Bayesian Model

Among MMV algorithms, Bayesian algorithm has attracted much attention because it can usually obtain the best recovery performance.Sparse Bayesian learning (SBL) is very important in Bayesian algorithm.MSBL algorithm USES SBL to solve the sparse signal recovery problem of MMV model.The advantage of MSBL is that the local minimum is much smaller than some classical algorithms such as the FOCUSS series.

In addition, based on Bayesian theory, block sparse Bayesian learning (bSBL) framework can transform the original MMV model into a new SMV model.This makes it easy to model the time dependencies of the source using this model framework. On this basis, an algorithm named T-SBL is derived.The algorithm is very efficient, but the conversion speed from MMV to SMV is very slow in the high-dimensional parameter space.Therefore, the t-MSB algorithm is generated by approximating some steps of the algorithm, and the fast algorithm runs in the original parameter space.Like t-SBL, T-MSBL is very efficient, but its computational complexity is much lower.

Pc-msbl algorithm is a mode coupled hierarchical model for MMV to deal with the block sparsity of ISAR image scene of fast rotating targets.The model makes use of the fact that for the ISAR image of a rapidly rotating target, MTRC usually exists and therefore the scattering characteristics of adjacent distance elements are correlated.Thus, the sparse pattern of adjacent coefficients is statistically correlated. Specifically, the Gaussian likelihood model of each coefficient involves not only its own parameters, but also its immediate neighbor hyperparameters.Tobe more precise, there is the following formula:

$$p(\boldsymbol{X}|\boldsymbol{\alpha}) = \prod_{i=1}^{N} p(\boldsymbol{x}^{(i)}|\alpha_i, \alpha_{i+1}, \alpha_{i-1})\, p(\boldsymbol{x}^{(i)}|\alpha_i, \alpha_{i+1}, \alpha_{i-1}) \tag{16}$$

Among them $p(\boldsymbol{x}^{(i)}|\alpha_i, \alpha_{i+1}, \alpha_{i-1}) = \mathcal{N}(\boldsymbol{x}^{(i)}|0, (\alpha_i + \beta\alpha_{i+1} + \beta\alpha_{i-1})^{-1})$

In fact, MMV is a special kind of structural signal.If we add X to a column of a visual vector, the visual vector is a discrete structural signal, and it has a known group model.We assume and for the terminal sum, the parameters indicate the pattern correlation between the range cells and their adjacent {,}.$\alpha_0 = 0\alpha_{N+1} = 0\boldsymbol{x}^{(1)}\boldsymbol{x}^{(N)}0 \leq \beta \leq 1\boldsymbol{x}^{(i)}\boldsymbol{x}^{(i+1)}\boldsymbol{x}^{(i-1)}$If, the Gaussian likelihood model is simplified to the traditional M-SBL model, and the sparse modes of adjacent distance cells are independent of each other. $\beta = 0$ Therefore, a compression or data reduction process that can reduce the sample size and restore the most important characteristics is required.Effective compression of EEG data should not only reduce the number of sampled data, but also enable rapid wireless transmission in clinical diagnosis.

Similarly, sparsity is not only determined by hyperparameters, but also by adjacent hyperparameters. $\boldsymbol{x}^{(i+1)}\alpha_{i+1}\{\alpha_{i+1+1}, \alpha_{i+1-1}\}$ Thus, the hyperparameters associated with each coefficient are larger than those of the standard Bayesian hierarchical model.And the sparse patterns of adjacent range cells are coupled by the hyperparameters they share.However, unlike general discrete structural signals, the correlation of MMV is not only shown in the discrete fixed distribution of all measurements, but also in the temporal correlation between different measurements.A deeper exploration of temporal correlation is important for more effective recovery. In addition, during the learning process, super parameters are associated with each other through the units they are connected to.

We use the Gamma distribution as the super priority of the hyperparameter, similar to the traditional M-SBL:α_i

$$p(\boldsymbol{\alpha}) = \prod_{i=1}^{N} \text{Gamma}\ (\alpha_i|a,b) = \prod_{i=1}^{N} \Gamma(a)^{-1} b^a \alpha_i^a e^{-b\alpha_i} \quad (17)$$

Here is Gamma.$\Gamma(a) = \int_0^\infty t^{a-1}e^{-t}dt$The parameter B is usually assigned a small value, for example.10^{-4}However, make the parameters larger, such as between 0.5 and 1.a

This chapter mainly introduces two main models of sparse signal reconstruction in computer graphics design: the model based on mixed norm and the model based on Bayesian theory.On this basis, various signal reconstruction algorithms based on these two models are introduced in detail: SOMP algorithm and M-FocUSS algorithm based on mixed norm model, and MSBL algorithm based on Bayesian model, TMSBL algorithm and PC-MSBL algorithm.

4. Computer graphics design model reconstruction algorithm simulation experiment

In this section, we will use Matlab software to illustrate the reconstruction performance of the algorithm through the evaluation of simulated data, and compare the reconstruction performance of various algorithms.

The simulation data used is sparse signal matrix, the signal length is 250, the number of signals is 5, monte Carlo simulation times is 200.Gaussian white noise is used and the SNR changes from 5 to 30. The definition formula of SNR is as follows:

$$SNR(db) = 10\log_{10}(\|\Phi X\|_F^2/|E|_F^2) \quad (18)$$

4.1. Evaluation criteria for signal reconstruction quality

Several important performance indicators were used in the whole experiment:

The first performance index to measure the accuracy of sparse reconstruction is mean square error (MSE), which is calculated as follows:

$$MSE = \left\|\hat{X} - X\right\|_F^2 / \|X\|_F^2 \quad (19)$$

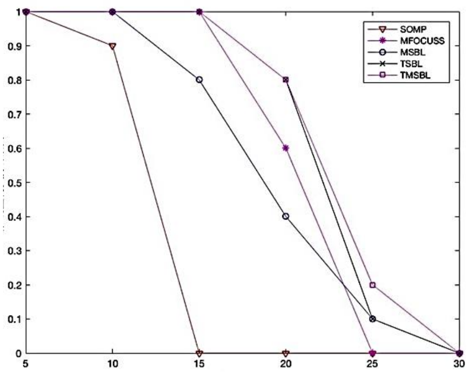
Where, and respectively represent the actual signal and the reconstructed signal.$X\hat{X}$

The second performance index to measure the accuracy of sparse reconstruction is the support set recovery rate.

The experiments include the following methods: SOMP algorithm, M-FocUSS algorithm, MSBL algorithm, TMSBL algorithm and TSBL algorithm.Among these algorithms, TMSBL is an algorithm that considers time correlation, while M-FocUSS and MSBL are effective algorithms that do not consider time correlation. SOMP algorithm and M-FocUSS algorithm are based on mixed norm model, while MSBL algorithm, TMSBL algorithm and TSBL algorithm are based on Bayesian model.In the experiment, the iteration is repeated until the convergence criterion is satisfied.

4.2. Simulation comparison and analysis of reconstruction performance of each algorithm

4.2.1. Comparison of reconstruction performance under different sparsity degrees



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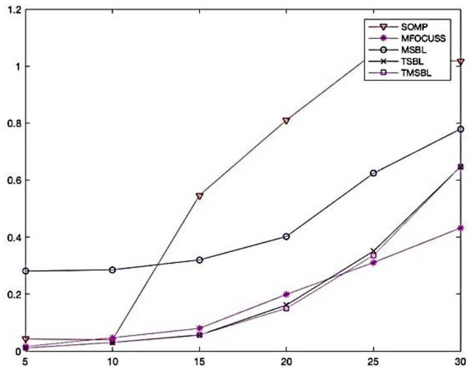

Figure 1. Reconstruction performance comparison of SOMP, M-FocUSS, MSBL, TMSBL and TSBL under different sparsity degrees.

It can be seen from the figure that the probability of accurate reconstruction support set of SOMP, M-FocUSS, MSBL, TMSBL and TSBL algorithms increases with the increase of sparsity, which indicates that the more sparse the algorithm is, the more difficult it will be to reconstruct the signal.Under the same sparsity, SOMP has the lowest probability of accurate reconstruction of support set, which indicates that its reconstruction performance is the worst.Similarly, THE reconstruction performance of TMSBL is the best. The reconstruction performance of TMSBL is better than THAT of TSBL, MFOCUSS and MSBL.

In addition, as the sparsity increases, the MSE value of each algorithm increases.The accurate reconstruction support set of M-FocUSS has a high probability and a minimum MSE value, so it has the best reconstruction performance.The reconfiguration performance of TMSBL and TSBL is similar, slightly inferior to m-FocUSSalgorithm.SOMP has the worst refactoring performance.

4.2.2. Comparison of reconstruction performance under different SNR

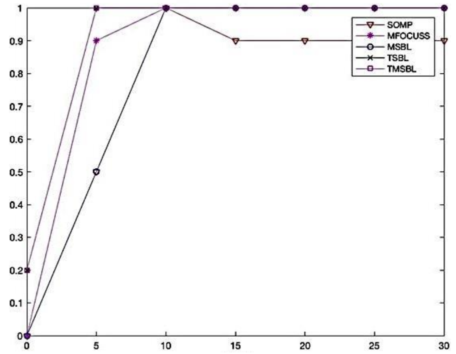

Figure 2. Reconstruction performance comparison of SOMP, M-FocUSS, MSBL, TMSBL and TSBL under different SNR.

It can be seen from the figure that, when the SNR is greater than or equal to 10, the probability of accurate reconstruction of the support set of the four algorithms except SOMP algorithm is 1. It can be seen that all the algorithms except SOMP algorithm can complete signal reconstruction perfectly.

In addition, with the increase of SNR, the reconstructed mean square error of the five algorithms gradually decreases. MSE of MSBL is the largest, followed by MFOCUSS and SOMP, and MSE of TMSBL and TSBL is the smallest.This shows that TMSBL, TSBL, and MFOCUSS have better refactoring performance.

4.2.3. Comparison of reconstruction performance under different observed quantities

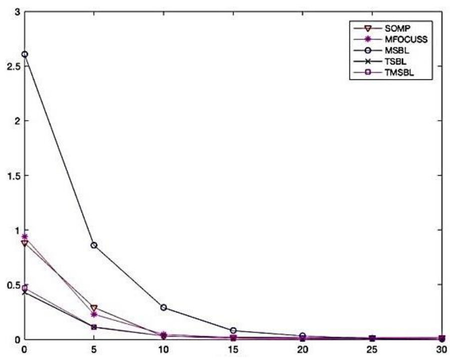

Figure.3 Reconstruction performance comparison of SOMP, M-FocUSS, MSBL, TMSBL and TSBL under different observed values.

It can be seen from the figure that, when the observed quantity is greater than or equal to 40, the probability of accurate reconstruction support set of the four

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algorithms except SOMP algorithm is 1. It can be seen that other algorithms except SOMP algorithm can complete signal reconstruction relatively perfectly.

5. The application of computer graphics design model reconstruction algorithm in ISAR imaging

5.1. ISAR imaging model

We assume that the translational motion of the target has been corrected after motion compensation.Therefore, as shown in Figure 5-1, the movement of the target is limited to the 2D plane during the CPI period.We assume that the target is located in the far field of the radar, and then the instantaneous distance between the radar and the scatterer can be approximated as: $P_k(x_k, y_k)$

$$R_k(t) \approx R_0 + x_k\omega_0 t + y_k \quad (20)$$

Where is the distance between radar and target center O, and is the rotation speed. $R_0\omega_0$ If the maneuverability of the target is not very strong, then the approximate equation of the above equation can be established.

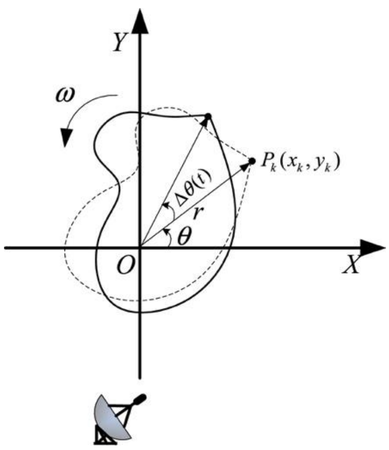

Figure 4.ISAR geometric imaging.

If we assume that the radar sends a linear frequency modulation (LFM) signal, we need to use compressed sensing theory.Compressed sensing theory is different from the traditional Nyquist sampling theorem, it shows that if the signal is rift valley, or can be in a transition area for rift, and satisfy the RIP properties, it is an observation matrix and an unrelated rift valley said base, so it can be from was much lower than Nyquist sampling theorem requirements of sampling points in recovery and reconstruction.In addition, data compression is completed in the sampling process to avoid the collection of a large number of redundant data in the sampling process, which saves a lot of resources and time.

5.2. Inverse SYNTHETIC aperture radar imaging simulation experiment

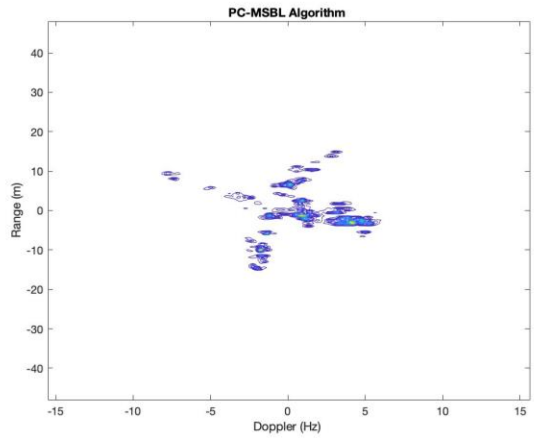

Figure 5.ISAR image obtained by PC-MSBL algorithm.

Pc-msbl algorithm can be used in the imaging of inverse synthetic aperture radar. From the results of simulation experiment, it can be seen that the reconstructed imaging signals are very close to the original initial signals, with a small error, and show better performance to the real data.

The simulation of ISAR imaging shows that the algorithm can produce ISAR images with good focus.

6.Conclusion

With the increase of the amount of observation, the visual transmission of computer graphics design becomes more and more obvious, and the reconstructed mean square error of the five algorithms gradually decreases. Generally, MSE of MSBL and SOMP is larger, while MSE of MFOCUSS, TMSBL and TSBL is smaller.This shows that TMSBL, TSBL, and MFOCUSS have better refactoring performance.We will use Mat Lab software to explain the reconstruction performance of the algorithm by evaluating the simulation simulation

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data, and compare the reconstruction performance of the five algorithms.Through the simulation results, we can find that compared with MSBL and SOMP, TMSBL, TSBL and MFOCUSS have better reconstruction performance.

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