International Journal of Advanced Information Science and Technology (IJAIST) ISSN: 2319:2682
Vol.4, No.6, June 2015 DOI:10.15693/ijaist/2015.v4i6.141-143

Compressive Sensing and JPEG Compression: A Comparative Approach

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Abstract- **Compressive sampling (CS) is a novel sampling theorem where one can recover certain signals and images from far fewer samples than Shannon's Nyquist rate. In the conventional Nyqusit sampling theorem if we skip one byte in a signal or image of white noise, we can't restore the original signal. Most of the signals and images are generally not white noise. These signals when represented in terms of appropriate basis functions, such as wavelets have relatively few non-zero coefficients. In CS terminology, they are called *Sparse.* Compressive Sensing relies on two principles, Sparsity and Incoherence which describe the signals of interest and the sensing modality. In this paper, CS is applied to different images and the resultant compressed images are reconstructed usingMultihypothesisBlock-Based CS smooth Projected Land weber (MH-BCS-SPL) were explored to investigate the performance of JPEG and CS mechanism to measure the quality of reconstruction of the image comparing the Peak Signal to Noise Ratio (PSNR). Experimental results demonstrate that the sparse based compression has 40.6 % better JEPGcompression. The result in different images and we will show how CS breaks the conventional way to tackle the problem of sensing and compression in imaging applications.**

Key words- Compressive Sensing; Sparse signals; Block based CS; MH-BCS-SPL; PSNR

I. INTRODUCTION

According to Shannon-Nyquist sampling theorem, a signal is band limited, *i.e.* that it does not contain frequencies higher than a certain limit ν, and it is indeed possible to realistically sample the signal at a period $\Delta T = 1/2\nu$ so that there exists a perfect interpolation procedure rebuilding the continuous signal. *ie,* no information has been lost during the sampling process. Time and cost of compression techniques are dependent on size of data. Image compression comes under the category of data compression and very important in order to provide economy storage, reliable data communication and security but it has grown as a fully-fledged field having standards of its own, along with providing all the features of data compression.

Most of the data is redundant and CS offers the Possibility of compressed data acquisition protocols which directly acquire just the important information. In CS the data compression is achieved to some extent at the first step of signal acquisition which leads to accumulation offewer amounts of data at the encoder and hence less number of measurements is involved at the encoder to compress this data. This paper presents a DCT based CS and MH-BCS-SPL [2] reconstruction algorithm. Natural signals such as image, sound or seismic data can be stored in compressed form, in terms of their projection on suitable basis. A large number of projection coefficients are zero or small enough to be ignored, when basis is chosen properly. If a signal has only non-zero coefficients, it is said to be Sparse. The Coherence measures the maximum correlation between any two elements of two different matrices. In CS, we are concerned with the incoherence of matrix used to sample/sense signal of interest (measurement matrix Φ) and the matrix, in where signal of interest is sparse representing a basis (representation matrix φ) .

II. BLOCK-BASED CS SAMPLING (BCS)

In BCS, an image is divided into $B \times B$ blocks and sampled using an appropriately-sized measurement matrix. In raster-scan fashion, block j is a vector representing of input image X_j. The corresponding Y_j, is then $Y_j = \Phi_B X_j$, where Φ_B is an $M_B \times B^2$. Orthonormal measurement matrix with $M_B = \left[\frac{M}{N} B^2\right]$. Using BCS rather than random sampling applied to the entire image X has several merits. First, the measurement operator Φ_B is conveniently stored and employed because of its compact size. Second, the encoder does need not to wait instead it may send each block after its linear projection and employ blocks of size B = 32.

To recover real-valued signal $X \epsilon R^N$ from M measurements such that M<<N; ie, $Y = \Phi X$, where $Y \epsilon R^M$, and Φis an M x N measurement matrix with subsampling rate, or sub-rate, being S = M/N. CS theory holds that, if X is sufficiently sparse in some transform basis, then X is recoverable from Y by the optimization, $\ddot{x} = \arg\min ||\varphi X||_1$ as long as Φ and φ are sufficiently incoherent, and M is sufficiently large. High-dimensional signals, such as images or video, impose a huge memory burden when explicitly storing the sampling operator Φ as a dense matrix. If the device is large, the reconstruction process will be time consuming. To assuage the computation complexity, an image is partitioned into smaller blocks while sampling is applied on a block by block basis.

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III. MH-BCS-SPL RECONSTRUCTION ALGORITHM

From reconstruction, the procedure BCS couples Projected Land weber (PL) iteration with a smoothing operation intended to reduce blocking artifacts. The overall technique was called BCS-SPL. Chen Chen, Eric W. Tramel, and James E. Fowler, are proposed the same algorithm [2] is used in this work. To improve reconstruction quality, BCS-SPL is deployed independently within each subband of each decomposition level of a wavelet transform of an image to provide multiscale sampling and reconstruction; the resulting algorithm for image reconstruction is called MS-BCS-SPL [2]. The Multihypothesis (MH) prediction for the CS of image is

$$\widehat{w} = \arg\min || y_i - \Phi H_i\, w||^2 + \lambda||\Gamma w||^2 \qquad (1)$$

and the matrix of hypotheses, H_i, is assembled from an initial reconstruction, of the image X using either BCS-SPL or MS-BCS SPL. That is, for each block in X, MH predictions are generated from blocks spatially surrounding X in the initial reconstruction. Suppose image X is split into blocks of size $B \times B$ in BCS; each block is further divided into sub blocks of size$b \times b$.

MH predictions are created for each individual subblock of the block by sliding a $b \times b$ mask across the entire search window to create all candidate predictions for each sub-block. Since the block size is $B \times B$, the region in the block outside of the $b \times b$subblock is set to all zeros; the resulting $B \times B$ zero-padded" block is then placed as a column in H_i; H_i thus contains all the predictions for the entire sub locks of block i. This n sub block based MH-prediction process. The parameter λ in equation (2) controls the regularization. Unfortunately, there doesn't appear to be a straightforward approach for finding an optimal value without fore-knowledge of X. Some possible approaches to choose an appropriate λ include the L-curve, generalized cross validation, and the discrepancy principle. Through empirical analysis, we test a set of λ values and choose the one gives the best performance. The proposed MH-based prediction into BCS-SPL image reconstruction, resulting in a technique is calling MH-BCS-SPL.

In MH-BCS-SPL, MH prediction and residual reconstruction are repeated with increasing sub block size in order to improve the quality of the recovered image. Specifically, the original BCS-SPL reconstruction of uses a block size of B = 32 and a dual-tree DWT (DDWT) as the sparsity transform. In MH-BCS-SPL, an initial sub block size of b =16 and an initial search window of w = 8. The sub block size b and search window Ware increased based on a criterion involving structural similarity (SSIM).Specifically, three measurements as a holdout set y_H are used for the performance test. For example, at sub rate 0.1 and block size B = 32, the measurement matrix $\Phi \in R^{102x1024}$ has three more rows than $\Phi_R \in R^{99\times1024}$ which is used for reconstruction. $\Phi_H \in$ H $2R^{3\times1024}$is the measurement matrix for the holdout set. In other words $\Phi = [\_\Phi_R\ ;\ \Phi_H]$.

IV. RESULTS & CONCLUSION

The JEPG [9] and Sparse based compression techniques are tested on different types of images (Natural image, medical image, satellite image) and the PSNR value computed. Figure 1 & 2 shows the some of these images and its reconstruction respectively. By comparing PSNR values obtained by the JPEG and sparse based compression is given by table1and it is clear that sparse based compression perform better performance than other.

The traditional process of image compression is quite costly. It acquires the entire image at beginning, then does the compression and throws most of the information away at the end. The new idea of image compression combines signal acquisition and compression as one step which improves the overall cost significantly. The process of compressive sampling is to find a measurement matrix $\Phi \epsilon R^{M\times N}$(M < N) and multiply it with the imageX ϵR^N that compress in order to get M linear measurements Y= ΦX where y is the compressed sample. Since M < N, the system is under determined when to reverse the process and reconstruct the image X. In theory, there are infinitely many X that satisfy the system, so it seems impossible to reconstruct the image. Fortunately, most of signals in reality are sparse under some basis (e.g. Wavelets) and also it used to find the location of those non-zero entries, and reconstruct the signal uniquely. Comparison of the JPEG and sparse based compression has been done here. Peak Signal-to-Noise Ratio (PSNR) is used to measure the quality of recovery. The higher PSNR value is the better recovery performance. By comparing PSNR values obtained by the JPEG and sparse based compression, it is clear that sparse based compression technique in medical image get better performance than other. The input image and reconstructed image are given in Figure 1and 2.

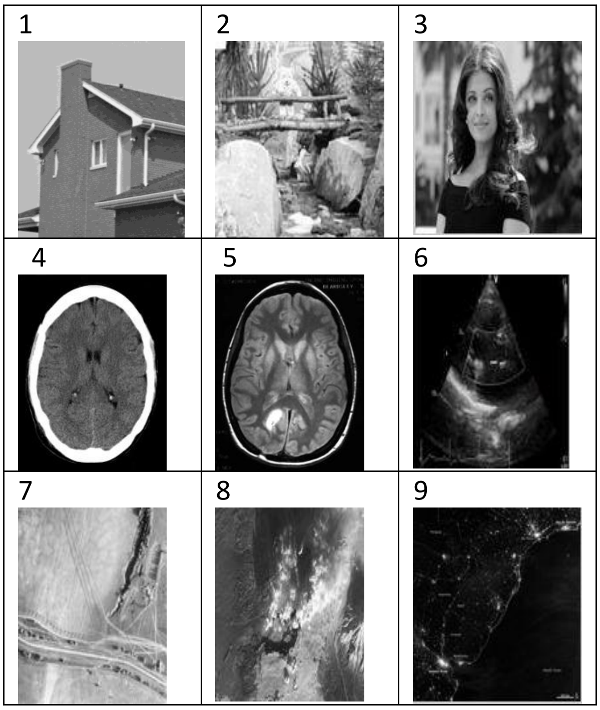

Figure 1: Input image

Figure 2: Reconstructed Image

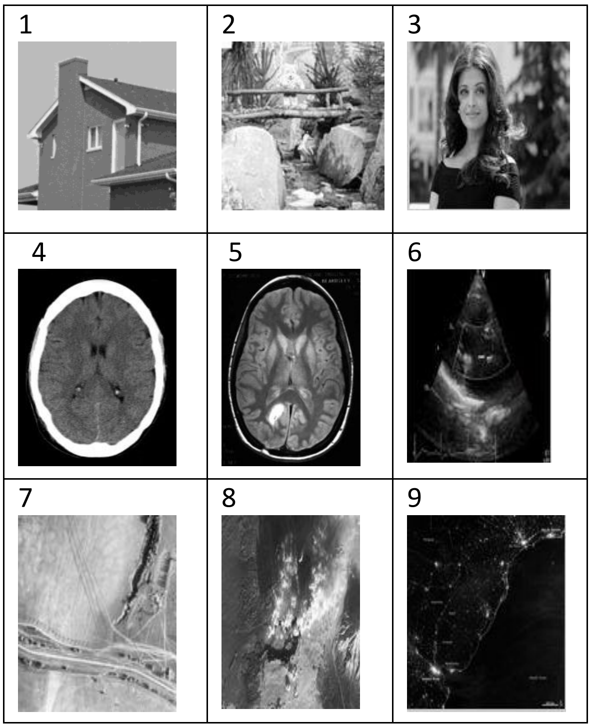

Table 1. Comparison of PSNR value for JPEG and CS

Image No:	PSNR Value (db)	
	JPEG	Sparse Based
1	34.87	91.97
2	28.38	87.93
3	32.55	89.69
4	31.21	88.66
5	40.46	92.78
6	33.48	89.99
7	31.73	87.64
8	30.21	87.52
9	32.06	88.16

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