Robust Transmission Techniques for Block Compressed Sensing

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Abstract. Compressed sensing is famous for its compression performances over existing schemes in this field. Conventional researches aim at reaching the larger compression ratio at the encoder, with acceptable quality of reconstructed images at the decoder. This implies the error-free transmission between the encoder and the decoder. Unlike existing researches which look for compression performances, we apply compressed sensing to digital images for robust transmission in this paper. For transmitting compressed sensing signals over lossy channels, error propagation would be expected, and the ways to apply some means of protection for compressed sensing signals would be much required for guaranteed quality of reconstructed images. We propose to transmit compressed sensing signals over multiple independent channels for robust transmission. By introducing the correlations between the compressed sensing signals from different channels, induced errors from the lossy channels can be effectively alleviated. Simulation results have presented the reconstructed image qualities, which depict the effectiveness for the protection of compressed sensing signals.

Keywords: compressed sensing, robust transmission, multiple channel

1 Introduction

Compressed sensing (CS) is one recently developed technique in lossy data compression researches and applications [1,2,3]. Lossy compression serves as an inevitable part in multimedia communications. With the widely use of smart phones or tablets, increasing numbers of multimedia contents are accumulated rapidly. These contents, mostly images, should be compressed at the encoder with international standards, such as JPEG or JPEG2000, in order to facilitate the use for different kinds of devices at the decoder. Then, compressed images can be stored, transmitted, and shared with the use of social networking services and wireless networks, which are commonly encountered in our daily lives. Thus, how to efficiently perform data compression, in addition to the robust transmission of multimedia contents, would be much required for practical applications [4,5,6]. Unlike conventional compression techniques applied to international standards such as JPEG, compressed sensing presents different perspectives in lossy compression. Considering the practical scenarios of data transmission over channels, the robust transmission of compressed sensing signals leads to the new branch in researches with potential applications.

In compressed sensing, it requires the sampling rate, which is far less than the Nyquist rate, with the capability of reconstructing the original signal for lossy compression. The major goal in compressed sensing researches would be the compression capability. Thus, how to effectively decode the extremely small amount of compressed signals, comparing to its counterparts in JPEG or JPEG2000, would be of great interest and it becomes the major challenge in researches [7,8]. In addition to looking for compression performances, we consider the robust transmission of compressed sensing signals. We transmit compressed signals over lossy channels to observe the effect caused by packet losses. To alleviate the quality degradation, we employ the transmission over multiple independent channels. For the better protection of compressed sensing signals, by use of adaptive sampling, improved quality of reconstructed image can be observed for the error controlled transmission.

We briefly describe the fundamentals of block compressed sensing in Sec. 2. We present proposed method for transmitting compressed sensing signals over multiple lossy channels in Sec. 3. We demonstrate the simulation results in Sec. 4 to show the protection capability with our method. Finally, we address the conclusions in Sec. 5.

2 Fundamentals of Block Compressed Sensing

In compressed sensing, based on the representations in [1,2,3], it is composed of the *sparsity* principle, and the *incoherence* principle. With block compressed sensing (BCS), we divide the original image $\mathbf{X}$ into the $B\times B$ block $\mathbf{X}_k$, and then perform the operations below block by block.

- For the *sparsity* principle, it implies the information rate in data compression. In compressive sampling, it can be represented with the proper basis Ψ, $\Psi \in C^{B^2\times B^2}$, and C means the complex number. More specifically, Ψ is the basis to reach sparsity with a k-sparse coefficient vector $\mathbf{X}_k$, $\mathbf{X}_k \in C^{B^2\times 1}$, with the condition that
  $$\mathbf{f}_k = \Psi\mathbf{X}_k. \quad (1)$$
  Here, $\mathbf{f}_k$ denotes the reconstruction corresponding to the original.
- For the *incoherence* principle, it extends the duality between time and frequency. The measurement basis Φ, $\Phi \in C^{m\times B^2}$, which acts like noiselet, is employed for sensing the signal $\mathbf{f}_k$, with the condition that
  $$\mathbf{Y}_k = \Phi\mathbf{f}_k. \quad (2)$$
  Here, $\mathbf{Y}_k$ denotes the measurement vector. We note that Eq. (2) is an underdetermined system.

When an image is represented by a BCS scheme, it focuses on the local characteristics of the image. Hence, it might be inefficient to assign the same number of measurement dimension to each sampled vector corresponding to the different image block. Due to the local characteristics, one block in the image has significantly different sparsity from another. With adaptive sampling in BCS, the entropy of a block may be used to evaluate the information included. It is expected to reach the better reconstructed quality under error-free transmission with adaptive sampling.

3 Transmission of CS Signals over Multiple Channels

For the effective delivery of compressed sensing signals, and considering the robust transmission depicted in [9,10,11], we employ the use of transmission over multiple lossy channels, which are mutually independent, in this paper. Fig. 1 describes the block diagram of our system.

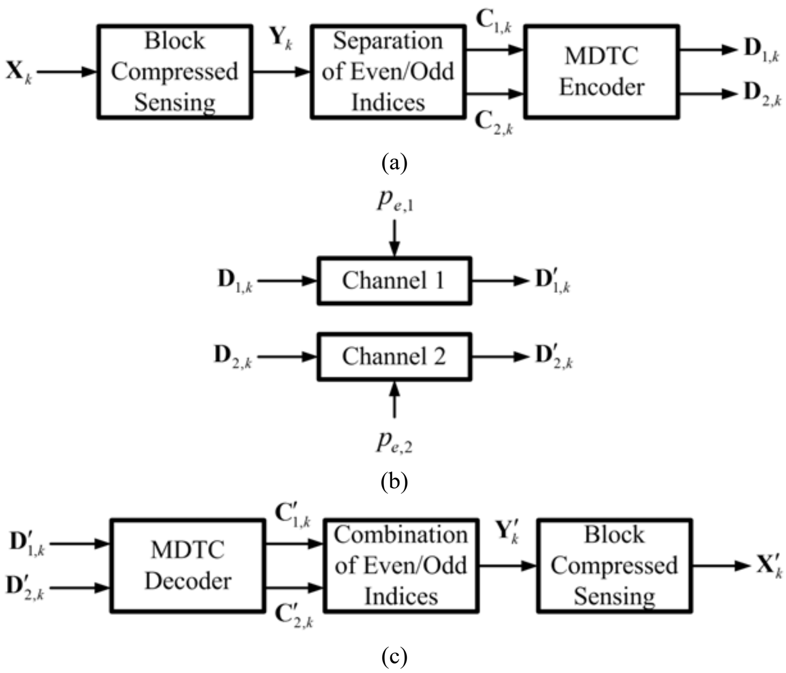


Fig. 1. Block diagrams for transmission with BCS and MDTC.

At the beginning, in Fig. 1(a), the input image $\mathbf{X}$ is divided into $\mathbf{X}_k$, then it is compressed with BCS, and compressed sensing signal is denoted by $\mathbf{Y}_k$. For the ease of separating the compressed coefficients, we choose the odd-numbered indices to form $\mathbf{C}_{1,k}$, and the even-numbered ones to form $\mathbf{C}_{2,k}$. After that, we employ the multiple description transform coding (MDTC) [9] to form the two descriptions of $\mathbf{D}_{1,k}$ and $\mathbf{D}_{2,k}$, with Eq. (3).

$$\begin{bmatrix} D_{1,k} \\ D_{2,k} \end{bmatrix} = \begin{bmatrix} r_2 \cos\theta_2 & -r_2 \sin\theta_2 \\ -r_1 \cos\theta_1 & r_1 \sin\theta_1 \end{bmatrix} \begin{bmatrix} C_{1,k} \\ C_{2,k} \end{bmatrix}, \tag{3}$$

with the conditions that $r_1 r_2 \sin(\theta_1 - \theta_2) = 1$, leading to the determinant of one. Next, $\mathbf{D}_{1,k}$ and $\mathbf{D}_{2,k}$ are transmitted over two independent lossy channels, with the loss probability of $p_{e,1}$ and $p_{e,2}$ for Channel 1 and Channel 2, respectively, as depicted in Fig. 1(b). Due to the induced errors, the two descriptions have become $\mathbf{D}'_{1,k}$ and $\mathbf{D}'_{2,k}$, respectively. At the decoder, as shown in Fig. 1(c), by employing [9], and by taking the inverse operations to Eq. (3) for reconstruction, we can obtain $\mathbf{C}'_{1,k}$ and $\mathbf{C}'_{2,k}$ from received descriptions. After the combination of the even- and odd-indexed components, we can obtain $\mathbf{Y}'_k$. Finally, with compressed sensing, we can compose the blocks $\mathbf{X}'_k$ and obtain the reconstructed image $\mathbf{X}'$.

4 Simulation Results

With the proposed method, we choose the test image `cameraman`, with the size of 128×128, for conducting simulations. For protection with MDTC, we set $r_1 = r_2 = 1$, $\theta_1 = \frac{\pi}{4}$, $\theta_2 = \frac{-\pi}{4}$, and choose the lossy probabilities for verifications. Regarding to adaptive sampling (AS) [7], the normalized DCT coefficient d' can be calculated by

$$d' = \frac{d - d_{\min}}{d_{\max} - d_{\min}}. \tag{4}$$

Here, $d_{\max}$ and $d_{\min}$ denote the maximal and minimal DCT coefficients in block $\mathbf{X}_k$. Then, the entropy in $\mathbf{X}_k$ can be calculated by

$$H_k = -\sum_{d'=0}^{1} p_{d'} \cdot \log p_{d'}. \tag{5}$$

Considering the practical implementation for adaptive sampling, we quantize the entropy values with the stepsize of 0.1, and reach the relationships in Fig. 2. Smaller entropy values imply the smoother blocks.

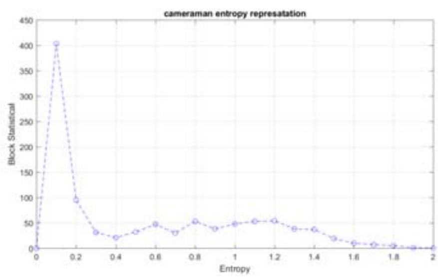


Fig. 2. Relationships between the entropy and the number of blocks for BCS.

(a) BCS, under L_1
PSNR: 30.51dB SSIM: 0.45

(b) BCS+AS, under L_1
PSNR: 32.60dB SSIM: 0.74

(c) BCS, under L_2
PSNR: 30.32dB SSIM: 0.50

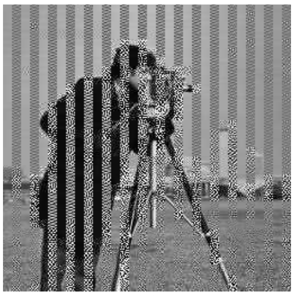
(d) BCS+AS, under L_2
PSNR: 31.44dB SSIM: 0.71

Fig. 3. Simulations for BCS under L_1 and L_2 constraints for test image `cameraman`.

In Fig. 3, we depict the results of error-free transmission of compressed sensing signals under L_1 and L_2 constraints. We choose to have 12 DCT coefficients for BCS in the 8×8 block on the average, leading to the rate of 0.1875. In Fig. 3(a) and Fig. 3(b), we can easily see that adaptive sampling provides the better reconstruction; we can find the similar phenomena with their counterparts in Fig. 3(c) and Fig. 3(d).

From the presentations in Fig. 3(a) and Fig. 3(c), it seems that the blocks with larger entropies present poorer subjectively. From the results in Fig. 3(b) and Fig. 3(d), it implies that by use of adaptive sampling, better reconstruction can be expected. Both the Peak Signal-to-Noise Ratio (PSNR) and the Structural SIMilarity index (SSIM) [12] are provided to measure the reconstructed image quality. From the four reconstructed images displayed in Fig. 3, under the error-free transmission condition, by use of adaptive sampling, both the PSNR and SSIM values are larger, which imply the better results. We choose BCS with AS in later simulations in Fig. 4 and Fig. 5. In addition, by use of the L_1 or L_2 constraint, the PSNR and SSIM values present differently. With BCS only, the L_2 constraint presents better in Fig. 3(c). In contrast, with BCS and AS, the L_1 constraint presents better in Fig. 3(b).

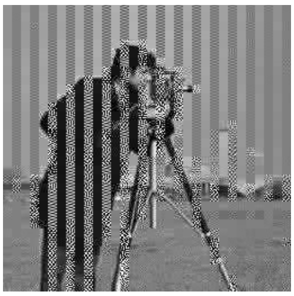
In Fig. 4, we present the results of packet-loss transmission of compressed sensing signals under the L_1 constraint. In order to test the error protection capability with multiple description transform coding, we choose to lose the even-numbered blocks, leading to the lossy rate of 50%. The BCS signals can be protected with MDTC.


(a)
PSNR: 28.40dB SSIM: 0.14


(b)
PSNR: 30.20dB SSIM: 0.21

Fig. 4. Simulations of reconstructed image qualities for BCS with adaptive sampling under the L_1 constraint for lossy rate of 50%. (a) No protection applied. (b) Protection with MDTC.

Under the L_1 constraint for training, Fig. 4(a) presents the reconstructed image without protection, and Fig. 4(b) is the result with the protection of MDTC. We can easily tell the error protection capability with MDTC. When comparing the error protection result in Fig. 4(b) to the error-free result in Fig. 3(b), even though the protection with MDTC is applied, there is some room for the improvement of reconstructed quality. Note that we set the lossy rate to 50% to test the protection capability, which is hardly seen in real environments. Thus, for practical applications, we can expect the better reconstructed quality for smaller lossy rates.


(a)
PSNR: 30.18dB SSIM: 0.30


(b)
PSNR: 29.87dB SSIM: 0.37

Fig. 5. Simulations of reconstructed image qualities for BCS with adaptive sampling under the L_2 constraint for lossy rate of 50%. (a) No protection applied. (b) Protection with MDTC.

In Fig. 5, it presents the training results under the L_2 constraint. We can find similar phenomena that the reconstruction with MDTC protection in Fig. 5(b) presents better than the no protection case in Fig. 5(a). When comparing the error protection result in Fig. 5(b) to the error-free result in Fig. 3(d), there is still some room for the improvement under the lossy rate of 50%. Again, we expect to have the better reconstructed quality with the smaller lossy rates. Parameter selection for MDTC in Eq. (3) may help to reach the improvements.

5 Conclusions

In this paper, we have employed the use of adaptive sampling for block compressed sensing, with the capability of robust transmission over multiple lossy channels. Multiple description transform coding, which introduces the correlations between neighboring chunks of block compressed sensing signals, may help to alleviate the data loss during transmission. Under the error-free transmission condition, we observe that by use of adaptive sampling, better reconstruction can be observed. Simulation results have demonstrated the protection with MDTC, and the alleviation of reconstructed quality, under severe lossy rate of 50%. Enhanced quality of reconstructed images can be expected with reasonable amount of lossy rates and the appropriate selection of parameters in MDTC. These can be explored for future studies with block compressed sensing.

Acknowledgement

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