A Joint Source-Channel Error Protection Transmission Scheme Based on Compressed Sensing for Space Image Transmission

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Abstract. High reliable and efficient image transmission is of primary significance for the space image transmission systems. However, typical image compression techniques have the characteristics of high encoding complexity and limited resiliency to channel errors. And the typical channel decoding strategy is simply discarding the error data block. All of this results in the potential loss of the transmission performance. Due to the low encoding complexity and error-tolerance ability of the compressed sensing (CS), to improve the image transmission performance, this paper proposes a joint source-channel error protection transmission scheme based on CS for space image transmission. Meanwhile, we evaluate the performance of different CS reconstruction algorithms under the two schemes and solve the optimal decoding strategy under different conditions. Simulation results show that the proposed scheme can achieve a better performance than the typical transmission scheme that the error data block is simply discarded in the bottom layer.

Keywords: Compressed sensing · Error-tolerance
Space image transmission · Deep Learning

1 Introduction

The typical image compression techniques, such as joint photographic experts group (JPEG), JPEG2000, set partitioning in hierarchical trees (SPIHT) [1,2], have characteristics of high compression efficiency. However, a critical problem with these techniques is that they have high encoding complexity and limited resiliency to channel errors [3]. The compressed sensing (CS) is known for its advantages including the high compression efficiency, the low encoding complexity, and the error-tolerance ability [4]. Consequently, more and more applications

D. Li, J. Luo and T. Zhang—These authors contributed equally to this work.
This research has been sponsored in part by the National Natural Science Foundation of China (Grant nos. 61371102, 61001092, 61201144 and 91638204) and the Natural Science Foundation of Guangdong Province (Grant no. 2015A030310343).

X. Gu et al. (Eds.): MLICOM 2017, Part II, LNICST 227, pp. 455–462, 2018.
https://doi.org/10.1007/978-3-319-73447-7_49

use the CS for image compression in the application layer. Ref. [5] proposes a cross-layer framework for high-efficient deep space image transmission, the CS image compression and the Spinal code is incorporated in the framework to jointly work with the LTP [6]. And we usually assume that the bottom layer has perfectly corrected the bit errors and the received compression values have no bit error. However, in the space network which is characterized by high error rate [7], it is impossible to completely eliminate the bit errors from the bottom-layer to the application layer. Therefore, it is inevitable that the received data has a portion of the error bits after channel coding. To ensure the data passed to the upper layer is all correct, the typical channel decoding strategy is simply discarding the error data blocks which can not pass the cyclic redundancy check (CRC) check [8]. Although this way guarantees that the data passed to the application layer is all correct, but it also imposes the burden of the error protection in the bottom layer, and increases the number of feedback indirectly, leading to the loss of the transmission performance.

Due to the limited resiliency to channel errors in the application layer and limited ability of error protection in the bottom layer, typical image transmission schemes cannot cope with the above challenges. In this paper, to improve the image transmission performance, we aim to propose a joint source-channel error protection transmission scheme based on CS. Different from the scheme proposed in [5], the proposed scheme in this paper allows a portion of the error blocks that meet the certain condition to be passed to the application layer for the CS reconstruction, this also causes that there are the error CS compression values in the image reconstruction. Moreover, we expect to take advantage of the CS error-tolerance ability to further improve the image performance. Meanwhile, the performance of various CS reconstruction algorithms are investigated, and we select the optimal CS reconstruction algorithm for the proposed scheme. Simulations are carried out for performance evaluation. Results show that the proposed image transmission scheme can improve the image performance compared with the typical scheme.

The main contributions of the paper are summarized as follows:

– We propose a joint source-channel error protection transmission scheme based on CS. And the proposed scheme shows a performance improvement compared with the existing typical scheme.
– We evaluate the performance of different CS reconstruction algorithms when adopted in the two schemes, and then the optimal decoding strategy under different conditions are indicated.

The remainder of this paper is organized as follows. In Sect. 2, the model of image transmission system is introduced. The Sect. 3 presents the proposed scheme. The performance analysis through the simulation results is introduced in Sect. 4. Finally, we conclude this paper in Sect. 5.

2 System Model

In this section, we present the model of image transmission in deep space communications and and introduce the basics of CS.

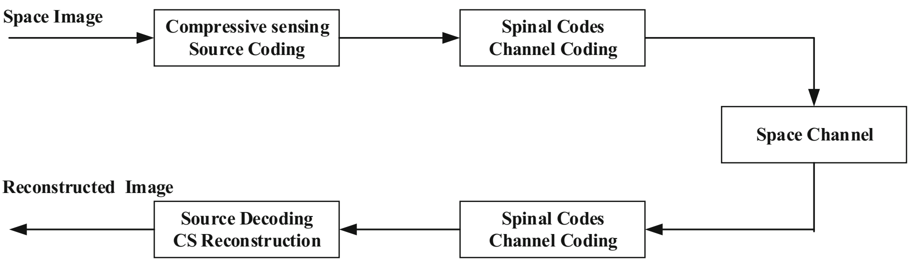


Fig. 1. The space image transmission system model.

2.1 Space Image Transmission System Model

As illustrated in Fig. 1, the image transmission in deep space communications [9] typically involves the modules including the source coding module, the channel coding module, space channel module, channel decoding module and source decoding module. In the process of image compression, the source coding module firstly performs the CS image compression [10], and then we adopt the Spinal codes as the channel coding technique for error protection. After being transmitted through the space channels, the images received are channel decoded and CS reconstructed at the receiver module.

In the module of channel coding, the Spinal code [11] is a rateless code which has been proved to be capacity-achieving over both additive white gaussian noise (AWGN) and binary symmetric channel (BSC). Different from other typical codes, Spinal code employs a nonlinear hash function as the coding kernel, and the Spinal symbols encoded are sent pass-by-pass. In the module of channel, the Earth-Mars communication scenario and the Gilbert-Elliot channel model for Ka-band transmission [12] are used for case study.

2.2 The Basics of CS

For the basic process of CS image compression and reconstruction, the process is shown in Fig. 2, the image signal X of size N is said to be sparse in the domain Ψ, if its transform coefficients $\alpha\,(\alpha = \Psi x)$ are mostly zeros or close to zeros. The signal X is measured by taking $M\;(M \leq N)$ measurements from linear combinations of the element vectors through a linear measurement operator Φ. The CS reconstruction of image signal X from y is formulated as the following constrained optimization problem:

$$\min_{\alpha} \|\alpha\|_0 \; s.t. \; y = \Phi x = \Phi \Psi^{-1}\, \alpha = A\alpha, \tag{1}$$

where Φ denotes the measurement matrix, and A represents projection matrix.

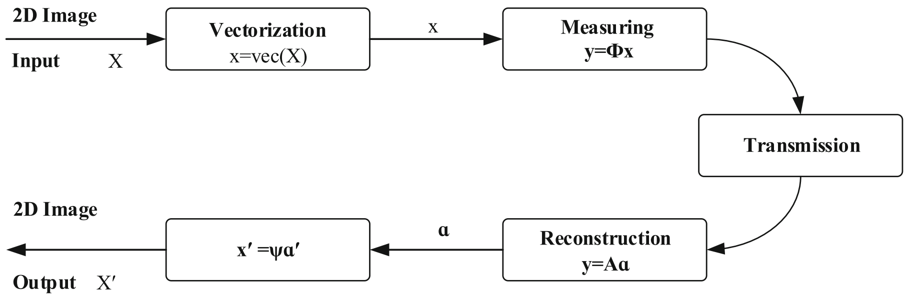


Fig. 2. The process of CS image compression and reconstruction.

3 The Proposed Scheme Based on CS

In this section, we present the framework of the proposed scheme based on CS.

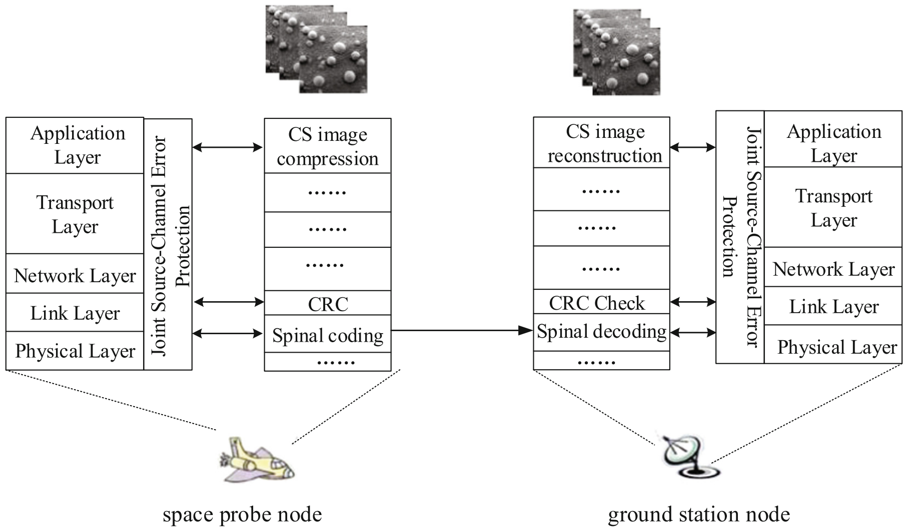


Fig. 3. The framework of the proposed scheme based on CS.

As illustrated in Fig. 3, the node of space probe firstly performs the CS image compression. By the global projection operation, all the CS compression values are equally important, which means that each compression value carries the global information of the whole image. In case of partial loss of compression values (e.g., packet loss of lower layers), the receiver may also reconstructs the image through the CS reconstruction algorithm. Therefore, we can do erasure correcting coding at the same time by generating some redundant compression values. After a cluster of compressed values are generated by the CS image compression and CS erasure coding modules, they are sent to the lower layers for cyclic redundancy check (CRC) encoding. After that, the bitstreams are encoded by the Spinal code in the physical layer and then the Spinal symbols are sent to the ground station node. On receiving the Spinal symbols, the receiver conducts decoding sequentially, and take CRC check on each decoded block. Meanwhile, the parameter of the bit error rate (BER) that after channel coding is calculated, and the indexes of failed decoding blocks are saved.

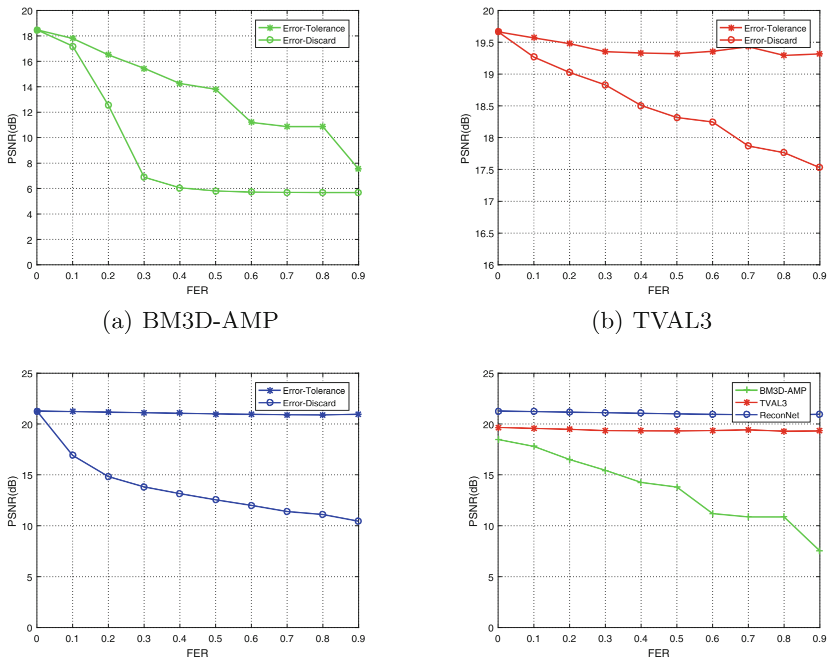
Different from the decoding strategy adopted in [5], the proposed scheme adopts the decoding strategy that allows a portion of the error blocks which meet the certain condition to be passed to the application layer for the CS reconstruction. We expect to take advantage of the CS error-tolerance ability to achieve the joint source-channel error protection and further improve the image performance. To derive the detailed decoding strategy, we investigate the performance effect of the relevant parameters in different CS reconstruction algorithm. The performance evaluation is shown in next section.

4 Performance Evaluation

In this section, we introduce three advanced CS reconstruction algorithms which are respectively the BM3D-AMP [13], TVAL3 and ReconNet algorithms [14]. Furthermore, we make performance comparison for the proposed scheme that adopts the error-tolerance strategy and the typical scheme that adopts the error-discard strategy among the three CS reconstruction algorithms.

Firstly, we briefly introduce the three CS reconstruction algorithms. BM3D-AMP algorithm is capable of high-performance reconstruction. We use BM3D denoiser since it gives a good trade-off between time complexity and reconstruction quality. TVAL3 algorithm performs excellent when solving a class of equality-constrained non-smooth optimization problems. The algorithm effectively combines an alternating direction technique with a nonmonotone line search to minimize the augmented Lagrangian function at each iteration. And the ReconNet reconstruction algorithm which based on the fully connected neural network (CNN), its intermediate reconstruction is fed into an off-the-shelf denoiser to obtain the final reconstructed image.

Next, we conduct a series of simulation experiments and make performance comparisons. Figure 4 illustrates the performance comparison of TVAL3, BM3D-AMP, and ReconNet (Deep Learning) algorithms under the two transmission schemes when the CS compression ratio is 0.04. It can be seen that when the CS compression rate is very low, the three algorithms perform better under error-tolerance transmission scheme. In the case of a very low CS compression ratio, we can obtain a limited number of compression values, and the effect of the amount of compression values on the reconstruction performance is greater than the error in the compression values. To a certain extent, even if the compression values return to the application layer remain some errors, it can also guarantee the image reconstruction performance. But if we choose the error-discard transmission scheme, the return values will be further reduced, which has a much



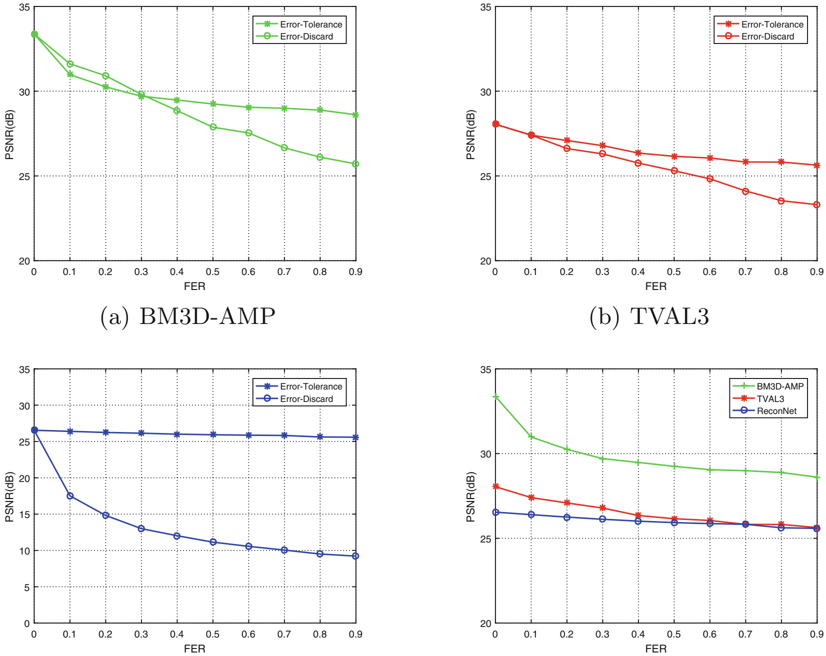
(a) BM3D-AMP (b) TVAL3

(c) ReconNet (d) Error-tolerance scheme

Fig. 4. CS reconstruction performance comparison (compression ratio = 0.04).

greater effect on the reconstruction performance than the errors. With the frame error rate (FER) goes up, the advantage of error-tolerance transmission scheme increases, and the PSNR improvement of the Deep Learning reconstruction algorithm can reach about 11 dB. Figure 4 also shows the performance comparison of the three algorithms under the error-tolerance transmission scheme. The results show that, in this kind of transmission scheme, Deep Learning has a certain advantage compared with the other two reconstruction algorithms.

Figure 5 illustrates the performance comparison of the three CS reconstruction algorithms when the CS compression ratio is 0.25. It can be seen from the figure that there is an intersection between the performance curves of the two schemes. When FER is less than the intersection value, the error-dicard transmission scheme is better in PSNR, and when the FER goes up, we should choose the other scheme to guarantee the reconstruction performance. To some extend, we can obtain more compression values under this compression ratio. When the FER is low, the performance of typical error-dicard transmission scheme is better the error-tolerance scheme. Figure 5 also shows the performance comparison of the three algorithms under the error-tolerance transmission scheme. The results show that, in this kind of transmission scheme, BM3D-AMP has a certain advantage compared with the other two reconstruction algorithms. Meanwhile, when the compression rate increases gradually, the intersection of the two per-



(a) BM3D-AMP (b) TVAL3

(c) ReconNet (d) Error-tolerance scheme

Fig. 5. CS reconstruction performance comparison (compression ratio = 0.25).

formance curves moves in the direction of increasing FER, which shows that as the compression ratio increases, the influence of the return compression values number on the reconstruction performance is gradually reduced. Only when the FER reaches a certain value, the performance advantage of the error-tolerance will be revealed.

5 Conclusion

In order to improve the image transmission performance, this paper proposes a joint source-channel error protection transmission scheme based on CS for space image transmission. Meanwhile, we evaluate the performance of different CS reconstruction algorithms under the two schemes and solve the optimal decoding strategy under different conditions. Simulation results show that the proposed scheme that adopts the error-tolerance strategy and reconstructs with ReconNet algorithm can achieve a better performance than that typical transmission scheme in the case of a very low CS compression ratio. When the compression ratio increases gradually and the FER is in low range, the typical error-discard scheme that reconstruct with BM3D-AMP algorithm performs better. When the FER increases to a certain threshold, we should turn to the error-tolerance transmission scheme to obtain high image performance.

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