LETTER

Adaptive Perceptual Block Compressive Sensing for Image Compression

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SUMMARY Because the perceptual compressive sensing framework can achieve a much better performance than the legacy compressive sensing framework, it is very promising for the compressive sensing based image compression system. In this paper, we propose an innovative adaptive perceptual block compressive sensing scheme. Firstly, a new block-based statistical metric which can more appropriately measure each block's sparsity and perceptual sensibility is devised. Then, the approximated theoretical minimum measurement number for each block is derived from the new block-based metric and used as weight for adaptive measurements allocation. The obtained experimental results show that our scheme can significantly enhance both objective and subjective performance of a perceptual compressive sensing framework.

key words: *perceptual compressive sensing, adaptive measurements allocation, discrete cosine transform, image compression*

1. Introduction

Compressive sensing (CS) [1] is a new signal processing technique which can simultaneously accomplish signal sampling and compression. It provides us a complete new paradigm for image compression [2], [3]. Because block compressive sensing (BCS) [4], [5] can significantly reduce complexity and memory storage of CS sampling and reconstruction, it has become an indispensable component in a practical CS-based image compression system. However, the legacy BCS scheme has relatively poor rate-distortion performance, especially at low measurement rates. Based on the observation that human eyes have unequal perceptual sensitivity to different frequency components of image signals, Yang et al. [6] proposed a perceptual BCS scheme in the discrete cosine transform (DCT) domain. In the perceptual BCS scheme, the random measurements matrix is multiplied with a perceptual weighting matrix to emphasize the perceptually important DCT coefficients during sampling, thus such DCT coefficients can be more precisely recovered in the reconstruction procedure.

An intuitive approach to enhance the performance of perceptual BCS is to introduce adaptive sampling into the perceptual BCS framework. However, direct implementation of existing adaptive sampling methods [7]–[10] on the perceptual BCS framework cannot obtain the best perceptual performance. One important reason is that the block-based statistical metrics adopted by the existing adaptive BCS schemes could not appropriately measure both the sparsity and perceptual sensibility of each block. By devising a new block-based statistical metric which can more appropriately measure each block's sparsity and perceptual sensibility and developing a efficient adaptive measurements allocation algorithm based on the new block-based statistical metric, an innovative adaptive perceptual BCS scheme is proposed in this paper. The obtained experimental results show that our scheme can significantly enhance both objective and subjective performance of a perceptual compressive sensing framework.

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2. The Proposed Scheme

2.1 Perceptual Weighting Matrix

In order to conduct adaptive perceptual BCS on DCT domain, it is compulsory to obtain the perceptual weighting matrix W for DCT coefficients. Similar to [6], we also derive the perceptual weighting matrix from the JPEG quantization table. However, a new method is adopted to generate the perceptual weighting matrix in different sizes. Specifically, we treat the original JPEG quantization table as an "imitated" 8×8 image block, and use image resizing techniques to obtain a resized image block whose value is regarded as a resized quantization table. Specifically, we obtain the resized image block by using Matlab function *imresize*. Let q be the "imitated" 8×8 image block corresponding to original JPEG quantization table, then the quantization table of other size can be obtained as $Q = imresize(q, s)$, where Q is a new quantization table whose size is s times of q. For example, when $s = 4$, a 32×32 quantization table can be obtained.

After obtaining a $B \times B$ quantization table Q, the corresponding perceptual sensitivity weights matrix $\hat{Q}$ for DCT coefficients can be calculated as follows:

$$\hat{Q} = \kappa \cdot Q(0,0) \cdot (I./Q) \quad (1)$$

where I is a $B \times B$ matrix of ones and ./ is defined as the elementwise division of two matrices. The parameter κ is used to adjust the amplitudes of $\hat{Q}$ to a proper range. We set $\kappa = 1.2$ in our experiments. Suppose that $\omega = (\omega_1, \omega_2, \ldots, \omega_{B^2})$ is the vector representation of $\hat{Q}$ in the column scanning order, we represent the DCT coefficient's perceptual sensitivity weights W as a $B^2 \times B^2$ diagonal matrix (i.e., $W = diag(\omega)$) to make it convenient to multiply with DCT coefficients in vector form.

2.2 Metric of Block Perceptual Compressibility Level in DCT Domain

Currently, there are generally two kinds of block-based statistical metric used for adaptive measurements allocation: pixel domain based [7], [8] and transform domain based [9], [10]. Our scheme adopts the latter kind of block metric because it is easier for implementation and has a relatively better performance.

When an image block is transformed into DCT domain, the majority of its spectral energy is concentrated in the the DC component and the lower frequency AC components. However, different kinds of blocks have a different energy distribution among the AC components. More specifically, since most of spectral energy of a smooth block is occupied by its DC component, the smooth block only has a limited number of AC components with big magnitudes; on the other hand, a textured or edged block has relatively larger number of AC components with big magnitudes. Those AC components with big magnitudes are called significant AC components here. The latter kind of block generally needs more measurements in CS reconstruction. Therefore, the number of significant AC components of a block can be used as an indicator for block compressibility. The more significant AC components a block contains, the less compressible it is, and the more sampling rate needed for CS reconstruction.

The first question we are seeking to answer is which type of AC components can be classified as significant AC components. Since we need to allocate the overall measurement budget for all the blocks in an image, it is reasonable to use a frame-wise threshold to do such classification. A simple way is to use the average of the absolute magnitude of all AC component in an image as the threshold. When the absolute magnitude of an AC component is larger than this threshold, it is described as significant AC component.

In order to achieve a better perceptual performance, we do not directly determine the threshold by using the original value of each AC component. Instead, we choose to use the perceptual weighted value of each AC component. This can be achieved by multiplying the original DCT block with the perceptual weighting matrix W. Consequently, the threshold can be mathematically represented as follows.

$$T = \frac{1}{n \cdot (B^2 - 1)} \sum_{i=1}^{n} \sum_{k=1}^{B^2-1} |w_k \cdot AC_i(k)| \tag{2}$$

where $AC_i(k)$ denotes the k-th AC component of the i-th block, w_k is the perceptual weight of the k-th AC component, B refers to the block size and n is the number of block in a given image.

Subsequently, we can use the number of perceptually significant AC components for the i-th block, denoted as K_i, to represent its block perceptual compressibility level, as described below.

$$K_i = \sum_{k=1}^{B^2} sig_i(k),$$
$$\text{where } sig_i(k) = \begin{cases} 1 & |w_k \cdot AC_i(k)| > T \\ 0 & otherwise \end{cases} \tag{3}$$

2.3 Adaptive Measurements Allocation Strategy

When a block has a larger perceptual compressibility level, it obviously needs more measurements for CS reconstruction. However, we don't directly use the perceptual compressibility level of each block as weight for adaptive measurements allocation. Instead, we use a derivative value from block perceptual compressibility level as weight for adaptive measurements allocation.

If the perceptual compressibility level of the i-th block is K_i, this block is approximately treated as a K_i-sparse block. According to the CS theory [1], a K-sparse signal can be exactly recovered with high probability using $M \geq C \cdot K \cdot \log(N/K)$ independent and identically distributed (i.i.d.) Gaussian measurements only, where C is a small constant to adjust the desired probability of successful signal recovery. Then, the theoretical minimum measurement number of i-th block can be approximated as follow

$$M_i = C_i \cdot K_i \cdot \log(B^2/K_i) \tag{4}$$

where B represents the block size and C_i is a constant to adjust the recovery probability of the i-th block. Since a block with a higher perceptual compressibility level generally needs more measurements in CS reconstruction to achieve a good quality, a relatively bigger constant C is used for such a block and vice versa. It is not necessary to individually assign a different constant parameter for each block. A simple strategy is to classify all the blocks of an image into l categories (i.e., $2 \leq l \leq 5$) based on the block perceptual compressibility level and assign a fixed constant for each category.

We subsequently use the approximated theoretical minimum measurement number M_i as weight for adaptive measurements allocation. Suppose that R is the overall sampling rate of an image, r_i is the sampling rate for the i^{th} block and $\bar{r}$ is the mean of all blocks' sampling rate. Let $\bar{M}$ denotes the mean of all blocks' theoretical minimum measurement number (i.e., $\bar{M} = \sum_{i=1}^{n} M_i/n$). The following iterative approximation algorithm is adopted to adaptively allocate different sampling rate for each block.

1. Initialize $P = 1$;
2. Assign the sampling rate r_i as $r_i = R \cdot P \cdot M_i/\bar{M}$;
3. In order to avoid over-sampling or under-sampling, adjust the sampling rate r_i as (5);
4. Update the value of P as $P = R/\bar{r}$;
5. Repeat step 2 to step 4 until P satisfies $|P - 1| < \delta$;

$$r_i = \begin{cases} UB & r_i \geq UB \\ LB & r_i \leq LB \\ r_i & otherwise \end{cases} \quad (5)$$

where UB and LB represent the upper bound and lower bound of the sampling rate, respectively. $UB = min(1, 2 \cdot R)$ and $LB = P \cdot R/\gamma$, where γ is a constant to regulate the minimum sampling rate. Meanwhile, a small constant δ is used to control the accuracy of allocated sampling rates. We set $\delta = 10^{-5}$ in our experiments. After the sampling rate r_i is determined, the measurement number of the i^{th} block can be given as $M_i = r_i \cdot B^2$.

After the measurement number of the i-th block is determined, its corresponding measurement matrix can be generated by selecting the first M_i rows of a $B^2 \times B^2$ orthogonal Gaussian random matrix. Suppose that Φ_{B_i} represents the random measurement matrix for the i-th block, the adaptive perceptual BCS can be be represented in matrix form as:

$$y_i = \frac{1}{a'}\Phi_{B_i} W x_i = \Theta_{B_i}\alpha_i, \ (i = 1, \ldots, n) \quad (6)$$

where $a' = \|\Phi_{B_i} W\|_2$ and $\Theta_{B_i} = \frac{1}{a'}\Phi_{B_i} W \Psi^{-1}$.

For the implementation, neither the total n random measurement matrixes nor the n measurement numbers need to be transmitted to the CS decoder. Instead, the CS encoder only need to transmit a random seed to the decoder. The decoder can deduce the individual measurement number for different blocks from the length of the received measurements and then use the random seed to regenerate the same random measurement matrix sets.

3. Experimental Results

In this section, we evaluate the performance of our proposed Adaptive Perceptual BCS scheme (denoted as AP-BCS). The orthogonal i.i.d. Gaussian matrix and 2D DCT are employed to be the measurement matrix Φ and transform basis Ψ respectively. The test data are 512×512 8-bit grey level natural images. Due to the limitation of space, we only demonstrate the results for Lenna and Barbara with the block size of 32×32.

We compare our proposed scheme to three benchmark schemes. That is, the conventional perceptual BCS scheme [6] (denoted as PBCS), the conventional adaptive BCS scheme [8] (denoted as ABCS) as well as the original BCS scheme [4]. For fair comparison, all of these BCS schemes adopt the $l1 - ls$ algorithm [11] for CS reconstruction. In all experiments, the regularization parameter λ of the $l1 - ls$ algorithm is set to 0.1. Besides, as for AP-BCS and ABCS, the parameter δ is set to 10^{-5} and γ is set to 2.4.

In our proposed AP-BCS, all the blocks of a given image are classified into $l = 5$ categories by using the K-means algorithm based on the block perceptual compressibility level K_i. Subsequently, the blocks of each category are all assigned a same constant C to calculate their theoretical minimum measurement number M_i according to Eq. (4). In our evaluation, the constant C takes the following five values (1.0, 1.1, 1.2, 1.5, 2.0) for different categories of blocks. More specifically, let us assume that $class1$ to $class5$ are ordered in an ascending manner according to their class mean, therefore the C_i of the blocks in $class1$ are all set to 1.0, the C_i of the blocks in $class2$ are set to 1.1, and so on.

To assess the image quality we have chosen the following image quality metrics: the peak signal to noise ratio (PSNR) and structural similarity indexes (SSIM).

As shown in Fig. 1, AP-BCS can steadily achieve the best objective performance (both PSNR and SSIM) com-

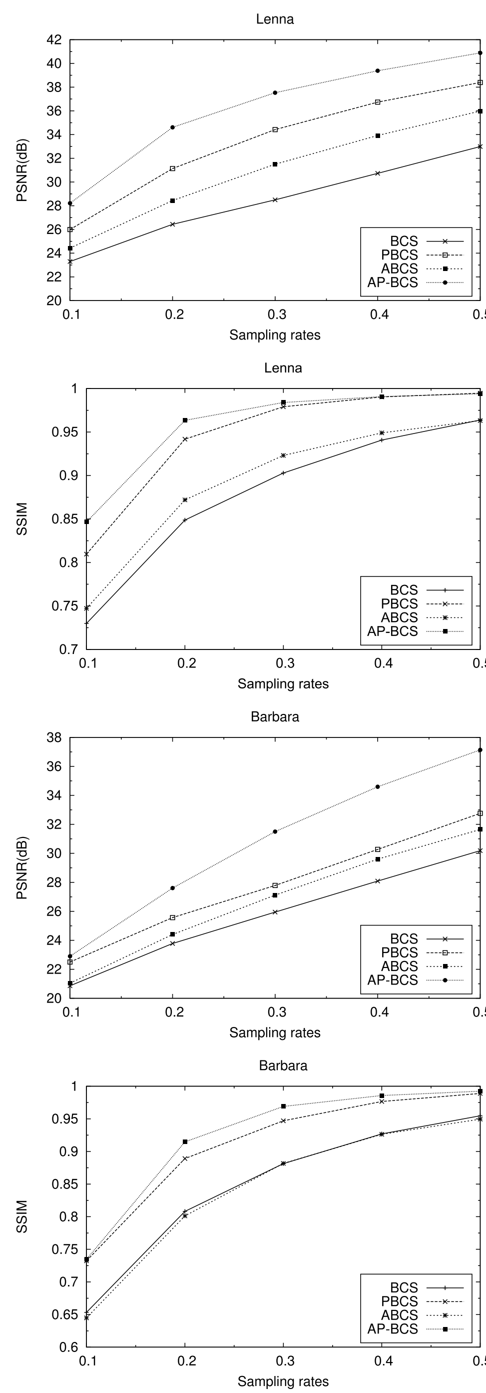

Fig. 1 Objective performance comparison of different BCS schemes.

(a) BCS(PSNR=26.436,SSIM=0.8488) **(b)** ABCS(PSNR=28.435,SSIM=0.8720)

(c) PBCS(PSNR=31.135,SSIM=0.9418) **(d)** AP-BCS(PSNR=34.609,SSIM=0.9634)

Fig. 2 Subjective performance comparison of different BCS schemes.

pared to the benchmark BCS schemes at different sampling rates. The main reason of such performance gain is that AP-BCS combines the advantages of both perceptual BCS and adaptive BCS.

We also compare the subjective performance of different BCS schemes. Figure 2 illustrates the reconstructed images obtained by various schemes under a sampling rate of 0.2. From this figure we can also observe that AP-BCS achieves the best subjective quality compared to the benchmark BCS schemes.

In order to further validate the effectiveness of the proposed AP-BCS scheme, we implement two existing adaptive sampling methods on the conventional perceptual BCS framework [6] and get two benchmark adaptive perceptual BCS schemes: scheme *A* and scheme *B*. Scheme *A* adopts the same adaptive measurements allocation strategy as ABCS [8] and scheme *B* adopts the same adaptive measurements allocation strategy (i.e.,based on the number of the significant DCT coefficients of each block) as reference [9]. Scheme *A* and scheme *B* respectively use a pixel domain based metric and a transform domain based block metric for adaptive measurements allocation.

As shown in Fig. 3, our AP-BCS scheme steadily outperforms these two benchmark schemes at different sampling rate. Such performance gain is mainly because that our scheme can more efficiently allocate the overall measurement budget based on the new devised block-based statistical metric. In the other words, direct implementation of the existing adaptive sampling method on the perceptual BCS framework cannot obtain the best perceptual performance.

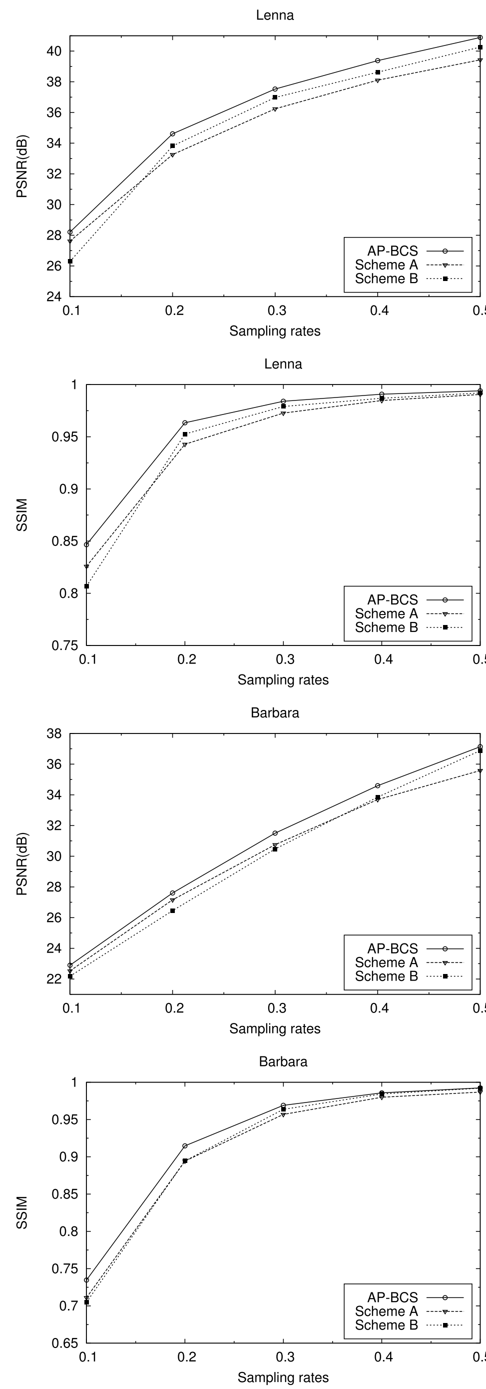

Fig. 3 Evaluation of different adaptive perceptual BCS schemes.

4. Conclusion

To fully exploit potential of the perceptual BCS technique and maximize its benefits, an efficient adaptive perceptual BCS scheme is proposed in this paper. The main idea behind our scheme consists in developing an efficient adaptive measurement allocation strategy based on devising a new block-based statistical metric which can more appropriately measure each block's sparsity and perceptual sensibility. The obtained experimental results have proven that our scheme can significantly enhance both objective and subjective performance of a perceptual compressive sensing framework. Our future work will focus on investigating efficient quantization and entropy coding techniques for CS measurements to achieve highly efficient and robust image compression based on the proposed adaptive perceptual BCS scheme. Although so far the CS-based image codec cannot achieve equivalent rate-distortion performance as the state-of-the-art conventional image codec (i.e., JPEG 2000) under error-free circumstance, it is very promising for the emerging applications like low-cost wireless image sensor networks and wireless low-power visual surveillance due to its built-in robustness and light-weight encoder.

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