

Fast reconstruction with adaptive sampling in block compressed imaging

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Abstract: This paper presents an efficient reconstruction method in block compressed imaging (BCI) for natural images. To avoid the high complexity and give a time-efficient approach, block-based separable two-dimension (2D) linear reconstruction method is proposed. The techniques of adaptive sampling (AS) and separable reconstruction are combined to yield a competitive solution for BCI. The AS is utilized by employing more measurements in the texture redundant blocks. The separable 2D reconstruction uses linear approach based on minimum mean square error (MMSE) to reduce the decoder complexity. Experiment results demonstrate that the proposed scheme can efficiently reduce the reconstruction complexity and give a competitive image quality compared to non-linear approaches.

Keywords: compressed imaging, adaptive sampling, separable operator, linear reconstruction

Classification: Electron devices, circuits, and systems

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1 Introduction

Compressed sensing (CS) first proposed in [1] is a new theory in signal processing. It can recover signal at a high probability (near exact) from much lower measurements compared with traditional Shannon-Nyquist theory. The exact reconstruction is based on the assumption that the signal is sparse or compressible in time/space domain or some projected domains. CS has a wide application in compressed imaging (CI), remote sensing, medical imaging and etc. In CI, the computational complexity of encoder and decoder becomes much heavy when the image size is large. Low image quality, huge memory requirement and computational reconstruction are the main challenges faced in CI. To avoid the storage/transmission of huge measurement matrix, a block CI is introduced in [2]. The same measurement operator is utilized in all blocks and non-separable operator is employed in each block. A large random matrix will be needed to observe samples for non-separable operator. It could be a practical issue on the complexity when the image size becomes large. To overcome this issue, separable operator is introduced in [3], where the measurement matrix is separated into two dimensions. Thus, the encoder needs to store only a small measurement matrix which leads to a complexity reduction in encoder. A general framework using separable sampling operator is proposed in [4], in which a low complexity encoder is achieved either. Note that they are all focused on the encoder side, aiming at reducing the complexity of sampling process. The reconstruction complexity at the decoder side is still high. To achieve a low complexity at encoder and decoder sides, a parallel CI scheme has been presented in [5], where sampling and reconstruction can be conducted for individual columns in parallel. However, the column-by-column reconstruction is only employed along the horizon direction, which does not well exploit the image characteristic in spatial domain. Normally, it is a tradeoff between complexity and performance to give a best design. To improve image quality, adaptive sampling (AS) has been proposed in [6]. It is based on the image's statistical property that more measurements are acquired in rich texture blocks. But, the smoothed projected landweber (SPL) reconstruction algorithm used in [6] is iterative and non-linear approach, which increases the burden of reconstruction. To recover the images effectively, the methods of orthogonal matching pursuit (OMP) [7] and total variation (TV) minimization [8] have been developed. However, they are all nonlinear methods which are not time-efficient.

Different from [3] and [4], an efficient reconstruction method aiming at reducing the decoder computational complexity has been proposed in this paper. The proposed method uses two-dimension (2D) reconstruction along horizontal and vertical direction respectively, which differs from only one direction adopted in [5]. Parallel column-by-column reconstruction is employed in each direction. The separable 2D linear reconstruction alleviates the computational burden in decoder side and improves the image quality by exploiting the 2D characteristics in spatial domain. AS is adopted to improve the image quality further. The combination of AS and separable 2D method yields a competitive solution for BCI. Experiment results show that the proposed method gives a competitive performance with much lower complexity compared to existed non-linear approaches.





2 Proposed compressed imaging

2.1 Adaptive sampling

Adaptive sampling is an effective method for improving image quality [6]. It can assign different sampling rate to each block according to its variance. It also guarantees that the total sampling rate of all blocks meets the set measurement rate (MR) roughly. Typically, smooth area of image will be assigned few measurements. Suppose an image has N pixels and M samples, the MR of the image is R = M/N. The image is divided into $B \times B$ blocks, thus the mean of all blocks' variance is denoted by Eq. (1), where σ_i^2 is the variance of block i ($i = 1, 2... N/B^2$). The assigned MR of block i is determined in Eq. (2), in which K is the coefficient to control the MR of each block. In order to avoid over-sampling and sub-sampling, sampling rate r_i should be limited by Eq. (3), where γ is a constant controlling the minimum sampling rate. The initial value of K is 1 and it can be updated by Eq. (4), in which \bar{r}_i is the mean of all blocks' sampling rate r_i after the last iteration. r_i can be updated by Eq. (2) to Eq. (4) until K satisfies |K - 1| < 0.001.

$$\bar{\sigma}^2 = \left(\sum_{i=1}^{N/B^2} \sigma_i^2\right) / \left(N/B^2\right) \tag{1}$$

$$r_i = R \cdot K \cdot \sigma_i^2 / \bar{\sigma}^2 \tag{2}$$

$$r_{i} = \begin{cases} 1, r_{i} \ge 1 \\ R/\gamma, r_{i} \le R/\gamma \\ r_{i}, else \end{cases}$$
(3)

$$K = R/\bar{r}_i \tag{4}$$

2.2 Separable 2D linear reconstruction

In CS theory, it has to solve the l_0 -norm combinational optimization problem in order to exactly recover the original signal, which is NP-hard. To solve this issue, a l_1 -norm linear programming problem has been developed at the constraint of restricted isometry property (RIP) [9]. Although the l_1 -norm method has near optimal recovered result, it is a time consuming approach and it has bottleneck in near real-time applications. MMSE-based linear reconstruction is an effective method for time-efficient applications. It can be regarded as a l_2 -norm approach and it is also the initial guess for most of the non-linear iterated methods. Different from the traditional non-separable reconstruction used in [10], a 2D separable linear reconstruction is proposed in this paper. The proposed separable 2D method exploits the image properties of horizon and vertical. It uses a parallel column-by-column reconstruction along two directions (horizon and vertical). It also leads to a small measurement matrix size in encoder at the same MR. The separable 2D reconstruction not only reduces the complexity but also improves the image quality by exploiting characteristic of spatial domain in each block (indicated by experiments in section 3). The AS approach employed in the encoder side is used to improve the





reconstructed image quality without increasing the complexity of decoder.

Fig. 1 illustrates the proposed block compressed imaging system with AS and separable 2D linear reconstruction. In Fig. 1, y is the measurement sample and \hat{x} is the recovered image. The reconstruction process is accomplished by separable operators $(H_h \text{ and } H_v)$, respectively. Each operator is a linear MMSE-based optimal operator. The operators are different block-by-block and determined by the measurement rate (r_i) in each block. In the MMSE-based linear estimation, estimated error e can be explained as Eq. (5), where x is the original image and H is the reconstructing operator. The optimal solution of H can be acquired by Eq. (6). Thus, the solution of H_{opt} is denoted in Eq. (7), in which R_{xx} is the auto-correlation matrix of image block x_i and ϕ_B is the random measurement matrix. In our experiment, R_{xx} is derived by Eq. (8) with correlation coefficient (ρ) and Euclidean distance (τ) among pixels in x_i .

$$e = \hat{x} - x = Hy - x \tag{5}$$

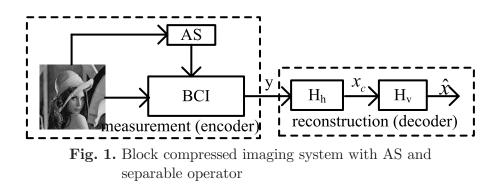
$$\underset{H}{\operatorname{arg\,min}} \{ \mathbf{R}_{ee} = E \left[e e^T \right] \} \text{ subject to } e = Hy - x \tag{6}$$

$$H_{opt} = R_{xx}\phi_B^{\ T} \left(\phi_B R_{xx}\phi_B^{\ T}\right)^{-1} \tag{7}$$

$$R_{xx} = \rho^{\tau} \tag{8}$$

In the block based separable 2D linear reconstruction, columns along horizontal direction of each block are first reconstructed using separable operator H_h . Then, rows of vertical direction are reconstructed by separable operator H_v . The parallel column-by-column reconstruction is applied in horizontal and vertical direction of each block respectively. Different block can also be reconstructed parallel. Thus, the exploitation of parallel among blocks and within blocks (both horizontal and vertical directions) gives a fast reconstruction for BCI. Operators of H_h and H_v may be different in practice according to images' characteristic. In order to reduce the decoder complexity, Eq. (9) is used to represent the two operators in this paper. It can be regarded that equivalent weight has been assigned to horizontal and vertical directions. The separable operator reconstruction also leads to a complexity reduction in encoder side by a smaller-size measurement matrix (ϕ_B).

$$H_h = H_v = H_{opt} \tag{9}$$







3 Experiment results

Evaluate the efficiency of our proposed method, the comparison experiments are given. The experimented 512×512 natural images are from SIPI image database [11]. Six images (Barbara, Mandrill, Lena, Peppers, Couple and Boat) are chosen. Images are divided into block size 32×32 as indicated in [2]. Gaussian random matrix is used as the measurement matrix (ϕ_B). Constant γ is set as 2.4 and ρ is 0.999 in our experiments. The simulations are all running on an Intel i5 CPU with 8 G RAM. The objective image quality is evaluated by the peak signal to noise ratio (PSNR) in Eq. (10), where MSE is the mean square error which gives the difference measurement between the original image and the reconstructed image.

$$PSNR = 20 \cdot \log\left(\frac{255}{\sqrt{MSE}}\right) \tag{10}$$

The proposed reconstruction method has been compared to SPL [2], OMP [7] and RecPF [8] in terms of PSNR and time as shown in Table I and Table II. The experiment results are averaged by ten iterations in each method. Table I illustrates the PSNR performance comparison of different reconstruction methods. The SPL and OMP approaches are combined with AS as the anchor methods (AS_BCI_SPL and AS_BCI_OMP). SPL uses discrete cosine transform (DCT) domain projected soft threshold shrinkage. OMP also bases on a DCT domain sparse representation. RecPF is a TV method which has been shown effective in Phantom images [8]. It uses partial Fourier measurement matrix. It can be seen from Table I that the PSNR of proposed method outperforms other methods for some images (Lena, Peppers, Couple and Boat, these images tend to have large area of smoothness) when the MR is low. The AS_BCI_SPL method gives a better

 Table I. PSNR (in dB) performance comparison of different methods

urement rate	0.1	0.2	0.3	0.4	0.5
AS_BCI_SPL	21.0236	23.3014	24.9022	27.0060	28.5843
AS_BCI_OMP	19.8849	22.4003	24.3705	26.0320	27.4448
RecPF	8.5385	13.9345	18.7062	24.1221	29.0580
Proposed	20.9176	23.3447	24.8180	26.6306	28.2716
AS BCI SPL	19.7365	21.7036	22.8074	24.5099	26.0344
AS BCI OMP	16.0253	17.3326	18.6651	20.0888	21.6333
RecPF	6.6420	10.0452	13.6144	18.1698	28.2570
Proposed	19.4226	21.0923	22.7528	23.8024	25.9779
AS BCI SPL	23.5626	26.9334	29.0412	31.2838	32.5791
AS BCI OMP	22.8761	25.6025	27.7032	29.3266	30.6279
RecPF	13.9906	22.0809	24.9583	28.6561	32.4316
Proposed	27.5234	30.0123	31.8291	33.3618	34.1368
AS BCI SPL	23.2856	26.6944	28.5634	30.6674	32.3126
AS BCI OMP	21.6676	25.1039	27.0696	28.5729	29.8664
RecPF	15.3608	23.0041	25.1598	26.5691	31.0021
Proposed	26.2908	29.0914	29.6444	31.0559	31.9485
AS BCI SPL	23.1237	25.7794	27.1590	28.6913	29.8840
AS BCI OMP	20.0635	22.1162	23.8509	25.2676	26.3681
RecPF	11.7429	17.8837	22.3831	25.5001	28.9039
Proposed	23.4163	25.9857	27.7914	27.9876	29.3099
AS BCI SPL	23.4055	26.0045	27.5196	29.4384	30.6436
AS BCI OMP	20.4913	22.7595	24.4689	25.9931	27.0896
RecPF	12.4371	18.7315	21.9824	25.0209	29.9357
Proposed	24.1976	26.3370	27.9114	29.3769	30.3272
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rable II. Thile (5) comparison of different methods									
Meas	urement rate	0.1	0.2	0.3	0.4	0.5			
Barbara	AS_BCI_SPL	20.3750	46.8859	77.0844	132.8969	158.7094			
	AS_BCI_OMP	119.7438	224.3000	320.8328	413.3594	441.7109			
	RecPF	1.0859	1.0094	1.0844	1.0156	0.9594			
	Proposed	0.0437	0.0578	0.0406	0.0344	0.0406			
Baboon	AS_BCI_SPL	17.7922	42.4828	81.6859	121.1653	157.6578			
	AS_BCI_OMP	130.4141	336.0500	681.0094	1193.7297	1579.4281			
	RecPF	0.8094	0.7844	0.8156	0.8063	0.8156			
	Proposed	0.0297	0.0281	0.0594	0.0563	0.0344			
Lena	AS BCI SPL	22.8313	53.8757	99.9094	136.2562	157.3094			
	AS BCI OMP	103.3484	177.8172	243.1797	281.6969	305.0141			
	RecPF	1.0703	0.9734	0.9641	0.9578	0.9031			
	Proposed	0.0453	0.0734	0.0313	0.0734	0.0531			
Peppers	AS BCI SPL	23.1750	52.3281	91.9906	136.0672	160.0578			
	AS BCI OMP	110.4141	195.6687	259.3859	298.3469	319.0078			
	RecPF	1.2266	1.0203	0.9969	0.9078	0.9250			
	Proposed	0.0281	0.0297	0.0641	0.0828	0.0359			
Couple	AS BCI SPL	26.8281	54.8125	75.2516	95.6844	112.4391			
-	AS BCI OMP	265.7016	453.5266	534.4234	584.1969	605.9469			
	RecPF	0.9219	0.8844	0.8875	0.9063	0.8125			
	Proposed	0.0625	0.0297	0.0391	0.0516	0.0547			
Boat	AS BCI SPL	23.5266	55.2141	94.3438	135.0891	154.2312			
	AS_BCI_OMP	135.8266	274.9672	395.8578	475.1047	511.4031			
	RecPF	0.9563	0.9328	0.8469	0.8406	0.8203			
	Proposed	0.0734	0.0531	0.0453	0.0328	0.0359			

Table II. Time (s) comparison of different methods

image quality for Barbara and Mandrill, which implies that it is more effective for images with redundant details. However, the proposed method can provide a comparable image quality compared to SPL as shown in Table I. It can also be found that the image quality reconstructed from RecPF improves rapidly with the increasing MR. RecPF is more effective for texture clear images (Barbara and Mandrill) than smooth images at a high MR (0.5). This can be explained that the texture clear images can be well sparse represented by their gradient and reconstructed by TV method. From Table I, it can be indicated that the proposed AS and separable 2D linear reconstruction method is effective especially for fairly smooth natural images at a low MR.

In Table II, the reconstruction time of different methods is compared. It can be seen that the proposed method has the highest efficiency, which indicates that the complexity is low. Thus, it gives a competitive option for near real-time applications. The complexity reduction is achieved by the separable 2D linear reconstruction. The parallel advantage of the proposed method has not well reflected in Table II, because single thread is used in our experiments. It can also be found that there is an approximately 90% time reduction compared with RecPF.

In order to validate the efficiency of AS and separable operator in MMSE-based linear reconstruction, the PSNR and recovered time of different combination methods (proposed AS with separable operator, AS with non-separable operator, non-AS with non-separable operator and non-AS with separable operator) are compared. The AS with non-separable method is similar to [10] except that a different AS method is adopted in this paper. In Fig. 2, the objective image quality (a) and reconstruction time (b) of Lena are drawn according to different MR. It can be seen that AS can improve the image quality (Fig. 2 (a)) with relatively increasing complexity in decoder (Fig. 2 (b)). The PSNR (Lena) devoted by AS is improved by an average of 1.3753 dB and 1.5303 dB for non-separable and





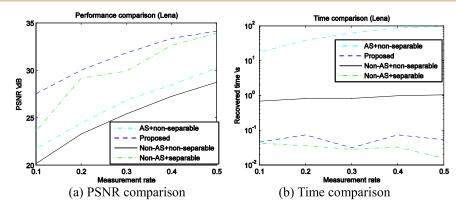


Fig. 2. Performance and complexity comparison of image Lena for different methods

separable method respectively. It can also be figured out that separable reconstruction not only improves the PSNR but also reduces the decoder complexity significantly. There is an average of 5.0315 dB and 4.8764 dB gain in separable 2D reconstruction (Lena) for AS and non-AS approach respectively. The reason of the improved image quality is that horizontal and vertical statistical properties are concerned by a separable operator

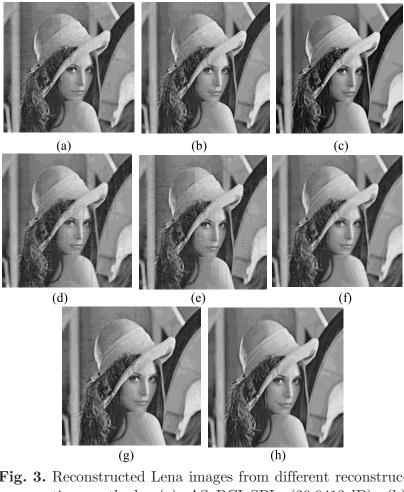


Fig. 3. Reconstructed Lena images from different reconstruction methods: (a) AS_BCI_SPL (29.0412 dB); (b) AS_BCI_OMP (27.7032 dB); (c) RecPF (24.8910 dB); (d) Non-AS+non-separable (25.3962 dB); (e) AS+non-separable (26.7617 dB); (f) Non-AS+separable (29.9140 dB); (g) Proposed (31.7939 dB); (h) Original





while one dimension property is concentrated in a non-separable approach. As a result, the best performance is achieved by the proposed method (AS with separable operator, dashed blue line in Fig. 2 (a)) with much reduced complexity (dashed blue line in Fig. 2 (b)).

The subjective image quality is compared for different methods. Shown in Fig. 3, the reconstructed Lena images are illustrated at the MR of 0.3. It can be seen that Fig. 3 (g) best fits the original image. Fig. 3 (c) has a best subjective view because the noise is removed in the TV based RecPF reconstruction. Fig. 3 also implies that the proposed method benefited from separable reconstruction can efficiently alleviate the blocking artifact caused by the block imaging. From the comparison of subjective images, the proposed method outperforms SPL, OMP and non-separable approaches. Thus, a fast reconstruction approach with high image quality is achieved in this paper.

4 Conclusions

A time-efficient block compressed imaging has been investigated in this paper. The efficiency is accomplished by separable 2D linear reconstruction, which also leads to a high parallel CI and a high image quality. The separable 2D reconstruction exploits the characteristics of both parallel and image property in spatial domain. Adaptive sampling is employed to improve the image quality further by assigning different MR to every block. The combination of AS and separable linear reconstruction offers a competitive approach for BCI. Our proposed scheme could be efficiently alleviating the computational burden in reconstruction side and be an efficient alternative for near real-time applications. High quality and robust image reconstruction in block sampling is our future work to be deeply carried out.

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