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공간 스케일러블 Kronecker 정지영상 압축 센싱

(Spatially Scalable Kronecker Compressive Sensing of Still Images)

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(Nguyen Canh Thuong and Byeungwoo Jeon©)

요 약

압축센싱 기술이 직면하고 있는 두 가지의 도전과제는 복원 알고리즘의 연산 복잡도 개선과 부호화 효율 향상 문제이다. 이에 대한 해결방안으로, 본 논문은 최대 3 가지의 공간 해상도 조절 및 향상된 압축센싱 부호화 성능을 가능하게 하는 공간 스케일러블 Kronecker 압축센싱 구조를 제안한다. 제안 방법의 기저 계층(base layer)에서는 quincunx 샘플링 격자에 기반 하는 듀얼-해상도 센싱 행렬을 사용한다. 해당 센싱 행렬은 낮은 해상도의 영상에 대한 고속-프리뷰(preview) 기능을 가능케 한다. 향상 계층(enhancement layer)에서는 획득한 측정값과 예측 측정값 간의 잔차 측정값을 부호화 한다. 복원과정에서는 기저 계층으로부터 낮은 해상도의 복원 영상을 획득 할 수 있는 반면, 두 개의 계층을 모두 사용하여 복원하는 경우 높은 해상도의 영상을 획득할 수 있다. 실험 결과, 제안하는 구조가 종래의 단일 계층방법 및 다중-해상도 기반 구조에 비해, 2.0bpp일 때 PSNR 성능이 각각 5.75dB 및 5.05dB 더 향상됨을 확인하였다.

Abstract

Compressive sensing (CS) has to face with two challenges of computational complexity reconstruction and low coding efficiency. As a solution, this paper presents a novel spatially scalable Kronecker two layer compressive sensing framework which facilitates reconstruction up to three spatial resolutions as well as much improved CS coding performance. We propose a dual-resolution sensing matrix based on the quincunx sampling grid which is applied to the base layer. This sensing matrix can provide a fast-preview of low resolution image at encoder side which is utilized for predictive coding. The enhancement layer is encoded as the residual measurement between the acquired measurement and predicted measurement data. The low resolution reconstruction is obtained from the base layer only while the high resolution image is jointly reconstructed using both two layers. Experimental results validate that the proposed scheme outperforms both conventional single layer and previous multi-resolution schemes especially at high bitrate like 2.0 bpp by 5.75dB and 5.05dB PSNR gain on average, respectively.

Keywords : compressive sensing, spatially scalable, Kronecker sensing, multi-resolution, total variation

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Ⅰ. Introduction

Compressive sensing (CS) which allows simultaneous sensing and compression[1~2, 23~24] has attracted significant interest due to its promising potential in wireless communication and image/video processing, etc. Relying on signal sparsity property, it can reconstruct sparse signals from much smaller number of measurements than Nyquist sampling theorem originally specifies. The CS measurement data formed into a column vector, $y \subset R^{m^2}$ of signal $f \subset R^{n^2}$ is modeled as a linear projection $y = \Phi f$ where the sensing matrix Φ, which is typically a random matrix, needs to satisfy the restricted isometry property[1,2]. A fully random sensing matrix requires huge memory space for its storage and high computation complexity for the random projection and recovery especially for high dimensional signal. In this regard, the block-based CS (BCS)[3~4] and the Kronecker CS (KCS)[5] have been introduced. In the view point of conventional frame-based sensing, the sensing matrix of BCS has only block diagonals, thus it loses global characteristics of the images despite preserving the local ones. The Kronecker CS senses measurement data still in frame-based fashion but in separate manner for each signal dimension. Its sensing complexity is considerably reduced by using a Kronecker product. For a 2D signal, $F \subset R^{n \times n}$, the sensing matrix is given as $\Phi = R \otimes G^T$ where $\otimes$ denotes the Kronecker product, R and G respectively represent the sensing matrices for each dimension. The KCS measurement data formed into a matrix is rewritten as $Y = RFG$, and its vectorized version y and measurement constraint are related as:

$$\| \Phi f - y \|_2^2 = \| RFG - Y \|_2^2 \quad (1)$$

where the notation $\| . \|_p$ denotes the Lp norm.

One of the widely used CS reconstruction methods is the total variation (TV) technique[6~8] which is known to achieve good CS recovery performance while preserving image edges relatively well by solving the problem below:

$$\min_F \left\{ \begin{array}{l} \| \nabla_H F \|_1 + \| \nabla_V F \|_1 \\ + \frac{\mu}{2} \| RFG - Y \|_2^2 \end{array} \right\}$$

where μ is a constant parameter and ∇_H, ∇_V stand for gradient operators respectively in horizontal and vertical direction. The problem can be efficiently solved by the split Bregman techniques[5].

CS still faces challenges of huge computational complexity in reconstruction which hinders its practical usage, not to mention real-time application. Roughly speaking, its reconstruction complexity is directly proportional to the spatial resolution. The multi-resolution sensing matrix is one approach to alleviate this problem. By the way, CS at current status has much space to improve in coding efficiency when compared to conventional techniques such as JPEG or MPEG-4[7]. In addition to the coding efficiency, additional desirable practical feature is scalability functionality with which a transmitted bitstream can be selectively (or adaptively) decoded according to user's purpose or capability in picture (spatial and temporal) resolution, quality, resource status (energy, computation, etc), and so on. This scalable coding framework allows clients to have much freedom in decoding. In this paper, we are particularly interested in having the CS support spatial scalability. Under the spatially scalable framework, one can first have fast preview of low resolution for real-time application and later higher resolution as needed. The study in this paper proposes a novel spatially scalable KCS sensing with following contributions. Firstly, we introduce a quincunx sensing matrix which not only enables dual-resolution measurement but also improves final performance of CS. Secondly, we propose a novel two layer scalable framework: the low resolution base layer and the high resolution enhancement layer. The low-resolution image is obtained at encoder side and utilized for predictive coding. Thirdly, we jointly reconstruct the high resolution image based on an up-sampled version of the base layer image utilizing post processing[10].

The rest of this paper is organized as follows. Section II investigates some related work and Section III introduces our scalable framework with the proposed matrix. Numerical experiments are presented in Section IV, and the paper is concluded in Section V.

Ⅱ. Related Work

1. Multi-resolution sensing matrix

Recently the problem of multi-resolution CS has attracted high-level of attention. For example, Baraniuk et al. proposed a dual scale sensing matrix (DSS) in CS-MUVI framework[11,12] which can generate an efficiently computable low-resolution video pre-view. To further reduce computational complexity, Goldstein et al.[14] proposed a new multi-resolution framework based on the STOne transform. These algorithms were designed for a single pixel camera imaging system[15] in which the elements of the sensing matrices are chosen as either +1 or -1 to achieve easier and faster implementation. Toward more general multiscale framework, the work [13] proposed a multi-resolution sensing matrix for Kronecker Compressive Sensing which focuses on sampling low frequency component. However, they only considered perfect measurement without quantization, which is not practical.

2. Scalable compressive sensing of images

The problem of scalable compressive sensing has also drawn much attraction recently[16~18]. For scalable videocast[16], Xiang et al. proposed to select a small portion of DCT coefficients in key frame measurement to enable predictive coding. The hybrid sensing matrix[19] they used does not support the so called, democracy property[20] of CS, so in terms of resilience to noise, it is slightly less attractive. By the way, Jiang et al.[17] used a multi-resolution sensing matrix between each group of the same resolution, so it can keep the democracy property satisfied. The multi-resolution sensing matrix is based on randomly permutated Walsh-Hadamard matrix and it can provide multi-resolution CS measurements under the scalable framework. However, it should be noted that no predictive coding was used. Utilizing a dual resolution sensing[11], Valseia et al.[18] was able to obtain fast low resolution image and performed predictive coding at decoder. However, both algorithms[17~18] were designed for the single pixel camera system[11].

This paper develops a multi-resolution sensing matrix and a novel spatially scalable framework for Kronecker compressive sensing for still images. The proposed method is not limited to binary sensing matrix and also can take into account the quantization error.

III. Proposed Dual-Resolution Quincunx Matrix

Even though the multi-resolution measurement is desirable for enabling a fast preview of an image/video, it however is supported neither by the conventional CS[11~12, 14] nor by KCS[13]. In order to enable multi-resolution measurement, it is important to study the relationship between the HR (high resolution) and LR (low resolution) in measurement domain. The KCS measurements of a same image at low resolution, $F_{LR} \subset R^{\frac{n}{2}\times\frac{n}{2}}$ and at a high resolution $F_{HR} \subset R^{n \times n}$ can be expressed as:

$$Y_{LR} = R_{LR}F_{LR}G_{LR} \tag{2}$$

$$Y_{HR} = R_{HR}F_{HR}G_{HR}$$

Let's assume that the LR image is a bi-linearly down-sampled version of the HR image as follows:

$$F_{LR} = D_S F_{HR} D_S^T$$

$$D_S = \frac{1}{2}\begin{bmatrix} 1 & 1 & 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & 1 & 1 & \dots & 0 & 0 \\ \dots & \dots & \dots & & \dots & \dots & \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 \end{bmatrix} \subset R^{\frac{n}{2}\times n} \quad (3)$$

where the down-sampling operator is denoted by D_S and simple up-sampling operator as a corresponding up-sampling operator D_S^T. Then a smoothed version of F_{LR} can be delivered by:

$$\overline{F_{HR}} = D_S^T F_{LR} D_S = D_S^T \left(D_S F_{HR} D_S^T\right) D_S \quad (4)$$

Let's further assume that the difference in (5) between these two images is very small.

$$F_{HR} - \overline{F_{HR}} = F_{HR} - \left(D_S^T D_S\right) F_{HR} \left(D_S^T D_S\right) \quad (5)$$

Since CS satisfies the Johnson-Lindenstrauss lemma (i.e., energy is preserved in the measurement domain)[22], subsequently it can be safely assumed that the corresponding measurement residual in (6) is also very small.

$$\epsilon = R_{HR}\left(F_{HR} - \overline{F_{HR}}\right) G_{HR} \quad (6)$$

This assumption behind (5) is validated through experiment using various resolutions and subrates as shown in Fig. 1. We achieve SNR value around 22.8 dB and 25.5 dB for resolution 256x256 and 512x512, respectively. Note that it is SNR of the CS measurement not the one of the reconstructed image. The SNR is calucualted as below:

$$SNR = 10\log_{10}\left(\frac{\| Y_{LR} \|_2^2}{\| Y_{HR} - Y_{LR} \|_2^2}\right)$$

When the HR subrate equals to 0.25, the recovered LR image achieves very high PSNR value as in Fig 2. It is because the subrate of LR image is exactly 1.

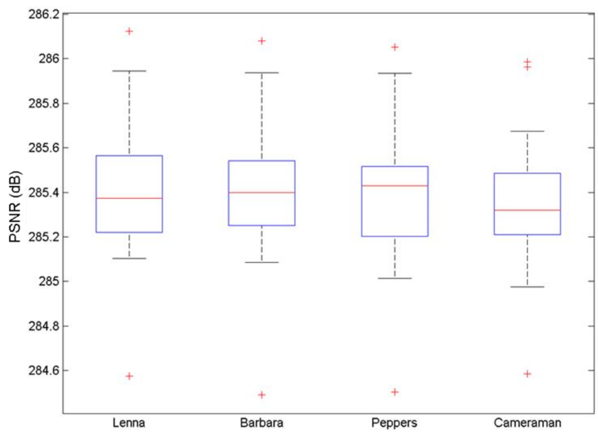
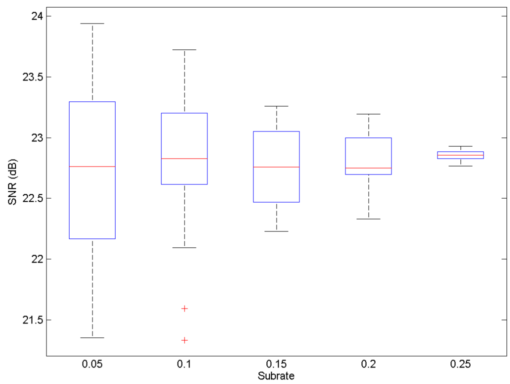


그림 2. 측정율 0.25 에서 512x512 해상도의 HR 영상에 대해 제안된 행렬을 사용하여 복원된 LR영상의 PSNR 성능

Fig. 2. PSNR performance of recovered LR image using with the proposed matrix for HR image of size (512x512) at subrate 0.25.



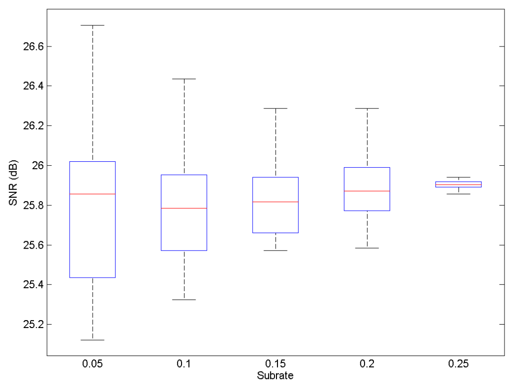


그림 1. 제안하는 HR 행렬을 적용 시 LR 측정값에 대한 SNR 그래프 (20개의 서로 다른 랜덤 행렬에 대한 평균 결과를 표시함; 256x256 해상도(왼쪽) 및 512x512 해상도(오른쪽)의 Lena 영상 사용)

Fig. 1. SNR of LR measurement when the proposed HR matrix is applied to Lena image at resolution 256x256 (left) and at 512x512 (right) (It shows average values over 20 different random matrices).

For lower subrate than 0.25, we also expected high PSNR performance for LR image since it is sensed at four times subrate than the HR one. In addition, it is worthwhile mentioning that our algorithm offers even better performance as the image resolution increases. Beside, the higher subrate gives the more stable SNR performance.

With this error, we can interpret the LR compressed measurement via $\overline{F_{HR}}$ image as:

$$\begin{aligned} Y_{LR} &= R_{HR}\left(\overline{F_{HR}} + \left(F_{HR} - \overline{F_{HR}}\right)\right)G_{HR} \\ &= R_{HR}\left(\overline{F_{HR}}\right)G_{HR} + R_{HR}\left(F_{HR} - \overline{F_{HR}}\right)G_{HR} \end{aligned} \tag{7}$$

From (7), the LR measurement can be drawn from the HR measurement by enforcing the following constraint:

$$R_{HR}\left(\overline{F_{HR}}\right)G_{HR} = R_{LR}F_{LR}G_{LR} \tag{8}$$

$$Y_{LR} = Y_{HR} + \epsilon$$

To achieve this goal, we propose a new sensing matrix based on the quincunx sampling grid. After constructing a low resolution sensing matrix R_{LR}, its values are then mapped to the high resolution sensing matrix $\overline{R_{HR}}$ with the quincunx grid as illustrated in Fig. 4. By doing so, we actually sense LR image at quincunx grid with fully random sensing matrix R_{LR}. Therefore, we guarantee the RIP condition of LR image. In another hand, the

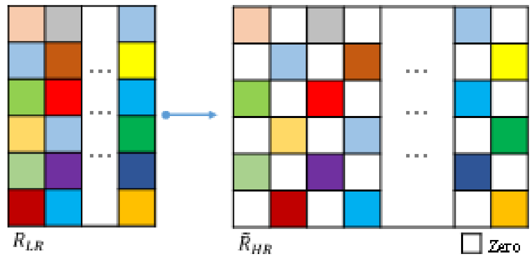


그림 4. 제안하는 quincunx 센싱행렬
Fig. 4. The proposed quincunx sensing matrix.

acquisition using the proposed matrix is equivalent to following two step sampling approach: (1) extract the LR image using the quincunx down-sampling pattern, (2) compress sensing this LR image using the random R_{LR} matrix. Therefore, the RIP of HR sensing matrix is also guaranteed considering that we actually sense the HR image at quincunx sample locations. However, it is expected to lose some details of image. By using the proposed quincunx dual resolution sensing matrix to sense HR image, both LR and HR images can be reconstructed with the same set of measurements. Therefore, if the target subrate of HR image is r, then we can construct the proposed sensing matrix R_{HR} from the LR sensing matrix R_{LR} at subrate $r \times 4$. As a result, the proposed sensing matrix R_{HR} prefers a subrate smaller than 0.25, otherwise the subrate of LR will exceed 1. However, rather than discarding all high frequency components as in [13] (i.e., the authors actually sample the low resolution image only), the

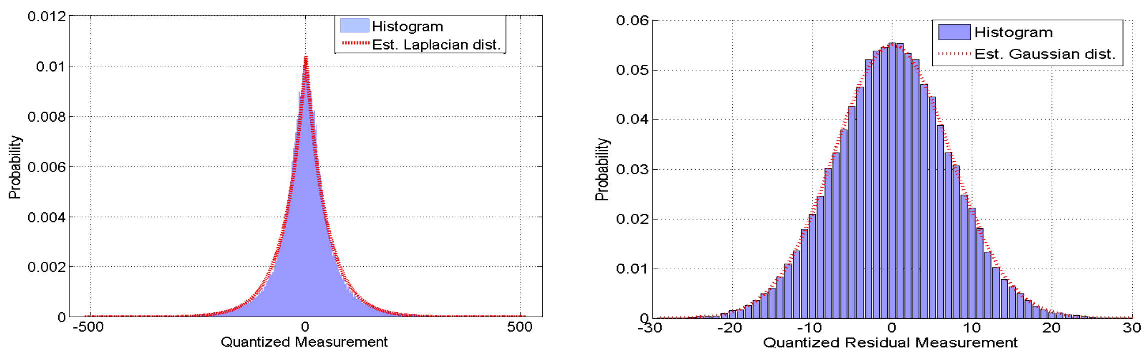


그림 3. KCS 측정에 대한 예측 분포도 (측정율 0.2 및 균일 양자화, Lena 영상)
Fig. 3. Estimated distribution of KCS measurement (subrate 0.2 with uniform quantization, Lena image).

proposed sensing matrix tends to preserve the image texture better. But, it comes with a cost of noise in low resolution image. Since the LR image is obtained at much higher subrate than HR image, we can easily get rid of LR measurement noise especially by utilizing the state of the art denoising algorithm like BM3D[9].

Ⅳ. Proposed Spatially Scalable KCS

1. Compressed sensing and encoding

The detail of the proposed spatially scalable scheme is explained here by referring to Fig. 5. The sensing part senses an input image at two spatial resolutions: LR image for base layer and HR image for enhancement layer using respectively ($R^B, G^B \subset R^{m_B \times \frac{n}{2}}$) and ($R^E, G^E \subset R^{m_E \times n}$). The proposed framework, therefore, support three image resolutions: $n/4 \times n/4$ and $n/2 \times n/2$ with base layer and $n \times n$ with enhanced layer. In case of the base layer, we use the proposed quincunx sensing matrix at subrate 0.25 for LR image of size $n/2 \times n/2$. The enhanced layer is sensed at resolution nxn. The base layer is sensed at resolution n/2 x n/2. Therefore, the LR image that we can reconstruct from base layer is n/4 x n/4. This quincunx matrix is constructed from the lower resolution matrix $R_{LR}^B,\ G_{LR}^B \subset R^{m_B \times \frac{n}{4}}$ at a subrate 1.0. Therefore, we can enable fast preview the lower resolution image of size $\frac{n}{4} \times \frac{n}{4}$ by a simple inverse processing:.

$$\widetilde{F_{LR}^B} = \left(R_{LR}^B\right)^{-1} Y^B \left(G_{LR}^B\right)^{-1} \tag{9}$$

where Y^B is de-quantized measurement of the base layer. The recovered image is obtained at a high quality with very high SNR. For the enhancement layer, the HR image is sensed by the conventional KCS sensing matrix $R^E, G^E \subset R^{m_E \times n}$.

Inspired by [10], we also up-sample the low resolution image $\widetilde{F_{LR}^B}$ to predict the high resolution image $\widetilde{F_{\mathrm{Pred}}^E}$ and re-sample to deliver predictive measurement $Y_{\mathrm{Pred}}^E = R^E\left(\widetilde{F_{\mathrm{Pred}}^E}\right)G^E$. Subsequently, we perform uniform quantization followed by Huffman entropy coding for measurement data of the

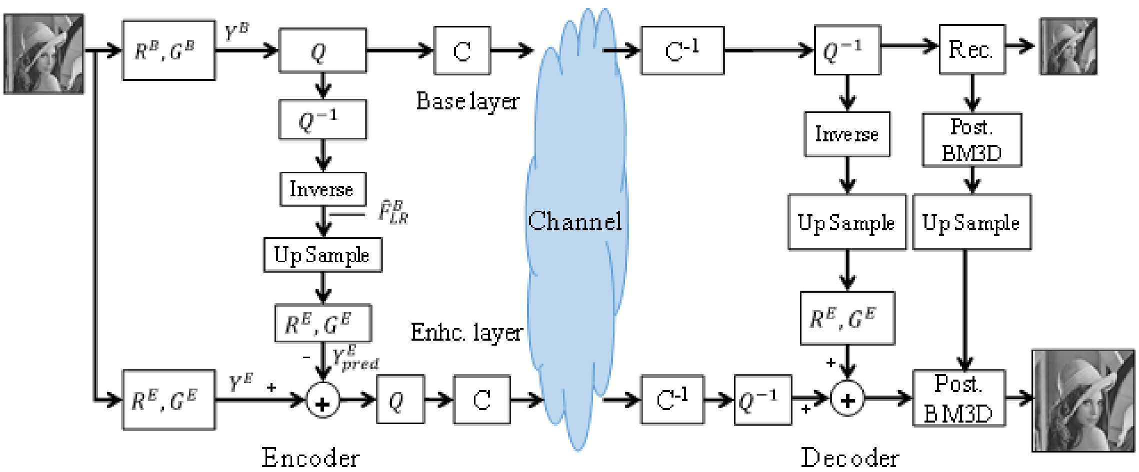


그림 5. 제안하는 공간 스케일러블 KCS 프레임웍 (Q, Q^{-1}는 균일양자화 및 역양자화이며, C, C^{-1}은 Huffman 엔트로피 부호화 및 복호화를 의미)

Fig. 5. Proposed spatially scalable KCS framework (here Q, Q^{-1} refer to uniform quantizer and dequantizer; C, C^{-1} refer to Huffman entropy coder and decoder, respectively).

base layer Y^B and the enhancement layer $Y^E - Y^E_{\mathrm{Pred}}$.

From out experiment, we note that, the KCS measurement does not follow Gaussian distribution as conventional CS measurement as in [11] but Laplacian distribution. In addition, the KCS residual measurement follows Laplacian distribution. Fig. 3 shows experimental results to see how well the Laplacian & Gaussian distributions fit with real data. It shows that KCS measurement and residual measurement match pretty well respectively with Laplacian and Gaussian distribution. Therefore, depending on the type KCS measurement, its corresponding distribution is selected for use in Huffman encoding process. The base layer is always available to decoder, while the additional bitstream of enhanced layer is sent only upon receiver request.

2. Decoding and compressed sensing recovery

As an inverse processing to the compressed sensing, we first carry out the huffman decoding and dequantize the received bitstream for both the base and enhanced layers (if available). Decoder will reconstruct the LR image from the base layer then HR image as necessarily. Because HR and LR image sensing is designed to share the same measurements, reconstructing the HR and LR images can use the TV[6] straightforwardly without modification. On the other hand, in this paper, the LR image is reconstructed first from the measurements using the sensing matrices and the super resolution/upsampling technique, such as bi-cubic interpolation[16]. We utilize this upsampling technique to generate the predicted HR image from preview LR image.

표 1. 후처리 알고리즘에 대한 가상 코드[10]
Table 1. Description of post processing algorithm[10].

Input: Initial image F^0, measurement Y, sensing matrices R, G
Output: image F_S^{i+1}
Estimate image: $F^{B_S} = BM3D(F^0), i = 0$
While $i < 10, (ssim^{i+1} - ssim^i) < \xi$
$\quad Y_{res} = Y - RF_S^i G$
$\quad F_{res}^i = TVrec(Y_{res}, R, G)$
$\quad \widetilde{F_S^{i+1}} = F_S^i + F_{res}^i$
$\quad F_S^{i+1} = BM3D(\widetilde{F_S^{i+1}})$
$\quad ssim^{i+1} = SSIM(F_S^{i+1}, F_S^i)$
$\quad i = i+1,$
End

표 2. 다양한 CS 복원방법
Table 2. Description of various CS methods.

Algorithm	Descriptions
SQ-TV-w/BM3D	Single layer by TV recovery with BM3D post processing
SQ-TV-w/oBM3D	Single layer by TV recovery without BM3D post processing
MR-KCS	Multi-resolution sensing matrix[13]
Proposed	Proposed spatially scalable KCS framework

Because both LR and HR images contain significant staircase artifacts, BM3D filtering as post-processing[10] is applied to alleviate this drawback. Due to the structure preservation of the state of the art denoising filter - BM3D, we can suppress the staircase artifact by iterative filtering of image and reconstructing the residual measurement. Details of the algorithm are in Table 1 where the BM3D(.) stands for a filtering operator with BM3D algorithm[9], TVrec(Y, R, G.) denotes TV[7] reconstruction with input measurement Y and sensing matrix R, G. SSIM(.) represents the structural similarity SSIM[15] metric which is used as the stopping criterion because the aim is to preserve the nonlocal structures. The two BM3D processes depicted in Fig. 5 are identical.

V. Experiment and Discussion

1. Experimental conditions

In this section we compare the proposed method with the conventional single layer framework[7] with/without BM3D post processing and the multi resolution sensing framework of MS-KCS[13]. For the single layer and MR-KCS approaches, we follow the original framework with suggested parameters. In case of the proposed method, the base layer is sensed at subrate 0.25 with the proposed sensing matrix to deliver low resolution image at encoder side. Enhancement layer is sampled at various subrates using conventional KCS Gaussian sensing matrix. A simple bi-cubic interpolation method is used to deliver predicted HR images.

For measurement coding, uniform quantization followed by Huffman coding is used for both spatial and residual KCS measurement with selected distribution as mentioned in Section Ⅲ. The best combination of quantization bit depth is selected to offer the best performance. For the proposed method, bit depth of 6 bits or 4 bits are used for base layer and residual/enhancement layer measurement, respectively.

In receiver side, TV reconstruction is used with the same parameters for all algorithms and stopping criteria of $\left(\| F^{k+1} - F^{k} \|_2^2 / \| F^{k} \|_2^2 \right) < 2.10^{-5}$. For post processing, BM3D is used with $\sigma = 10$ and SSIM threshold of 0.002. All results are obtained by averaging five simulations with test images of size 512×512 at various subrates to obtain bitrate from 0.6 to 2.4 bbp. All test images are presented in Fig. 6.

그림 6. 512x512 해상도의 테스트 영상
Fig. 6. Various gray test images of size 512x512.

2. Experimental results

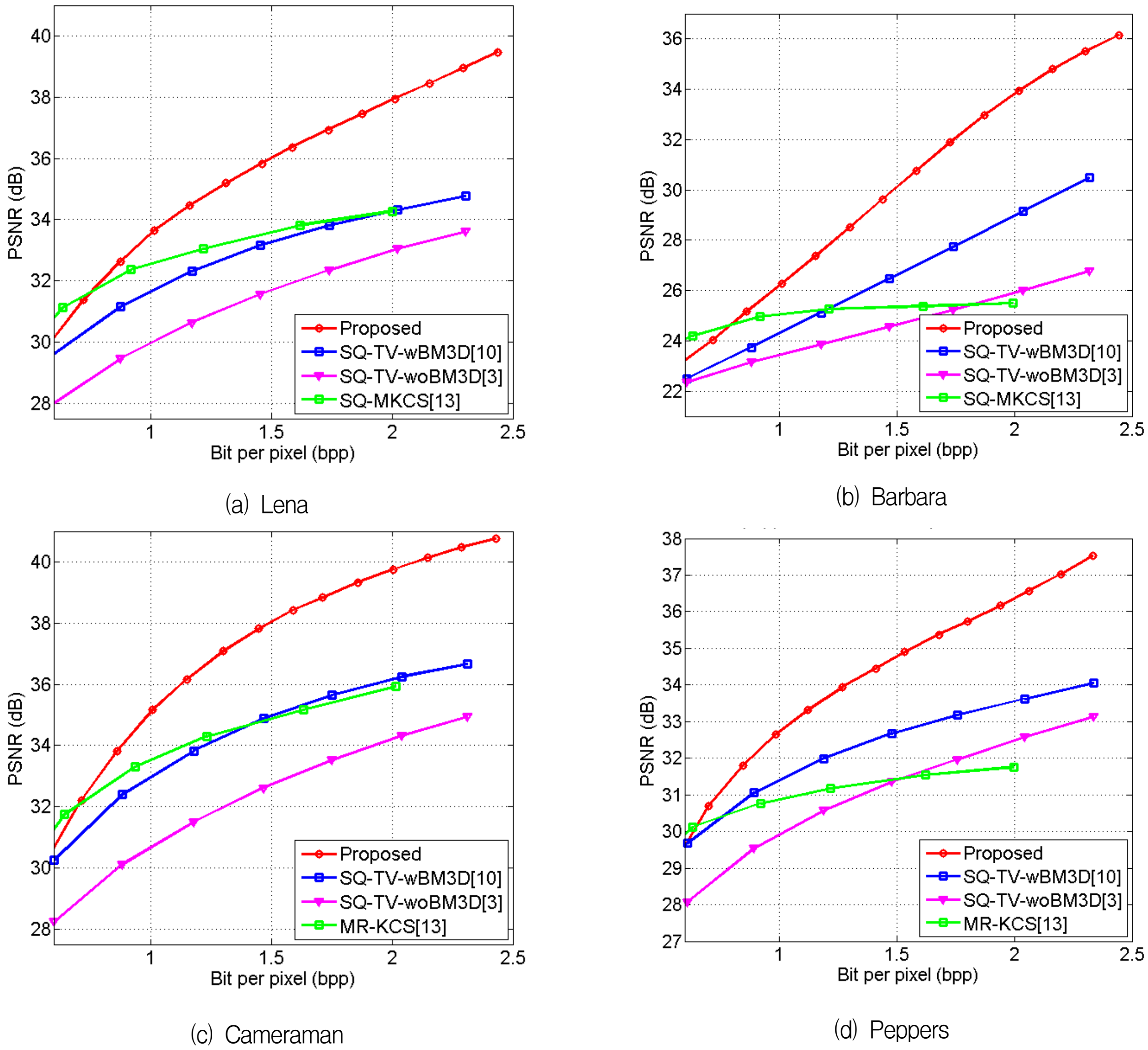
In order to evaluate performance of the proposed quincunx sensing matrix, we compare its performance with that of the conventional KCS sensing matrix, and its result is given in Table 3. In comparison with the conventional sensing matrix, it is not only able to provide LR image reconstruction but also can improve HR reconstruction performance. An improvement of 0.3 to 1.3 dB can be achieved by using the proposed sensing matrix. Thanks to the quincunx sampling scheme, we are able not to lose any high frequency component and even have gain in case of images having much edgeness. For instance, the proposed matrix offers 0.3dB gain on average on Barbara image.

Two single layer framework SQ-TV with and without BM3D post processing and the previous dual resolution images MR-KCS[13] are compared with the proposed two layers scalable method as well. Their rate distortion performances are depicted in Fig. 7 in which we can observe that the BM3D post processing gives almost 2dB gain on average over the conventional case. Surprisingly, the previous work MR-KCS does not show high performance as presented in the original paper[13] most likely due to presence of quantization noise. It offers limited perofrmance at high subrate while slightly better performance than other frameworks at low bitrate

표 3. 제안하는 quincunx 및 기존 KCS 행렬 간 TV 복원 알고리즘[3] 에서의 성능 비교 (PSNR: dB)
Table 3. Experimental result comparison of TV[3] reconstruction with the proposed quincunx and the conventional KCS matrix (PSNR: dB).

Image	Subrate	0.05	0.10	0.15	0.20	0.25
Lena	TV[3]	25.58	28.19	29.84	31.16	32.26
	TV[3]*	25.94	28.84	30.62	32.05	33.28
Barbara	TV[3]	21.06	22.39	23.23	23.94	24.67
	TV[3]*	21.28	22.68	23.54	24.29	25.04
Peppers	TV[3]	25.31	28.24	29.85	30.97	31.86
	TV[3]*	25.69	28.77	30.43	31.63	32.71
Camera-man	TV[3]	25.40	28.58	30.79	32.47	33.91
	TV[3]*	25.76	29.30	31.69	33.59	35.29

(*): using the proposed sensing matrix



(a) Lena (b) Barbara (c) Cameraman (d) Peppers

그림 7. 여러 테스트 영상에 대한 다양한 알고리즘 간 율-왜곡 그래프

Fig. 7. Rate distortion curves of various algorithms for several test images.

below 0.8 bbp. At a high bit rate, MR-KCS's performance is even lower than the single layer with BM3D post processing.

Thanks to the proposed two layer concept and proposed dual resolution sensing matrix, the proposed method, is not only able to produce different resolution reconstructions but also give the best performance among algorithms compared. It outperforms the single layer framework irrespective of with and without BM3D post processing (up to 8 dB and 5 dB gain at bit rate of 2.33 bpp of Barbara image, respectively). In comparison with MR-KCS, it gains up to by 8.2 dB at 2.0 bpp for Barbara image.

3. Further discussion

This paper is the first work addressing the scalable problem of Kronecker compressive sensing while the other existing ones are all about block-based CS or binary sensing matrix. So that we only compared with the previous works on multi-resolution sensing matrix and single layer scheme. Beside, it is possible to extend the proposed framework to other sensing matrix with only little modification on the base layer. We should change the quincunx sampling matrix suitable to the conventional sampling. Despite of the significant improvement of in coding efficiency, the two layered framework has to face some limitation. We could sense different image resolutions with the same size sensing matrix (see [13]). However, it requires sampling two times for sensing two different resolutions of base and enhanced layer. Thus, the proposed framework prefers the static scene. This limitation can overcome for video application. For instance, we use base layer for key-frame only.

Ⅵ. Conclusion

In this paper, a dual resolution sensing matrix based on quincunx sampling grid and a spatially scalable Kronecker sensing framework (dual layer design) are proposed, The proposed method enables fast preview image and using predictive coding in the encoder side. HR image is recovered by jointly reconstructing HR and LR images, and further enhancement by BM3D post processing. This work does consider quantization error with uniform quantization. Our method also offers remarkable improvement over the conventional single layer and multi-resolution scheme in terms of coding efficiency.

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