

Compressed Sensing Image Reconstruction Based on Joint Statistical and Structural Priors

Jiahui LI, Shaohua WU, Huan HUANG, Jian JIAO

Harbin Institute of Technology Shenzhen Graduate School, Shenzhen, Guangdong, China, 518055

Email: jiahui__1010@163.com, hitwush@hit.edu.cn, hhuanghit@163.com, jiaojian@hitz.edu.cn

Abstract—Due to proper use of the image sparsity, CS (compressed sensing) image compression has made great achievements in the field of image compression without the constraint of Nyquist sampling law. A great deal of researches indicate that there exist obvious statistical and structural priors regularity for image information distribution, while traditional CS image compression algorithms only use the sparse characteristic of the image information. In this paper, we propose a CS image reconstruction algorithm based on the joint statistical and structural priors which can achieve efficient image reconstruction via a small amount of measurements. With the full use of inter-scale and intra-scale relations of the sparse coefficients, we optimize the iterative hard thresholding CS algorithm specifically by building a GSM model to constrain the local coefficients distribution statistically, and a tree model to constrain the global coefficients distribution structurally. Extensive simulations have been conducted and the results show that the proposed method has achieved a considerable promotion both on the speed and the PSNR gain of image reconstruction, compared with the traditional recovery algorithms under the same compression ratio.

Keywords—compressed sensing, statistical priors, structural priors, GSM, wavelet tree model

I. INTRODUCTION

With the rapid integration development of IT industry and IC industry, multimedia communication, represented by the image signal, is gradually becoming the main stream of modern network communication form. However, with the large bandwidth of image signal, high sampling frequency has been the bottleneck of signal processing. The traditional image compression algorithms can't meet the increasing transmission bandwidth requirements, due to the insufficiency utilization of sampling information and the high requirements of the equipment capacity.

CS^{[1][2][3]} theory provides a new solution and states that under certain conditions, signals with sparse representations can be reconstructed from far fewer measurements than suggested by the Nyquist theory. As for the fact that most images have sparse representations in a transform domain, the applications of CS in images have been successfully developed^[4], even have a good performance in video frame reconstruction.^[5]

Traditional CS image reconstruction algorithms only use the sparsity of image under the orthogonal basis, however, image signal also has obvious structural features after the wavelet transformation. To efficiently exploit these dependencies of image wavelet coefficients for CS reconstruction, different dependency models need to be used for signals reconstruction. For example, Baraniuk et al. proposed a model-based image reconstruction algorithm based on wavelet tree structure^[6], and proved the correctness and validity of introducing the wavelet tree model into CS reconstruction theory. Tree-based Matching Pursuit (TMP) and Tree-based Orthogonal Matching Pursuit (TOMP) algorithms compared with MP (Matching Pursuit)^[7] and OMP (Orthogonal Matching Pursuit)^[8] algorithms proved that the image reconstruction algorithms based on the tree structure can greatly improve the quality of image reconstruction. However, due to the introduction of the tree structure model, the algorithms' complexity has been increased.

To further enhance the performance of the CS reconstruction algorithms, some scholars consider incorporating the statistical properties of the image sparse representation coefficients into it. In addition to the structural properties of the image sparse representation, there are some statistical properties: Mallat proposed a generalized Laplacian distribution of wavelet coefficients by studying the covariance of natural images in the same subband^[9], also called generalized Gaussian distribution (GGD) or exponential distribution. In [10] [11] [12], the Gaussian scale mixed model is used to describe the local features of image coefficients' sparsity and applied to the image reconstruction algorithm with good reconstruction effects.

Although the above algorithms improve the quality of image reconstruction to a certain extent, they consider only one aspect of statistical prior or structural prior. In this paper, a CS image reconstruction algorithm based on the joint statistical and structural priors is proposed which can achieve efficient image reconstruction via a small amount of measurements. With the full use of inter-scale and intra-scale relations of the sparse coefficients, the original image information can be reconstructed with high quality and high efficiency.

This paper is organized as follows. Section II provides a briefly review about image compressed sensing. Section III presents the wavelet tree model. Section IV presents Gaussian scale mixture model. Section V presents the compressed sensing image reconstruction algorithm based on the joint statistical. Section VI is the simulation results for natural images and performance comparison with the existing research. The last section gives the conclusion of this paper and plans the future work.

II. IMAGE COMPRESSION ALGORITHM PERCEPTION

A. Compressed Sensing

CS theory indicates that if signal x with length N is sparse in some domain, it can be expressed as:

$$x = \Psi \alpha \quad (1)$$

Where $\Psi \in R^{N \times N}$ is a multiscale wavelet transform matrix, and α is a $N \times 1$ sparsest coefficient vector with K non-zero entries, then we can recover signal x from M samples where $M < N$. In matrix expression, the samples can be measured by a $M \times N$ matrix $\Phi \in R^{M \times N}$ with the subsampling rate M/N :

$$y = \Phi x = \Phi \Psi \alpha \quad (2)$$

To recover the real-valued signal x from the samples, we can search for the sparsest coefficient vector α from solving combination optimization problems:

$$\hat{\alpha} = \arg \min_{\alpha} \|\alpha\|_0, \text{ s.t. } y = \Phi \Psi \alpha \equiv \Theta \alpha \quad (3)$$

Where the l_0 norm of α calculates the nonzero entries. The problem is a NP-hard problem, practically, we transform the l_0 norm minimization to the l_1 norm minimization under the so-called RIP property (restricted isometry property).

$$\hat{\alpha} = \arg \min_{\alpha} \|\alpha\|_1, \text{ s.t. } y = \Phi \Psi \alpha \equiv \Theta \alpha \quad (4)$$

This corresponds to a linear program that can be solved in polynomial problem. As a consequence, CS provides a solution that signals with high dimensions can be recovered from samples at the sub-Nyquist rate.

B. Compressed Sensing Model

Image compressed sensing system is shown in figure 1. On the coding end, vector processing operation means:

$$x = \text{vec}(X) = \{\text{col}_1(X), \text{col}_2(X), \dots, \text{col}_{N_2}(X)\} \quad (5)$$

Then vector $x \in R^{N_1 N_2 \times 1}$ is measured by operation $y = \Phi x$, where $\Phi \in R^{M \times N_1 N_2}$ is a measuring matrix. On the decoding end, the sparsest coefficient vector $\hat{\alpha}$ can be searched from $y = \Phi \Psi \hat{\alpha}$ by recovery algorithm. Then, the real-valued signal $\hat{x}$ can be obtained from inverse discrete wavelet transform by $\hat{x} = \Psi \hat{\alpha}$. "Matrix" operation means:

$$\hat{X} = \{\hat{x}(1:N_1); \hat{x}(N_1+1:2N_1); \dots; \hat{x}(N_1^2 - N_1 + 1:N_1^2)\} \quad (6)$$

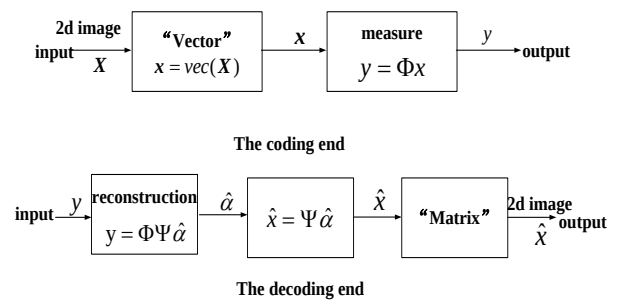


Figure 1. Image compressed sensing system

C. Iterative Hard Thresholding

The reconstruction algorithm plays an important role in the quality of the reconstructed image. The essence of CS reconstruction algorithm is to solve the underdetermined equation.

As a typical CS reconstruction algorithm, the Iterative Hard Thresholding (IHT) algorithm^[13] is widely used which is simple and has a good implementation guarantee. This paper chooses IHT reconstruction algorithm as the basis. The IHT algorithm, proposed by Blumenbach and Davies^[13], aims to solve the K -sparse problem:

$$\hat{\alpha} = \arg \min_{\alpha} \|y - \Theta \alpha\|_2^2, \text{ s.t. } \|\alpha\|_0 \leq k \quad (7)$$

The specific algorithm is to constrain the iterated estimates by nonlinear operators, so as to ensure that the same number of elements retained during each iteration. The iterative formula is shown in equation (8):

$$\hat{\alpha}^{(n)} = H_k(\hat{\alpha}^{(n-1)} + \Theta^T(y - \Theta \hat{\alpha}^{(n-1)})) \quad (8)$$

$H_k(\bullet)$ is the non-linear operator which is to retain the first k larger components and make the others to zero.

III. IMAGE WAVELET TREE STRUCTURE MODEL

Casual observations indicate that image wavelet coefficients not only have the sparse property but also occur in the clusters^{[14] [15]}. Traditional CS image compression algorithms only use the sparsity information, moreover, the wavelet coefficients can be naturally organized into a tree structure. Wavelet decompositions have found wide applications in the analysis, processing, and compression of signals because these signals are K -sparse and compressible, respectively. As for two-dimensional signals^[16], the hierarchical structure of decompositions is illustrated in fig.2, after each decomposition, there generates four subbands, LL, LH, HL and HH. The LL subband which has more low frequency information can be decomposed to generate a multiresolution representation. The coefficients at different scales can be naturally organized into a tree structure. The arrows illustrate the relationship between parent and children coefficients. The coordinates correspond to their location.

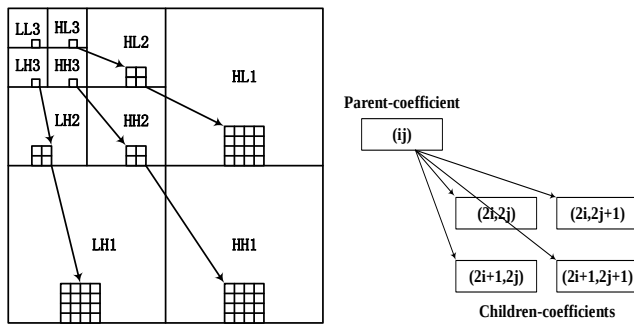


Figure 2. Image wavelet decomposition and tree model

Significant researches have theoretically shown it is the tree structure model that can be well applied in CS compression algorithm^[17], while the essence of the proposed algorithm is taking full use of the cluster and developing a new model from both structure and statistical perspective.

IV. GAUSSIAN SCALE MIXTURES

Despite of the sparsity, recent work has investigated that individual image statistics are highly inhomogeneous that contains smooth region and features region, which is reflected that the marginal distributions of wavelet coefficients are highly kurtosis, with a large peak at zero, and tails that fall significantly slower than a Gaussian of the same variance. These statistical dependencies can be modeled by a Gaussian scale mixture model.

GSM model well represents the wavelet coefficients distribution, especially the dependency between local coefficients' amplitudes and the associated marginal behaviors. Specifically, consider an image decomposed into oriented subbands at multiple scales, we assume the coefficient within each local neighborhoods around a reference coefficient of a subband can be characterized by the Gaussian scale mixture model^{[10][12]}.

And then we can denote α as a neighborhood of coefficients clustered set, formally, the random vector x can be represented as a Gaussian scale mixture if and only if it can be expressed as the product of a zero-mean Gaussian vector u and an independent positive scalar random variable z which is highly correlated with coefficients changing rule between the different scales:

$$\alpha = \sqrt{z}u \quad (8)$$

The density of α is determined by:

$$p_{\alpha}(\alpha) = \int p(\alpha|z)p_z(z)dz \quad (9)$$

The GSM model can effectively describe the distribution of coefficients and capture the local dependences between neighbors in the similar locations, scales, and orientations in the wavelet domain.

Generally, the noisy observations of coefficients can be represented as:

$$y = \alpha + w = \sqrt{z}u + w \quad (10)$$

w is a noisy vector, including measurement noise and under sampling artifacts. u and w are independent zero-mean

Gaussian random variables with covariance matrices C_u and C_w satisfying the equation:

$$C_y = E\{z\}C_u + C_w \quad (11)$$

Where C_w can be computed through the samples' variance of the noisy wavelet coefficients in the highest frequency diagonal orientation subband (HH), C_y can be compute from the observations. Without loss of generation, we assume $E\{z\} = 1$, resulting in

$$C_u = C_y - C_w \quad (12)$$

Under these conditions, the estimate of the reference coefficient at the center of the neighborhood $\hat{v}_c$ can be represented as

$$\hat{v}_c = E\{\alpha^n | y\} \quad (13)$$

We can obtain the estimate through y and the set of observed coefficients by the Bayes least squares estimate:

$$\begin{aligned} E(\alpha^n | y) &= \int \alpha^n p(\alpha^n | y) d\alpha^n \\ &= \int \int_0^{\infty} \alpha^n p(\alpha^n, z | y) dz d\alpha^n \\ &= \int \int_0^{\infty} \alpha^n p(\alpha^n | y, z) p(z | y) dz d\alpha^n \\ &= \int_0^{\infty} p(z | y) E\{\alpha^n | y, z\} dz \end{aligned} \quad (14)$$

Changing the order of integration, the result can be evaluated by two components indirectly: One is the Bayes least squares estimate of x when conditioned on z , $E\{\alpha^n | y, z\}$ and the other is the posterior distribution of the multiple $p_z(z | y)$.

$$E\{\alpha^n | y, z\} = z(C_y - C_w)(z(C_y - C_w) + C_w)^{-1}y \quad (15)$$

$$p_z(z | y) = \frac{p(y|z)p_z(z)}{\int_0^{\infty} p(y|\alpha)p_z(\alpha)d\alpha} \quad (16)$$

To complete this model, we need to specify the probability density of the multiplier, $p_z(z)$. A number of researchers have developed some ways to describe the wavelet coefficients marginal density. In this paper, Jeffrey's prior^[18] which is one of the broadest algorithms is used to approximate the amplitude distribution of wavelet coefficients:

$$p_z(z) \propto \frac{1}{z} \quad (17)$$

Under these conditions, the GSM which exploits the statistical dependences between sparse domain coefficients can model and estimate wavelet coefficients.

Javier Portola developed a method^[9] for image denoising using this model and has demonstrated the perfect performance of GSM model for the description of the image statistical information. Kim^[10] incorporated the model into the CS image compression algorithm which has gotten some benefits of PSNR compared with traditional algorithm. However, with the increasing of the compression ratio, the statistical prior's benefits would be fewer and even

interfere with the real-value information so as to the few growth of image reconstruction PSNR under the high compression ratio.

V. COMPRESSED SENSING IMAGE RECONSTRUCTION ALGORITHM BASED ON THE JOINT STATISTICAL AND STRUCTURAL PRIORS

Traditional CS image compression algorithms only use the sparsity of the image information. In this paper, we propose a CS image reconstruction algorithm based on the joint statistical and structural priors which can achieve efficient image reconstruction via a small amount of measurements.

With the full use of inter-scale and intra-scale relations of the sparse coefficients, we optimize the iterative hard thresholding image CS algorithm specifically by building a GSM model to constrain the local coefficients' distribution statistically, and a tree model to constrain the global coefficients' distribution structurally. Finally, a small amount of measured values can be used to achieve high quality and high quality reconstruction. The proposed algorithm includes the following core steps:

(1) First, the initial estimates of the image sparse signal are calculated by measurements from constrained plane projection.

(2) Then the Gaussian mixture scale model is used to model the local information of the coefficients in each scale, and the signal estimation value is updated for the first time.

(3) After obtaining the updated sparse coefficients' estimates, the tree structure model is used to further constrain the accurate estimated values by using the structural characteristics between the scales to achieve the second update. More specifically, we use CSSA algorithm for tree structure search which is one of the most commonly used wavelets tree approximation algorithms^{[14][15]}.

(4) Finally, the estimated residuals are updated and the final sparse coefficients' estimates are obtained by using the convergence conditions.

The specific algorithm is shown in Table 1:

TABLE 1. BLSGSM-CSSA-IHT ALGORITHM

Inputs: Matrix $\Theta = \Phi\Psi^{-1}$, measurements $\mathcal{Y}$, noise constant α_0 , BLS-GSM model $M_{BLS-GSM}$, sparse K .
Outputs: α^n -the estimates of spares coefficients $\hat{\chi}$
Function procedure:
initialize: $n = 0$, $\alpha^0 = 0$, $r^0 = y$;
While halting criterion false
do
Step1 $n = n + 1$, form signal estimate
$\alpha^n \leftarrow \alpha^{n-1} + \Theta^T r^{(n-1)}$;
Step2 prune residual estimate according to structure though GSM-model;
$\hat{\alpha}_B^n \leftarrow M_{BLS-GSM}(\alpha^n, \hat{\sigma}_n)$;
(1) calculate $\hat{\sigma}_n$ from HH_1 subband, $\hat{\sigma}_n = \alpha_0 STD(HH_1)$

(2) compute neighborhood covariance matrix:

C_w : compute neighborhood noise covariance from $\hat{\sigma}_n$ (by averaging the products of pairs of coefficients over all the neighborhoods of the subbands)

C_y : estimate noisy neighborhood covariance;

C_u : estimate from C_w and C_y using:

$$C_u = C_y - C_w \quad (E\{z\} = 1)$$

(3) compute the estimates of the reference coefficients at the center of the neighborhood and construct the reference matrix $\hat{V}_C$, using:

$$\hat{V}_C = E\{\alpha^n | y\} = \int_0^\infty p(z|y) E\{\alpha^n | y, z\} dz$$

computed by local wiener estimate $E\{\alpha^n | y, z\}$ and posterior distribution of the multiplier $p(z|y)$;

(4) obtain the best K -terms structured sparse approximation through the reference matrix $\hat{V}_C$, and indirect nonlinear operation.

$$\hat{\alpha}_B^n \leftarrow H_B \{\hat{V}_C \rightarrow \hat{\alpha}^n\}$$

H_B : Sorting the location information of the coefficients at each stage in descending order of magnitude, retaining the K largest coefficients with the corresponding location, and setting the remaining coefficients to zero.

Step3 update the estimates $\hat{\alpha}^n \leftarrow \hat{\alpha}_B^n + \Theta^T (y - \hat{\alpha}_B^n)$;

Step4 prune residual estimate according to structure

$$\alpha^n \leftarrow M_{CSSA}(\hat{\alpha}^n, S)$$

Step5 update measurement residual $r \leftarrow y - \Theta \alpha^n$;

End while $r^n \leq \text{threshold}$

Return α^n

VI. SIMULATION AND RESULTS

In this section, we take extensive simulations to compare the proposed algorithm with the traditional algorithm for evaluating the high performance of the proposed algorithm. The 256*256 8-bit image of "Lena" is used in the experiments, and the structurally random matrix (SRM) is used for sensing. The orthonormal Daubechies wavelet with five levels of decomposition is used as the sparsity basis. The compression ratio corresponding to measurements is 0.25, sparse constant K is set as one third of the amount of measurements; the threshold is 0.01. And the results are shown in figure 3.

Figure 3 shows the reconstructed image of "Lena" when the compression ratio is 0.25. IHT algorithm is iterative hard threshold reconstruction algorithm, IHT-tree algorithm is iterative hard threshold reconstruction algorithm based on wavelet tree model; BLSGSM-IHT algorithm is iterative hard threshold reconstruction based on Gaussian scale model, BLSGSM-CSSA-IHT algorithm is proposed in this paper,

which is compressed sensing image reconstruction algorithm based on joint statistical and structural priors.



Figure 3. "Lena" recovered image at 0.25compression ratio

It can be seen from the intuitive results that the BLSGSM-CSSA-IHT algorithm proposed in this paper has achieved the best reconstruction quality. The objective signal evaluation index for the performance of image reconstruction is peak signal to noise ratio (PSNR), which is defined as:

$$PSNR_{dB} = 10 \log_{10} \left[\frac{255^2}{MSE} \right] \quad (18)$$

Where MSE represents the mean square error between the original image and the reconstructed image, and is defined as:

$$MSE = \frac{1}{a * b} \sum_{\alpha=1}^a \sum_{\beta=1}^b (\hat{x}(\alpha - \beta) - x(\alpha - \beta))^2 \quad (19)$$

In order to evaluate high performance of the proposed algorithm, simulations are also presented at different compression ratios. The results are shown in figure 4 to figure 5.

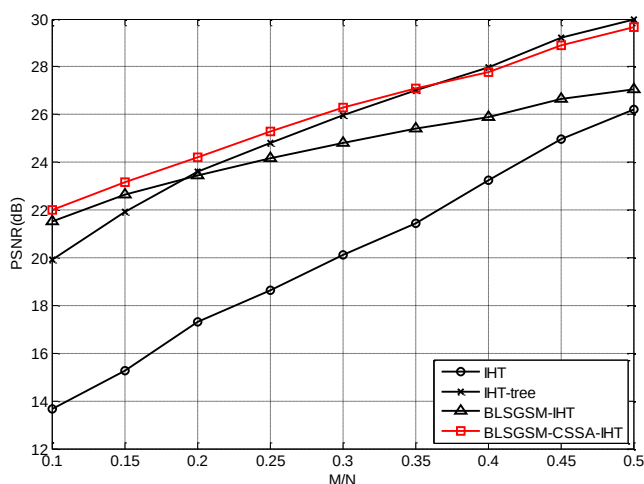


Figure 4. PSNR of different algorithms for "Lena" recovered image

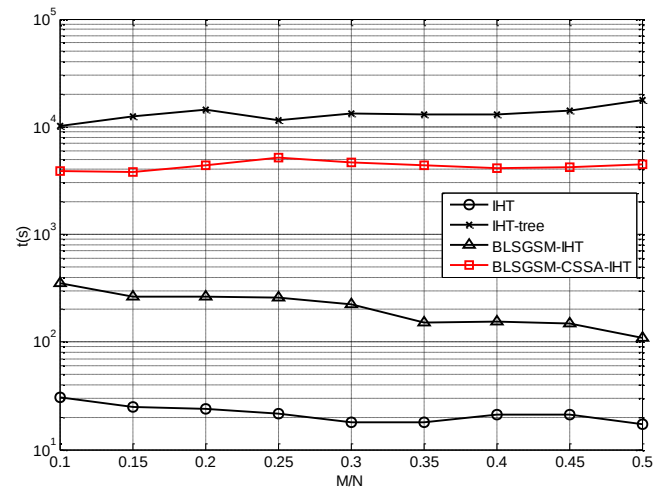


Figure 5. time of different algorithms for "Lena" recovered image

Experimental results in figure 4 and figure 5 show that: IHT-tree reconstruction algorithm based on tree structure can improve the accuracy of reconstructed image to a certain extent, but its complexity is high and reconstruction speed is slow. With low compression ratio, the reconstructing accuracy is significantly decreased.

The reconstruction algorithm of BLSGSM-IHT with local statistical prior information can greatly reduce the complexity of the algorithm and improve the reconstruction speed. Compared with the IHT algorithm, the reconstructing accuracy of BLSGSM-IHT is also improved. However, the BLSGSM model is limited by the local constraint of the priori information. With the increase of the compression ratio, the benefits of the priori information have been reducing, resulting in an undesirable reconstruction under the high compression ratio.

The BLSGSM-CSSA-IHT algorithm proposed in this paper makes full use of the dual information of statistical and structural prior. In terms of reconstruction accuracy, the proposed algorithm is almost the best in all test algorithms at different compression ratios. Specifically, under high compression ratios, the PSNR of the BLSGSM-CSSA-IHT algorithm is increased by 2.4 dB compared to the BLSGSM-IHT algorithm; under low compression ratios, the PSNR is increased by 2 dB compared to the IHT-tree algorithm.

In terms of reconstruction speed, this BLSGSM-CSSA-IHT algorithm has achieved a proper trade-off between BLSGSM-IHT and IHT-tree.

In summary, the BLSGSM-CSSA-IHT algorithm improves the reconstruction accuracy of the image to a certain extent, while the reconstruction speed is compromised when the compression ratio is changed, compared with the other algorithms which only use the single priori model. High-quality and efficient reconstruction of images can be achieved by the proposed algorithm under different compression ratios.

VII. CONCLUSION

In this paper, CS image reconstruction algorithm based on the joint statistical and structural priors has been proposed which is designed from the perspective of both statistical and structural prior to explore the inter-scale and intra-scale relations of the sparse coefficients. The Gaussian scale model is used to model the local coefficients while the best approximation tree algorithm is used to get the more accuracy structure constrain. Finally, the iterative thresholding algorithm is used to obtain the best estimates of the image sparse coefficients, and the high quality and high efficiency reconstruction of the image is realized through less measurements. The proposed algorithm, with both high precision and speed of reconstruction, would have more values for practical applications.

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Li Jiahui received the B.S. degree and the M.S. degree in Electronics and Information Engineering from Harbin Institute of Technology University, China. She is currently a researcher of wireless image video transmission based on compressed sensing at HITSZS. Her research interests include signal communication, images compressing and reconstruction.



Wu Shaohua was a Post Doc at the Department of Electronics and Information Engineering, Shenzhen Graduate School of Harbin Institute of Technology (HITSZS), where he has been working till now. He has been an Associate Professor of HITSZS since Jul. 2012. His current research interests include wireless image video transmission, deep space communication, IR-UWB ranging /localization /communication, and 5G wireless transmission technologies.



Huan Huang received the B.S. in information science & engineering from Lanzhou university, in 2015. She currently working toward the M.S. degree at the department of Electronic Information and Engineering in Harbin Institute of Technology, Shenzhen. Her research direction is compressed sensing.



Jiao Jian received his Ph.D. degree in communication engineering from Harbin Institute of Technology (HIT) in 2011. He received his B.S. degree in electrical engineering from Harbin Engineering University in 2005, and his M.A.Sc. degree in information and communication engineering from HIT Shenzhen Graduate School in 2007. He is an assistant research fellow in the Department of Electrical and Information Engineering of HIT Shenzhen Graduate School. His current interests include deep space communications, networking and channel coding.