Evaluating Effect of Block Size in Compressed Sensing for Grayscale Images

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Abstract— Compressed sensing is an evolving methodology that enables sampling at sub-Nyquist rates and still provides decent signal reconstruction. During the last decade, the reported works have suggested to improve time efficiency by adopting Block based Compressed Sensing (BCS) and reconstruction performance improvement through new algorithms. A trade-off is required between the time efficiency and reconstruction quality. In this paper we have evaluated the significance of block size in BCS to improve reconstruction performance for grayscale images. A parameter variant of BCS [15] based sampling followed by reconstruction through Smoothed Projected Landweber (SPL) technique [16] involving use of Weiner smoothing filter and iterative hard thresholding is applied in this paper. The BCS variant is used to evaluate the effect of block size on image reconstruction quality by carrying out extensive testing on 9200 images acquired from online resources provided by Caltech101 [6], University of Granada [7] and Florida State University [8]. The experimentation showed some consistent results which can improve reconstruction performance in all BCS frameworks including BCS-SPL [17] and its variants [19], [27]. Firstly, the effect of varying block size (4x4, 8x8, 16x16, 32x32 and 64x64) results in changing the Peak Signal to Noise Ratio (PSNR) of reconstructed images from at least 1 dB to a maximum of 16 dB. This challenges the common notion that bigger block sizes always result in better reconstruction performance. Secondly, the variation in reconstruction quality with changing block size is mostly dependent on the image visual contents. Thirdly, images having similar visual contents, irrespective of the size, e.g., those from the same category of Caltech101 [6] gave majority vote for the same Optimum Block Size (OBS). These focused notes may help improve BCS based image capturing at many of the existing applications. For example, experimental results suggest using block size of 8x8 or 16x16 to capture facial identity using BCS. Fourthly, the average processing time taken for BCS and reconstruction through SPL with Lapped transform of Discrete Cosine Transform as the sparifying basis remained 300 milli-seconds for block size of 4x4 to 5 seconds for block size of 64x64. Since the processing time variation remains less than 5 seconds, selecting the OBS may not affect the time constraint in many applications. Analysis reveals that no particular block size is able to provide optimum reconstruction for all images with varying nature of visual contents. Therefore, the selection of block size should be made specific to the particular type of application images depending upon their visual contents.

Keywords— Block based Compressed Sensing; block size effect; Optimum Block Size; PSNR improvement; BCS-SPL

I. INTRODUCTION

The Nyquist Shannon sampling theorem [1], [2] states that if a signal is sampled at a rate equal to or greater than twice the highest frequency component present, the original signal can be correctly re-constructed. Most of the sensing devices like cameras for images, microphones for audio and hydrophones for underwater acoustic signals, etc. sample data in accordance with the Nyquist Shannon sampling criteria. This leads to a large number of signal samples, pose large storage requirements and more bandwidth consumption for data transfer etc. What if the signal is sampled at a rate lower than the Nyquist rate and still be able to reconstruct the original signal correctly? With that in context, E. J. Candès *et al.* [3], [4] and D. L. Donoho [5] introduced a technique called Compressed Sensing (CS) in 2006.

CS aims to extract only the significant or non-zero elements from a signal space that can be used to exactly reconstruct the original signal. In order to extract the significant information through CS, we need to know the sparsifying basis of the original signal. Sparsifying basis stipulates how the significant information is distributed in the source signal. Knowledge of the sparsifying basis enables us to design the correct measurement operator. Most of the natural signals, like images, are sparse. While the sparsity of some signals is easily evident, deeper analysis may be required for others. Even if the signal does not seem to be sparse in the original domain, we can explore to find a lossless transformation, which when applied to the signal would make it sparse. This implies that if the domain or signal space of the signal can be shifted with the new domain representing the same signal in a sparse manner, then again CS will work. Sampling the signal at sub-Nyquist rates gives us an under-determined system of linear equations. An under-determined system has a lot of possible

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solutions. But we are interested in the sparsest solution that gives us least number of non-zero coefficients. The sparsest solution is unique for an under-determined system of linear equations. Thus, the original signal can be re-constructed.

There are some other associated queries, such as, is the Nyquist sampling theorem incorrect? Or is it not always valid? Well, Nyquist theorem provides sufficient conditions for correct re-construction of the signal. The condition is sufficient and not necessary. Whereas, CS focuses on the necessary or minimum conditions to achieve the same. Though, CS does seem to work well for a lot of applications like image sensing and an extensive research is underway to find more applications, but it may not work well in situations where we do not know the sparsifying basis of the signal or be able to find the sparsest solution to its underdetermined equations system. On the other hand, Nyquist Shannon theorem still provides sufficient conditions to sample and reconstruct any known signal.

Next, how do we find the sparsest solution to an under-determined system? We are basically interested to find the solution which gives us the least number of non-zero coefficients. This may be done by finding which solution gives the least *L0* Norm. *L0* norm has been discovered by D. L. Donoho [5]. However, finding the *L0* norm is computationally expensive. *L1* norm that sums up the absolute signal values has been reported to have similar performance while being computationally inexpensive. *L1* norm minimization is referred to as Basis Pursuit (BP). Other reported methods of image reconstruction will be discussed in the next section.

Initial works on CS of images suggested global random sampling, where all the image pixels are potential candidates for every acquired sample. The related works have reported this sampling method to be both computationally expensive and time inefficient, while providing superior reconstructions. This led to the adaptation of Block based CS (BCS). In BCS, the source image is divided into blocks of equal size and the blocks are accessed temporally in raster scan manner for sampling. BCS significantly improved the computational cost and time efficiency at the cost of lower reconstruction performance. Thereafter, different reconstruction methods have been proposed to improve the reconstruction quality while using BCS for sampling. This paper explores the effect of block size on reconstruction quality through experimentation on 9200 grayscale images, acquired from widely used image datasets [6]-[8].

The rest of the paper is organized as follows. Section-II discusses CS theory and salient advances in the field. Section-III provides an overview of the BCS sampling and reconstruction algorithm used for testing the effect of block size on reconstruction quality. Section-IV presents the results, while Section-V contains conclusion with some possible future directions.

II. CS Theory and Salient Advances

Research on CS started with the foundation works presented by E. J. Candes *et al.* [3], [4] and D. L. Donoho [5] in 2006. The works [3]-[5] provide mathematical proofs on the viability of CS and suggest global sampling in the sparse transform domain followed by reconstruction through convex optimization (basis pursuit) or total variation (TV). During the next decade that spanned from 2006 uptil now, the reported research has aimed to improve either or both time efficiency and reconstruction quality in CS. We will next review the basic CS theory followed by salient advances in the field.

A. CS Theory

Consider a signal or vector V of length n. Assume that V is sparse in the sense that only k coefficients or elements are significant and required for a faithful reconstruction. In this case, we can call V as *k-sparse*. V can be expressed as $V = \Psi\beta$ where Ψ is the sparsifying basis and β is the transform coefficient vector that has only k useful or non-zero coefficients. According to CS [9], [10], sampled vector of a signal can be obtained through its linear projection W having $m<<n$ samples in the form $W = \Phi V + e$ where Φ is a m x n dimensional matrix called the sensing matrix, n is the total number of samples in source signal and e is the error signal acquired during the process of linear projection. The theoretical optimal limit implies that V can be correctly recovered from only $\bar{O}(k \log n)$ measurements of the vector V. $\bar{O}$ refers to the order of complexity. It means that we can achieve the optimal sensing performance if our measurements are $m = \bar{O}(k \log n)$ and the re-construction is correct. It is highlighted here that while the sensing process is linear, the re-construction process is non-linear. We can write $W = \Phi V + e = \Phi\,\Psi\beta + e$. Ignoring the noise vector e, we get $W = \Phi\,\Psi\beta \; or \; \beta = W\Phi^{-1}\Psi^{-1}$. Now recovering β froms W involves using the matrices Φ and Ψ. In other words, the re-construction process depends upon the complexity of Φ^{-1} and Ψ^{-1} since it involves multiplication of the two matrices. Here, we want these two matrices to be highly incoherent or their mutual coherence should be minimal. The reported reconstruction algorithms will be discussed in next sub-section.

B. Salient Advances

M. A. T. Figueiredo *et al.* [10] proposed signal reconstruction through use of Gradient Projection (GP) algorithms that solve inverse problems like compressed sensing using bound-constrained quadratic programming. Experimental results have shown that GP algorithms outperform standard approaches of l_2 or l_1 norm minimization in terms of computation time. However, the performance of GP algorithms lowers with de-emphasizing the regularization term, which can be resolved by embedding the GP algorithm in a continuation scheme. J. A. Tropp *et al.* [11] introduced a greedy reconstruction algorithm called Orthogonal Matching Pursuit (OMP) which can recover a signal from only k measurements in n dimensions given $\bar{O}(k \log n)$ random linear measurements as opposed to $\bar{O}(m^2)$ measurements previously used. While the reconstruction accuracy of OMP is similar to that of *BP* [5], it offers advantage in terms of easy implementation and faster computation. M. Elad [12] suggests the use of optimized projections instead of random sampling projections for CS. The optimized projections exploit mutual coherence of effective dictionary to achieve better reconstructions. Reconstruction performance with OMP [11] as well as BP [5] has been found to increase with optimized projections [12] reducing the error rate by a factor of 10 or more. However, acquiring random projections is more time efficient than optimized projections, therefore, the later provides high accuracy at the cost of more computation time. R. Chartrand [13] has shown that l_p norm minimization with $p<1$ can provide similar reconstruction as achieved with *BP* using fewer measurements. The computation time of l_p norm minimization remained more than l_1 but sufficiently less than l_2 minimization. D. L. Donoho *et al.* [14] have proposed an improved variation of OMP called Stagewise OMP (StOMP). StOMP offers improvement in terms of computation time and complexity when trialed against OMP [11] and BP [5].

L. Gan [15] pioneered the idea of using BCS for images. The source image is divided into square blocks of fixed size. Samples from each block are acquired using the same measurement operator. Let z_i be the *i-th* sampled vector acquired from *i-th* block β_i during the raster scan. Let the total number of pixels in the original image and sampled version be represented by n and m respectively. If the block size is b x b, then the sub-Nyquist sampling rate $S_r = \left\lfloor \frac{mb^2}{n} \right\rfloor$ where the subscript $\lfloor x \rfloor$ represents the bottom floor value of x. The reconstruction in [15] is achieved through a two stage process comprising hard thresholding and projection onto convex sets. In hard thresholding, the highest magnitude values above a specified threshold are kept and the remaining values are zeroized. BCS [15] is superior in terms of less computation time than StOMP [14], OMP [11] and BP [5]. Moreover, while BCS provides an improvement of upto 2 dB in the Peak Signal to Noise Ratio (PSNR) of reconstructed images as compared to OMP and BP, it has a tie with StOMP in this regard. E. J. Candes *et al.* [16] gave forth the method of Projected Landweber (PL) for signal recovery that utilizes a smoothing filter to remove blocking artifacts in the measurements. The work in [16] provides a good introduction to the theory of CS and advances in the field till 2008. S. Mun *et al.* [17] suggests that images are sparser in Contourlet Transform (CT) and Discrete Dual-tree Wavelet Transform (DDWT) and recovery through hard thresholding in these transforms leads to better reconstructions as compared to TV [3], [4] and traditional Discrete Wavelet Transform (DWT) and Discrete Cosine Transform. The framework for CS in [17] has been called Block based CS – Smoothed Projected Landweber (BCS-SPL). The framework of [15] that has been used in the current work is also BCS-SPL. C. Deng *et al.* [18] explains how CS can replace the usual source and channel coding schemes for transmission of images through noisy channels. The work in [18] suggests that CS inherently provides error redundancy in addition to the compression, which can provide better performances than the existing joint source and channel coding schemes. J. E. Fowler *et al.* [19] proposed a multi scale Smoothed PL recovery method with BCS in the sampling phase. The framework in [19] is accordingly referred as MS-BCS-SPL. Different decomposition levels in the transform domain are sampled in [19], providing reconstruction performance better than BCS-SPL [17] and comparable to that of TV [3], [4] while having the advantage of considerably faster computation times. S. Zhu *et al.* [20] carries out deep analysis of the statistical information of each image block for adaptive sampling. The adaptive sampling mechanism improves the reconstruction quality as compared to random sampling. S. Zhu *et al.* [21] also proposed a variant of their previous work [20] called adaptive re-weighted BCS which varies the sampling rate of each block depending upon block analysis results. While reconstruction quality improvement through adaptive sampling [20], [21] is desirable, image analysis prior sampling increases the computational cost. J. G. Alaydin *et al.* [22] suggests reducing the storage requirements by using a graph-cut quantizer applied within BCS-SPL framework assuming the sparsity domain as DDWT. The graph-cut quantizer method [22] offers a 0.5 dB gain in the PSNR of reconstructed images compared to JPEG2000 compression [23] while achieving similar compression rates. L. Guo *et al.* [24] used global sampling in the contourlet sparse domain followed by extraction of high frequency components through Gaussian kernels. The signal recovery in [24] is done through an algorithm called Sparsity Adaptive Matching Pursuit (SAMP), tested on images acquired through a Synthetic Aperture Radar. SAMP is a variation of OMP that uses some iterative projections until a good reconstruction is achieved. The contourlet-SAMP [24] method provides improvement in the PSNR of reconstructed images as compared to OMP [11] using wavelet and contourlet transforms. M. Kalra *et al.* [25] carries out sampling in wavelet transform domain followed by vector quantization (VQ) encoding and the reconstruction process uses VQ decoding and inverse wavelet transform employing StOMP [14] framework. The Wavelet VQ-StOMP [25] method offers better compression and reconstruction performance as compared to image compression codec Set Partitioning in Hierarchical Trees (SPIHT) [26]. L. Weizman *et al.* [27] uses a compressive sampling mechanism that adopts to the possible similarities between successive MRI scans followed by a weighted reconstruction method that uses the similarity information acquired during sampling as priors. The method [27] is reported to outperform previous methods of MRI scans in terms of computation cost and reconstruction quality.

C. Chen *et al.* [28] have proposed a variation of the BCS-SPL framework [17] that uses the surrounding blocks in an image to predict the center block by generating a residual in the domain of CS projections. The new framework is named as Multi Hypothesis BCS-SPL (MH-BCS-SPL). During the evaluation of MH-BCS-SPL [28], a fixed block size of 32 is used as in the evaluation of BCS-SPL [17]. While the block size remains fixed at 32, MH-BCS-SPL uses a sub-block of size 16 and a search window of size 8 to generate the predictions. The sub-block and search window sizes are increased until a stopping criterion is met. In MS-BCS-SPL [19], block sizes of 16, 32 and 64 are used when the sparsifying DWT transform levels are 1, 2 and 3 respectively (level 3 being the highest resolution transform) irrespective of the image visual contents. In MH-MS-BCS-SPL [28], initial sub-block and search window sizes of one-eighth of block size and 1 respectively are used which are increased until a stopping criterion is met. While the MH algorithms MH-BCS-SPL and MH-MS-BCS-SPL [27] proved to be computationally expensive than the original works BCS-SPL [17] and MS-BCS-SPL [19], the reconstruction performance improved. The trend in the results of [27] remained consistent under varying sampling rates of 0.1, 0.2, 0.3, 0.4 and 0.5.

III. Methodology

A. Random Image Sampling through BCS

Block-wise sampling of an image is done using an orthonormal kernel with random measurement locations. The kernel is moved through the image in a raster scan fashion and the measurements obtained are stored in a column vector. The number of measurements is specified through sampling rates. Sampling rates of 0.1, 0.2, 0.3, 0.4, 0.5 and 0.8 are used. To investigate the effect of block size on reconstruction quality, the square block size is varied through sizes of 4, 8, 16, 32 and 64, while using a fixed sampling rate and same measurement kernel. The block-wise sampling enables the use of an inexpensive small sized kernel and option to transmit block wise measurements to receiver which is of great value in real time applications.

B. Image Reconstruction through LT-DCT based Smoothed Projected Landweber

A parameter variant of the reconstruction algorithm presented in [15] is used. The sparisying basis Ψ is assumed as a Lapped tranform version of the Discrete Cosine Transform (LT-DCT). An initial estimate of the reconstructed image is obtained using Minimum Mean Square Error [29] which is gradually improved through iterations. In each iteration, a projection onto the convex set is obtained through the method presented in [15]. A 4 x 4 weiner smoothing filter is applied and the image is again projected onto convex set. The image is then subjected to hard thresholding [30] in LT-DCT domain followed by projecting the image third time onto the convex set. The process is repeated six times. The parameter settings except the ones already specified are the same as used in [15].

C. Analysis Methodology

With each test image and a block size, the reconstruction quality is assessed by measuring the PSNR and Mean Square Error (MSE) of the reconstructed image with reference to the original image. Following is analyzed:

1) The block size that provides best reconstruction quality, hereafter is called the Optimum Block Size (OBS). OBS of each test image is noted.

2) Finding a ratio based relationship between image size and OBS.

3) Investigating relationship between the visual contents of an image and OBS. Finding if images of similar shaped objects, e.g., a football, a water melon, a basketball have the same OBS.

The works [17], [19], [27] kept the block size fixed for a specific configuration of the algorithms, however, this paper uses the BCS-SPL framework to carry out the novel experiment of varying the block size (4, 8, 16, 32, 64) at different sampling rates (0.1, 0.2, 0.3, 0.4, 0.5 and 0.8). Therefore, this work evaluates the important parameter of block size with an aim to further improve the performance of all BCS frameworks primarily including BCS-SPL, MS-BCS-SPL, MH-BCS-SPL and MH-MS-BCS-SPL.

D. Test Images

A total of 9200 test images acquired from popular databases are used for the analysis of reconstruction performance dependency on block size. The first batch of test images has been acquired from Caltech101 database [6] compiled by California Institute of Technology, which contains 9145 images labeled in 101 categories. The second batch includes 49 images acquired from online resources [7] provided by University of Granada (UGR). The third batch includes five popular images of Lenna, Barbara, goldhill, mandrill and peppers acquired from resources [8] provided by Florida State University (FSU). While the test images acquired from [7] and [8] are grayscale, the color ones acquired from [6] are converted to grayscale.

E. Testing Environment

MATLAB® release 2016a running on an average PC (6th generation Core i5 processor @ 2.3GHz, 8GB of DDR3 RAM and Nvidia 960M GPU) is used.

IV. Results

The experimentation carried out on 9200 images in this paper reflected some interesting results. Firstly, the effect of varying block size (4x4, 8x8, 16x16, 32x32 and 64x64) results in changing the PSNR of reconstructed images from at least 1 dB to a maximum of 16 dB. Few of the supporting results from Caltech101 [6] database using a Sampling rate of 0.5 are shown in Table-I. It has been learnt that significant improvement of upto 16 dB in reconstruction quality is possible just by selecting the OBS in BCS. This challenges the common notion that bigger block sizes always result in better reconstruction performance. Secondly, the variation in reconstruction quality with changing block size is mostly dependent on the visual contents of the image. For example, the PSNR variation with block size for 435 images in category *Faces_easy* of Caltech101 [6] remained within 3 dB whereas the 42 images in category *Anchor* showed a variation of upto 16 dB. Therefore, the selection of OBS may be of more value for some image types and of relatively lesser value to others. Thirdly, images having similar visual contents irrespective of the size, e.g., those from the same category of Caltech101 gave majority vote for the same OBS. This suggests that while the same block size may not work for all types of images, a particular block size can provide sufficient improvement in reconstruction performance if the images being captured have similar visual contents. The OBS for images of similar visual contents remained the same under conditions of varying sampling rates. This finding can be used to improve BCS based image capturing at many of the existing applications. For example, facial identity is required for issuance of identity cards, passports, company access permits, etc. Experimental results of this work suggest using block size of 8x8 or 16x16 to capture facial identity using BCS. This is established by finding the OBS for 435 images in category *Faces_easy* of Caltect101 with varying sampling rates. *Faces_easy* contains images of people faces with variations of scale, orientation and lighting. Seventy percent of images in *Faces_easy* had an OBS of 8x8 or 16x16. Images with OBS of 8x8 showed a PSNR degradation of less than 0.5 dB when block size of 16x16 was used and vice versa. However, switching to block sizes of 4x4, 32x32 and 64x64 caused PSNR degradation of upto 3dB. Fourthly, the processing time remained least with block size of 4x4 and increases as we increase the block size. The average processing time taken for BCS and reconstruction through SPL remained 300 milli-seconds for block size of 4x4 to 5 seconds for block size of 64x64. Since the processing time variation remains less than 5 seconds, selecting the OBS may not affect the time constraints in many applications. Moreover, while the reconstruction performance in some images degrades with increasing block size, the same renders improvement in other types of images.

Test results with the third batch of test images [8] of size 512x512 are given in Table II, whereas combined results from the three batches [6]-[8] of test images are shown in Table-III. The sampling rate in results shown in Tables II and III remained fixed at 0.5. The results reveal that block size of 4x4 could not optimally reconstruct any of the images. The reason is that 4x4 is too small a block to be able to capture image details properly and should therefore, not be used. Analysis of 9200 images reveals that no particular block size is able to provide optimum reconstruction for all types of images. Block size of 32x32 provided optimum reconstruction of 32% of the images, however, this result is not sufficient evidence to recommend it for all images. Therefore, the selection of block size should be made specific to the particular type of application images depending upon their visual contents and environmental dynamics. This syncs with the fact that objects in images have explicit shapes and features which

Table – I. Selective test results – Caltech101 image database - PSNR (in dB) of reconstructed image is tabulated under each block size, respectively

Name/ Category	Size	Block size (OBS in bold)				
		4x4	**8x8**	**16x16**	**32x32**	**64x64**
Image_0002/ Airplane	184 x 401	79.96	84.39	83.31	85.45	**85.79**
Image_0046/ Airplane	180 x 397	78.54	82.92	83.96	**84.20**	83.98
Image_0001/ Anchor	187 x 300	72.87	74.09	78.94	**88.30**	87.16
Image_0008/ Anchor	252 x 300	74.18	79.62	**81.62**	80.80	77.15
Image_0009/ Anchor	297 x 300	74.94	79.62	**81.57**	81.35	78.83
Image_0021/ Anchor	300 x 218	76.19	81.52	82.30	83.39	**83.81**
Image_0032/ Anchor	180 x 300	66.42	68.58	72.59	**82.88**	78.92
Image_0004/ Ant	235 x 300	71.49	78.20	80.92	**81.77**	79.67
Image_0002/ BACKGROUN D_Google(BG)	817 x 656	68.73	71.59	72.76	**72.86**	70.65
Image_0003/ BG	144 x 144	68.36	70.64	75.41	78.39	**79.32**
Image_0026/ BG	1071 x 1221	71.08	76.79	79.26	82.67	**84.47**
Image_0001/ Faces_easy	334 x 290	76.62	78.43	78.67	**78.80**	78.72

Table – II. Test results – FSU image database- PSNR (in dB)/ MSE (x 10^{-3}) of reconstructed image is tabulated under each block size, respectively

Name	Block size (OBS in bold)				
	4x4	**8x8**	**16x16**	**32x32**	**64x64**
Lenna	79.4/0.73	83/0.32	83.6/0.28	**83.8/0.27**	83.6/0.28
Barbara	74.4/2.3	76/1.6	76.9/1.2	77.8/1.06	**78.2/0.98**
Goldhill	78.7/0.87	80.3/0.6	80.4/0.59	80.4/0.59	**80.6/0.56**
Mandrill	71.3/4.85	72.4/3.7	72.6/3.59	72.7/3.52	**76.5/3.44**
Peppers	76.8/1.35	83.1/ 0.31	**83.4/0.29**	83.1/0.31	82.6/0.36

Table – III. Combined test results

Database/ No of images	Image size	Percentage of images optimally reconstructed with a particular block size				
		4x4	**8x8**	**16x16**	**32x32**	**64x64**
Caltech101 [6] / 9145	Varying	0	19.32	20	31.86	28.81
UGR [7]/ 49	512x512	0	20.4	48.9	28.5	2
FSU [8]/ 5	512X512	0	0	20	20	60
Combined results (9200 images)		0	19.53	22.74	31.78	25.95

are effectively captured using specific block sizes. Also different relevant and unique features are more effective in recognizing specific object categories present in the scene [31].

V. Conclusion

Block based compressed sensing promises time efficiency as well as reconstruction performance which can revolutionize today's and future's sensing devices. This paper has explored the effect of block size in BCS based reconstruction of images. A possible PSNR gain of up to 16 dB through varying block size is noticed. Through experimentation on 9200 images, this paper puts forth results that challenge the common notion of 32x32 being the optimum block size for all images and that larger block sizes provide better reconstruction performances. Object recognition supports that unique and invariant features are more useful in recognizing specific visual content with associated environmental settings. Similarly, certain block sizes work better for certain image categories. Knowledge of dependence of OBS on the visual contents irrespective of image size can be used to improve the sensing performance in many practical applications. While this paper has focused only on square structure of block, changing the block structure to rectangular, triangular or other shapes may also provide favorable results. Secondly, algorithms combining block based sampling with reconstruction through TV, OMP, StOMP with sparsifying transforms of CT and DDWT etc. may also be tested with varying block size. Though cues leading to similar directions are expected, the study will provide further generic and wide spectrum validation.

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