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영상 압축센싱을 위한 블록기반 변환영역 측정 부호화

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Block-Based Transform-Domain Measurement Coding for Compressive Sensing of Images

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요 약

압축센싱은 신호의 성긴 (Sparse) 성질을 활용하여 Nyquist 표본화율 보다 낮은 측정 율만으로도 신호의 완벽 복원이 가능하다는 측면에서 새로운 샘플링 기술로 주목 받고 있다. 블록기반의 압축센싱 기술을 사용하여 영상을 샘플링 하는 경우, 측정신호 영역에서도 공간 영역의 유사도가 보존되므로, 본 논문에서는 블록기반 압축센싱 기술을 사용하여 획득한 자연영상의 측정 신호에 대한 새로운 부호화 기술을 제안한다. 측정신호 간 유사성을 제거하기 위해 이산 웨이블릿 변환(DWT)을 적용한 후, 각 DWT 계수에 적절한 양자화를 수행한다. 이를 통해, 측정 신호 내의 중복성을 제거하고, 측정 신호의 비트 율 또한 절약할 수 있었다. 실험 결과, 기존의 블록기반 평활 Projected Landweber 알고리즘에 스칼라 양자화를 적용한 방법, DPCM 방법을 적용한 방법, 그리고 Multihypothesis 기반 블록기반 평활알고리즘에 DPCM을 적용한 방법과 비교할 때, 제안방법의 PSNR이 각각 최대 4dB, 0.9dB, 그리고 2.5dB 더 높은 성능을 보이는 것을 확인 할 수 있었다.

Key Words : Compressive Sensing, Measurement Coding, Image Compression.

ABSTRACT

Compressive sensing (CS) has drawn much interest as a new sampling technique that enables signals to be sampled at a much lower than the Nyquist rate. By noting that the block-based compressive sensing can still keep spatial correlation in measurement domain, in this paper, we propose a novel encoding technique for measurement data obtained in the block-based CS of natural image. We apply discrete wavelet transform (DWT) to decorrelate CS measurements and then assign a proper quantization scheme to those DWT coefficients. Thus, redundancy of CS measurements and bitrate of system are reduced remarkably. Experimental results show improvements in rate-distortion performance by the proposed method against two existing methods of scalar quantization (SQ) and differential pulse-code modulation (DPCM). In the best case, the proposed method gains up to 4 dB, 0.9 dB, and 2.5 dB compared with the Block-based CS-Smoothed Projected Landweber plus SQ, Block-based CS-Smoothed Projected Landweber plus DPCM, and Multihypothesis Block-based CS-Smoothed Projected Landweber plus DPCM, respectively.

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Ⅰ. Introduction

In conventional digital processing, if signal sampling follows the Nyquist/Shannon theorem with a sampling rate being at least twice of signal bandwidth, alias-free acquisition of band-limited signal is guaranteed. For many applications such as high resolution image/video data transmission, a huge amount of samples and their encoding might be impractical on some devices lacking in either computational resource or battery power or both of them, such as mobile phones. Recently, a new signal sampling technique, namely, Compressive Sensing (CS) sheds a light to overcome this problem by allowing a sparse signal to be sampled at a rate much lower than the Nyquist/Shannon one while still achieving exact reconstruction. In this sense, CS hints a promising way for those deprived applications.

Note that, for a practical CS of natural images, its measurement data has to be encoded with quantization and entropy coding to generate bit stream for efficient storage/transmission. The simplest method is to apply scalar quantization (SQ) directly to the measurement data where the CS measurement is mapped to several discrete values. The lower and upper bounds of the asymptotic rate-distortion performance of SQ for quantizing CS measurements was analysed by W. Dai et al. [1]. Following, J. N. Laska et al. [2] studied quantization of CS measurements under a constraint of saturation which is caused by physical limitation. It only allows a finite range of voltages to be accurately converted to bits and only a finite number of bits are available to represent each value. This quantization is known as finite-range quantization. The challenge in dealing with the errors imposed by finite-range quantization is the lack of priori bound on the CS measurements, saturation errors are potentially unbounded.

In practical CS for image, block-based CS (BCS) scheme shows some advantages over frame-based scheme in that measurement operator can be easily stored and implemented. By noting that block-wise spatial correlation of image is still preserved in measurement domain, S. Mun et al. [3] proposed an encoding method that combines SQ with differential pulse-code modulation (DPCM). In its encoding, measurement of a previous block, which is considered as a prediction for the current block, is subtracted from the measurement of a current block. The resulting residual measurements are then scalar quantized and sent to decoder. In this way, the system attains surprisingly competitive rate-distortion performance compared with an existing simple method of quantizing CS measurement by SQ alone.

However, in image/video processing, the transform coding has been known to give better performance than DPCM since it is less sensitive to data statistics than DPCM [4], especially for low bit rates such as 1 or 2 bits/pixel (the prediction mismatch of DPCM depends much on the data statistics themselves; the high variation of data statistics leads to high predictor mismatch and causes a quantizer mismatch). Transform coding is widely applied to coding image and video application such as JPEG[5], JPEG 2000[6], H.264/AVC[7,8], and H.265/HEVC[9-11] for which discrete cosine transform (DCT) and discrete wavelet transform (DWT) are most popularly used owing to their good efficiency in decorrelating signals. However, compared with DCT, DWT not only achieves high decorrelation and excellent energy compaction but also provides high spatial resolution. Motivated by these, in this paper, we introduce a method that uses DWT to decorrelate CS measurements to improve the compression performance of existing CS measurement coding methods using SQ alone or DPCM combined with SQ in [3].

At encoder, measurements of all blocks by the same projection of BCS are reshaped into 2D-form and then DWT is applied to remove redundancy among those CS measurements. It is worth emphasizing that each band of DWT has a different role in image representation; therefore, the bands of CS transform coefficients are assigned with different quantization schemes. By this way, number of bits for representing measurement data is saved remarkably. At decoder, a corresponding inverse process is performed to reconstruct CS measurements. Experimental results manifest superior improvements of the proposed method over other existing methods in terms of objective quality.

The remainder of this paper is organized as follows: Section II introduces background of CS, Section III presents the proposed method for coding BCS measurements. Experimental results and analyses are shown in Section IV. Finally, in Section V, we conclude our works.

Ⅱ. Background

A length-N signal x that has at most k non-zero coefficients for some $k \ll N$ is called k-sparse signal, i.e., $\| x \|_0 \le k$ where $\| * \|_0$ is l_0-norm. Compressive sensing [12-13] can recover the k-sparse signal x from its a few measurements $y \in R^M$ even if the number of measurements (i.e., samples) M is smaller than the one specified by the Nyquist/Shannon rate. The measurement vector y is a linear projection of the signal x by a measurement matrix Φ as:

$$y = \Phi x \tag{1}$$

It is well known that, CS theorem attempts to find the sparest solution that satisfies eq. (1). From a practical view point, most natural signals are not exactly sparse, but can be sparsely represented in a proper transform domain. For example, image/video signal is very often sparse in DCT or DWT, so the signal x can be represented as $x = \Psi^T \theta$, where θ is the transform coefficient of x, and Ψ is called a sparsifying transform. The sparse signal θ can be recovered from the M measurements, $y = \Phi x = \Phi \Psi^T \theta$ where $M \ll N$, by the l_0-minimization:

$$\hat{\theta} = \min_\theta \| \theta \|_0 \quad s.t. \quad y = \Phi \Psi^T \theta \tag{2}$$

However, the l_0-minimization is an NP-hard problem[14]; thus, as an alternative, CS typically solves (2) by l_1-minimization which leads to a convex optimization problem as:

$$\hat{\theta} = \min_\theta \| \theta \|_1 \quad s.t. \quad y = \Phi \Psi^T \theta \tag{3}$$

In order for accurate and stable recovery, the measurement matrix needs to satisfy some conditions such as restricted isometry property of order-k[15], i.e., there should exit a constant $\delta_k \in (0,1)$ holding for all k-sparse signal x such that:

$$(1-\delta_k) \| x \|_2^2 \le \| \Phi x \|_2^2 \le (1+\delta_k) \| x \|_2^2 \tag{4}$$

Then, CS can successfully recover a signal under a condition of enough measurements, typically, $M = O(k log \frac{N}{k})$[16]. Otherwise, the number of measurement can be adaptive to achieve high performance as in [17].

Ⅲ. Proposed Measurement Coding for Block-based Compressive Sensing of Image

In BCS, an input image is split into $B \times B$ non-overlapping blocks denoted by $x^{(i)} \in R^{B^2}$ where i is a block index. $x^{(i)}$ is a column vector with B^2 elements each of which is a pixel value inside the i-th $B \times B$ block. Each block is compressively sampled into measurement domain as $y^{(i)} = \Phi_B x^{(i)}$ where $y^{(i)} \in R^{M_B}$ and Φ_B is a $M_B \times B^2$ measurement matrix. $y^{(i)}$ is a column vector with M_B elements each of which is a CS measurement for the i-th $B \times B$ block. It is called a measurement vector. M_B is a number of measurements representing $x^{(i)}$, and the ratio of $s = M_B / B^2$ is called subrate (or, measurement rate). It represents how much sub-sampling is done since $M_B < B^2$. It is worth noting that block-wise spatial correlation among image blocks still exists in measurement domain. S. Mun et al. has empirically observed that such high correlation exits among measurements of BCS with the corresponding average correlation value even reaching above 0.95 in Lena image [3]. That high correlation is an evidence for lots of

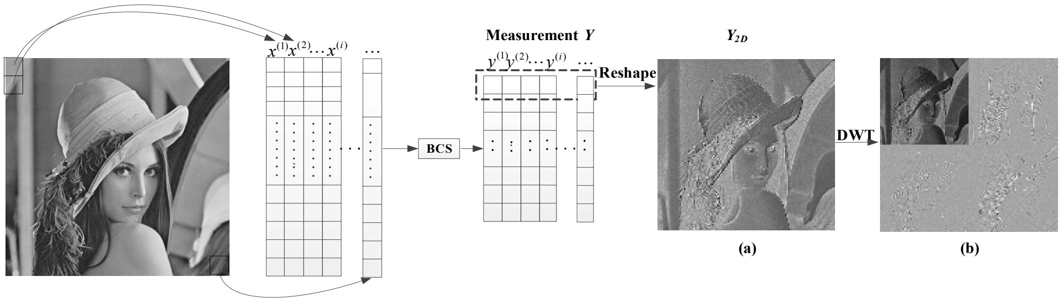


그림 1. BCS measurements of image. (a). 2D-reshaped representation (size 64×64) of BCS measurements of 512×512 Lena image with block size 8×8; and (b). its level-1 DWT representation
Fig. 1. BCS 영상 측정신호. (a) 512x512해상도를 갖는 Lena영상을 8x8크기로 획득한 BCS 측정신호를 64x64해상도의 2D 형태로 재구성 (b) 2D형태 Lena 측정 신호에 대한 level-1 DWT 표현

redundancy existing in measurement data. Therefore, one can expect to attain remarkably better rate-distortion performance by reducing the redundancies.

This paper aims to propose an improved such measurement encoding method by applying transform for removing the redundancy among CS measurements before quantization. Although the Karhunen-Loeve transform [18] is theoretically optimum decorrelating transform, it is impractical due to its data-dependence nature. By noting that DWT-based scheme usually shows better performance than DCT-based scheme [19-20] and it can provide a framework for decomposing signals into a hierarchy of frequency bands corresponding to higher spatial resolution than DCT, we design a method that utilizes DWT to decorrelate CS measurements.

Fig. 1 presents a process of forming 2D-reshaped representation created from BCS measurements associated with the same projection (i.e., the measurement matrix Φ_B) and its DWT representation. The DWT coefficients of 2D-reshaped representation are calculated by passing them through a series of filters [21] which can be represented as following equations (5) - (8).

$$\Omega_{LL}=\left(\left(\left((y_{2D}\ast g)\downarrow 2\right)_r \ast g\right)\downarrow 2\right)_c \tag{5}$$

$$\Omega_{LH}=\left(\left(\left((y_{2D}\ast g)\downarrow 2\right)_r \ast h\right)\downarrow 2\right)_c \tag{6}$$

$$\Omega_{HL}=\left(\left(\left((y_{2D}\ast h)\downarrow 2\right)_r \ast g\right)\downarrow 2\right)_c \tag{7}$$

$$\Omega_{HH}=\left(\left(\left((y_{2D}\ast h)\downarrow 2\right)_r \ast h\right)\downarrow 2\right)_c \tag{8}$$

where y_{2D} is 2D-reshaped representation of BCS measurement; g and h are impulse responses of low-pass filter and high-pass filter, respectively; $(.)_r$, $(.)_c$, $\ast$, and $\downarrow 2$ are row processing operator, column processing operator, convolution operator, and subsampling operator by 2, respectively; Ω_{LL}, Ω_{LH}, Ω_{HL} and Ω_{HH} are DWT coefficients of LL (Low-Low) band, LH (Low-High) band, HL (High-Low) band, and HH (High-High) band, respectively (see Fig. 2 for more clarity). Fig. 1 clearly shows that the structure of original image is also kept in a reshaped 2D-form. Therefore, we can use a proper transform for measurements y to remove redundancy. Obviously, most energy of reshaped 2D-form concentrates in LL band of DWT

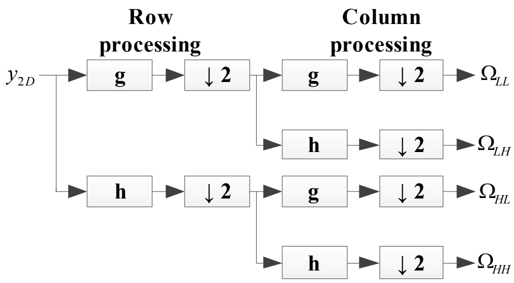


그림 2. BCS 측정신호의 2D 표현을 위한 DWT 과정
Fig. 2. DWT process for 2D-reshaped representation of BCS measurement

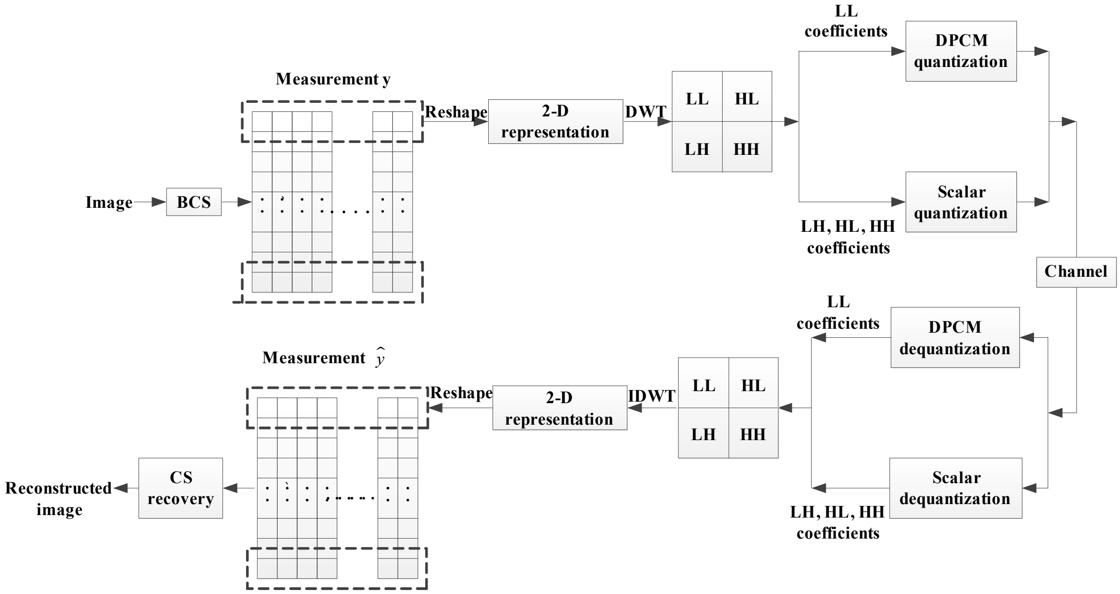


그림 3. 영상의 블록기반 압축센싱을 위한 제안하는 측정신호 부/복호화 구조
Fig. 3. Proposed measurement encoding and decoding for BCS of image

domain.

In this proposed encoding method, in order to exploit correlation among blocks in measurement domain, measurements of all blocks coming from the same projection are firstly reshaped into a 2D-form Y_{2D}, and then DWT is applied to decorrelate CS measurements. DWT compacts energy of data into a few low frequency coefficients while also represents high frequency coefficients with smaller value. Four bands of wavelet representation - LL, LH, HL, and HH - contain different frequency components so that some bands may need to be handled with different quantization schemes. More clearly, by natural characteristic, since DWT provides high spatial resolution and most energy of data is concentrated in LL band, thus leading the LL band to be the most important, it should be processed differently from other bands. As shown in Fig. 2, the LL band is created by passing 2D-reshaped representation of CS measurement through low pass filtering g along the rows and then the same low pass filter g along the corresponding columns. As a result, the LL band provides the coarse-scale approximated version of original 2D-reshaped representation at a half resolution. Therefore, LL band still contains most of spatial information of 2D-reshaped representation (i.e., coefficient of LL band still keeps high correlation, see Fig. 1(b) for more clarity), so that DPCM plus SQ is employed to quantize the LL band to give better redundant elimination. On the other hand, since LH, HL and HH band contain high frequency coefficients, the correlation among coefficients is small; for simplicity, they are quantized by SQ. Additionally, due to the importance of LL band coefficients, we also assign more bits to represent codewords in LL band than in other high frequency bands. At decoder, a matching dequantized process is performed to recover the CS measurements. A diagram of the proposed encoding and decoding scheme for the block-based measurement data is shown in Fig. 3.

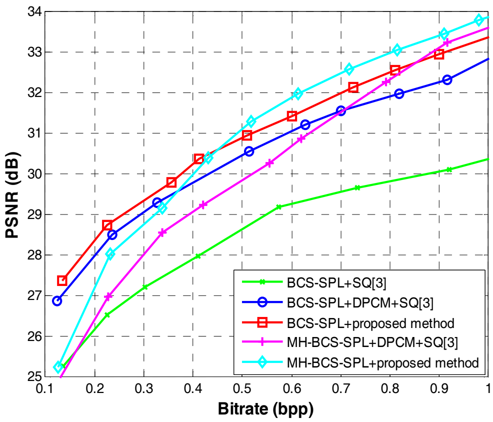
Ⅳ. Experimental results

In this section, performance of the proposed method is evaluated using four 512×512 natural images in Fig. 4, namely, Lena, Goldhill, Boat, and Cameraman. At encoder, an input image is split into non-overlapping blocks and then each block is

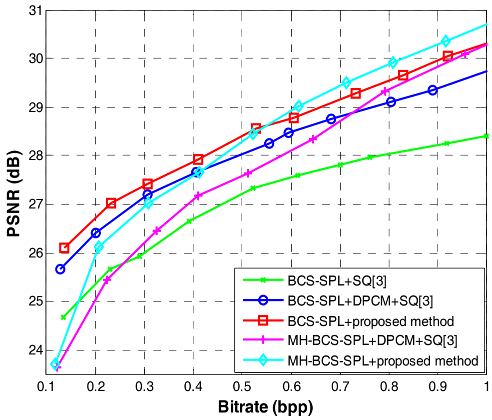
(a) Lena (b) Goldhill (c) Boat (d) Cameraman

그림 4. 원본 테스트 영상
Fig. 4. Original test images

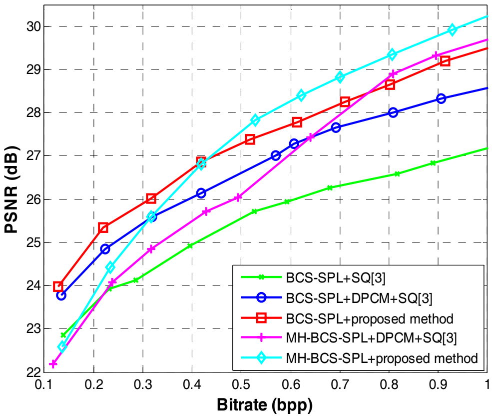
sampled using an i.i.d. random Gaussian measurement matrix. In our experiments, we employ two block sizes, 8×8 (i.e., $B=8$) and 16×16 (i.e., $B=16$). Performance of the proposed encoding method is compared with BCS-SPL [22] and MH-BCS-SPL [23] recovery schemes coupled with two quantization methods, namely, SQ alone and DPCM plus SQ [3]. The spasifying transform used in our paper for CS recovery at decoder is DWT. For fair comparison with previous coding schemes in [3], we also ignore the entropy coding part as the existing methods. Note that, for SQ alone



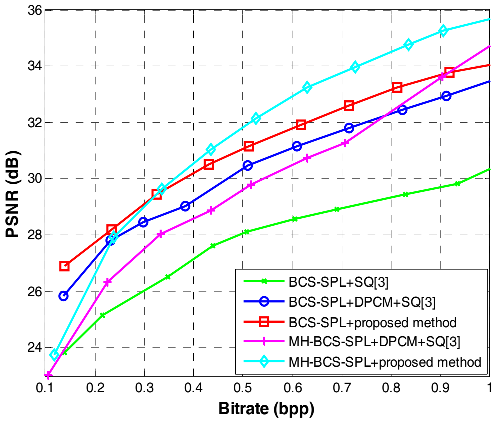
(a) Lena



(b) Goldhill



(c) Boat



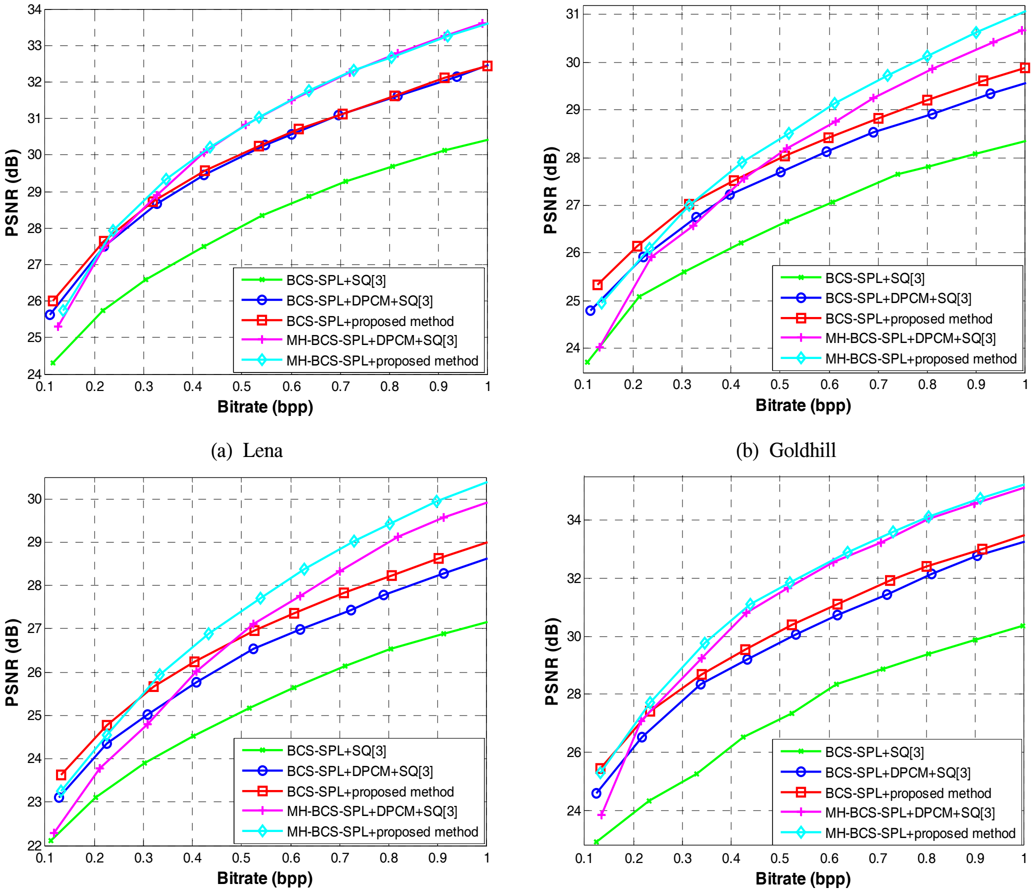
(d) Cameraman

Fig. 5. 제안방법 및 기존 방법간의 율-왜곡 성능비교 (블록크기 8×8)
그림 5. Rate-distortion performance comparison of the proposed method against exiting methods (block size 8×8)

and DPCM plus SQ, the obtained bitrate depends both on the quantization step size of SQ and the subrate of BCS measurement process. Especially, for a particular bitrate, each image and recovery algorithm have an optimal quantization step that generates the highest PSNR[24]. Consequently, for the experiments in this paper, the optimal combination of quantizer step size and subrate are chosen via exhaustive search over all possible pairs of step sizes and subrates as in [3]. In details, the rate-distortion performance of the proposed method is presented in Fig. 5 and Fig. 6 for a bitrate ranging from 0.1 bpp to 1 bpp. Note that, the results of BCS-SPL and MH-BCS-SPL coupled with SQ alone and DPCM plus SQ for block size 16×16 slightly differ from the results in [3] since different measurement matrix is used.

Fig. 5 shows the rate-distortion of the proposed method with block size of 8×8. Obviously, among those three methods, SQ which does a uniform quantization, deals with all CS measurements equally; i.e., the redundancy among CS measurements is not exploited. Therefore, performance of SQ method is the worst among the three methods. Thanks to high energy compaction property of DWT, the proposed method shows superior improvements compared with the SQ method. For example, compared with BCS-SPL plus SQ, PSNR gain of the proposed method is up to 3 dB, 1.9 dB, 2.3 dB and 4 dB, respectively for images, Lena, Goldhill, Boat, and Cameraman.

Moreover, Fig. 5 also shows that performance of



(a) Lena (b) Goldhill

(c) Boat (d) Cameraman

그림 6. 제안방법 및 기존 방법간의 율-왜곡 성능비교 (블록크기 16×16)
Fig. 6. Rate-distortion performance comparison of the proposed method against exiting methods (block size 16×16)

the proposed method is better than the method that applies DPCM plus SQ to measurement data. For those images with much texture and/or many strong edges such as Lena and Goldhill which contain much high frequency information in DWT domain, the proposed method only attains a slight gain. For example with Lena image, the improvement is up to 0.7 dB and 1.2 dB compared with BCS-SPL coupled with DPCM plus SQ, and MH-BCS-SPL coupled with DPCM plus SQ, respectively. Specially, for some smooth images like Boat or Cameraman containing plenty of repeated patterns, the performance of the proposed method is very good. For example of Cameraman image, the proposed method gains up to 0.9 dB and 2.5 dB compared with BCS-SPL coupled with DPCM plus SQ, and MH-BCS-SPL coupled with DPCM plus SQ, respectively.

Additionally, Fig. 6 shows rate-distortion of the proposed method with block size of 16×16. It is clear that performance of the proposed method is also better than those methods of SQ alone and DPCM plus SQ; however, the performance with block size of 16×16 is lower than that with block size of 8×8, this is because in natural image, correlation among blocks of size 8×8 is higher than that among blocks of size 16×16. Note that as block size becomes larger, blocks are more likely to contain different objects, which leads to lower statistical consistency among blocks. By our proposed method, most of redundancy among measurements is removed; so with block size of 8×8, more redundancy is eliminated successfully, leading to higher performance.

Ⅴ. Conclusion

In this paper, a measurement coding framework for BCS of images is proposed for improving rate-distortion of CS system based on transform coding. The high redundancy existing among BCS measurement is eliminated by applying DWT to 2D-reshaped representation of BCS measurement followed by proper quantizer scheme for each band. It helps to considerably save total bits for representing CS measurements. Our experimental results verify that the proposed method produces better rate-distortion performance compared with SQ alone and DPCM plus SQ.

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