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Analysis of Application of the Coefficient Random Permutation (CRP) in Image Compression and Reconstruction

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Abstract — The Conventional Compressive Sensing (CSS) which uses non-adaptive projection for the representation of natural images shows inefficient compression performance when compared to JPEG and JPEG 2000 which are the classical image compression standards. This paper investigates one of the methods of Block Compressive Sensing (BCS) called as coefficient random permutation (CRP).The effectiveness of the CRP method lies in balancing the sparsity of the sampled vectors the image's DCT domain and in improving the efficiency of Compressive Sensing Sampling. The analysis shows that the proposed method is effective in reducing the BCS-based image representation dimension and to improve the quality of the recovered image. The proposed method replaces the robust image compression and applications of the encrypted image compressions.

Keywords: image representation, image compression, encrypted image, robust coding, discrete cosine transform, block compressive sensing, coefficient random permutation

I. Introduction

Image and video compression techniques show a great improvement in the area of storage and transmission of visual information. The previously proposed image and video compression standards are JPEG, JPEG2000 and MPEG-4 AVC/H.264 etc. Digital multimedia transmission need robust coding over internet and wireless networks, where the image codec needs to have excellent compression performance to reduce data rate and also high robustness performance to resist transmission error due to channel noise and/or packet loss. When data is transmitted over insecure bandwidth-limited channels, the techniques such as data compression and encryption are always necessary. The traditional method in which the encryption process is followed by the compression process which is suitable for most of the applications; but there are applications which require encryption to be followed compression. These are the application where an information owner and a network operator do not trust each other, in such a case, to protect his data content, the information owner wants to encrypt his data before giving it to network operator. Since an encryption algorithm converts the data from comprehensible to incomprehensible structure, the encrypted data is difficult to efficiently compress using any of the classical compression algorithms.

The emerging compressive sensing theory also called as compressive sampling theory [1–4] has pointed us a hopeful way of developing efficient data compression techniques. It is proposed with original intention to achieve dimension-reduced sampling for saving sampling cost. The CS is a sampling theory in which exact recovery of the original signals is done through few measurements less than Shannon sampling rate if the signal is sparse or compressible, whereas in Shannon sampling theory the sampling rate must be at least twice of signal's highest frequency if we want to reconstruct a bandwidth limited signal without distortion. CS theory states that it is possible to achieve data sampling and compression at the same time. The CS technique has already been widely used in as signal processing, pattern recognition, communication and etc., besides signal sensing since the introduction CS theory [5]. Traditional CS in combination with ordinary quantization and entropy coding has shown not a good compression technique [6] in sight of compression efficiency, research on CS based image/video coding has gained more importance in recent years.

II. Compressive Sensing Overview

The compressive sensing (CS) theory has been introduced in public before several years [1, 2]. Regardless of a large number of researches in this related field have been reported, here is an overview of few Papers [3,4] on the CS theory. This Section gives a brief overview of compressive sensing. The CS structure includes the process of sampling in encoder side and the process of reconstruction in decoder side. The sampling process is done to get non-adaptive linear projection, which is called conventional compressive sensing (CCS) and described as follows:

$$y = \O x \quad (1)$$

where x denotes a real-value, discrete time signal with finite dimension N, i.e. $x \neq R^N$, y represents the obtained measurement values vector with reduced dimension n (n << N), and is a Ø sampling matrix (also called measurement matrix) with dimension n x N.

The requirement of CS is that the sampled signals are sparse in time/space domain, if not it can be sparsely represented in a certain transform domain w (e.g. DCT or wavelet), i.e. x can be represented as x = ws, and here the variable s denotes the sparse representation of signal x. So the above sampling process can also be described in a more general form [3,4] as follows:

$$y = \O\theta s = \Theta s \quad (2)$$

where Θ= Øθ is called a n X N sensing matrix. Although recovering x from y is an unsolvable problem in condition of n<< N, in CS theory the original signal can be exactly reconstructed by solving a combinational optimization problem expressed as long as x is sparse in some domain.

The i.i.d. Gaussian matrix is the generally used Sampling matrix U with entries being outcomes of i.i.d. Gaussian variables [3,4] and the structure measurement matrix is more simpler at cost of the CS performance for hardware implementation [31,32]. The product of an i.i.d Gaussian matrix and the transform matrix H ¼ Uw is also i.i.d Gaussian will have the RIP with high probability regardless the choice of transform basis w. In [31], Donoho et al. reported several families of random measurement ensembles which behave equivalently, including random spherical, random signs, partial Fourier and partial Hadamard. Among the various reconstruction algorithms, Basis Pursuit (BP) is the first proposed algorithm to solve this problem [1], and Orthogonal Matching Pursuit (OMP) [17] is proposed for fast reconstruction, etc.

III. CRP Based Block Compressive Sensing

The theory foundation of CS is that the signal to be sampled is sparse or compressible, and the sparsity of the sampled signals determines the required minimal number of measurement dimension for perfect recovery. It will be inefficient to assign the same number of measurement dimension to each sampled vector corresponding to the different image block when an image is represented by a BCS scheme, because the image block with different spatial characteristic has significantly different sparsity from each other. In general, the image blocks located at smooth region should have stronger sparsity than those located at texture region.

In communication system for design of interleaver, the method of bits random permutations is used in channel coding, which can maximally scatter the burst error generated in the process of data channel transmission. This increases the reliability of data transmission. The CRP in DCT domain of image is exploited to equalize the sparsity of the sampled vectors in CS encoding stage for enhancing measurement efficiency of BCS of image, which is followed by a CRP based BCS scheme. The proposed CRP can be used to achieve encrypting image in transform domain at information owner side.

In BCS, the intercoefficient correlation within a sampled signal vector is not exploited by the CS sampling; this makes the coefficient permutations across signal vectors not to adversely affect encoding performance. On the other side, the distribution of coefficients becomes randomization and homogenization because of random permutations. Such random permutations will make sparsity of all the sampled vectors nearly identical, this improves reconstruction performance because it is likely that before CRP some less sparse vectors will not be reconstructed well.

The CRP is proposed in DCT domain of image. The input image is first divided into B (M/m)X (N/n) image blocks with the same size of m x n, where M (N) denotes the number of row (column) of the original image, and is integer multiple of m (n). All image blocks are then sparsified by block 2-D DCT with block size of m _ n, obtaining the DCT coefficient arrays of all B image blocks, respectively denoted as ai, i = 1,2,...,B. The DCT coefficients in all arrays are further grouped to form m x n coefficient vectors, each corresponding to different frequency component of image, denoted as $\beta_j = \{\alpha^j_i, j=1,2,\ldots\ldots,B\}$, i=1,2,…..,m x n, where α^j_i, i represents the jth coefficient in array ai. The random permutation operations for different frequency component vector are carried out independently, modeled as $\beta^{\wedge}_j = \mathrm{Perm}[\beta_j]$, j = 1,2,. . .,m x n, and Perm[] represents random permutation operator. Finally, the block coefficients rebuilding operation (BCRO) is performed to form the coefficient vectors to be measured in the following sampling stage of CS. Every rebuilt coefficient vector to be sampled is still composed of m _ n coefficients, each from differentfrequency component vector after random permutations, represented a $^{\alpha\wedge}i = \{\beta^{\wedge i}_j$, j=1,2,……,m xn}, i= 1,2,….., B where $\beta^{\wedge i}_j$ is the i^{th} coefficient in vector $\beta^{\wedge}_j$.

The architecture of BCS scheme with CRP in DCT domain is shown in Fig. 1. The two main modules are a CRP-based BCS encoder module and a CRP-based BCS decoder module. The BCS encoder module receives an input image, and then performs block-based 2-D DCT (B2DCT), CRP and then Sampling. The measurement data for all sampled vectors is generated by the BCS encoder module. The CRP-based BCS decoder module receives the measurement data transmitted by the BCS encoder module, and then performs reconstruction or all sampled vectors, coefficients inverse random permutations (CIRP) and block-based 2-D Inverse DCT (B2IDCT). The CRP-based BCS decoder module generates the recovered image. The inverse operation of CRP is CIRP, used to obtain the reconstructed DCT coefficients for each original image block from the reconstructed vector by the BCS Reconstruction unit; since the reconstructed vectors are produced by the BCS

Reconstruction unit is scrambling representation in DCT domain of image blocks.

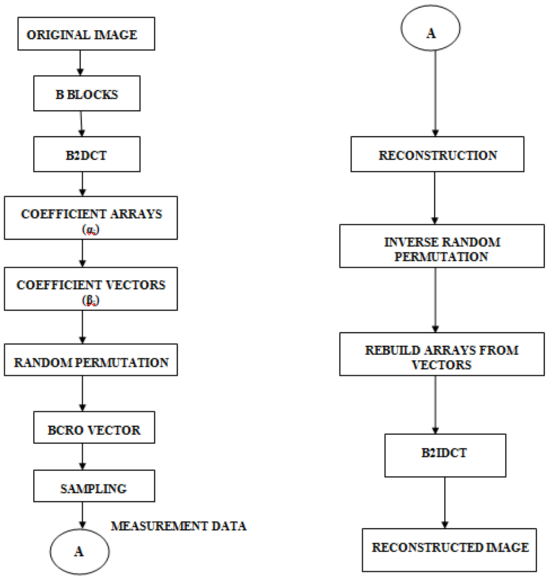

Fig. 1. The Overall architecture of CRP

The CRP introduced here is content-independent, so in order to transmit to the decoder side for CIRP only a seed for generating a pseudo random number is required. The CRP is image content independent, it can also reassign randomly (pseudo randomly) the position of all coefficients. It also has the ability to make them distribute approximately identical in order to guarantee that the rebuilt sampled coefficient vectors by the CRP have nearly identical sparsity.

IV. Experimental Results

To evaluate the efficiency of our proposed methods, the comparison experiments and results are given in this Section. Several sets of experiments are carried out to validate the efficiency of our methods: (a) the sparsity of coefficients vectors to be sampled is efficiently balanced by the proposed CRP ; (b) the CS representation performance is efficiently enhanced in both reducing measurement ratio and/or increasing PSNR and visual quality by the proposed CRP and/or AS can ; (c) re-orthogonalization of the weighted measurement matrix is efficient to enhance the measurement efficiency, and the weighted sampling by using energy of each frequency component is more efficient than that by using the linear combination of the absolute value of its mean and the square root of its variance of each frequency component;(d) performance comparison with other similar works.

The first step is to select several 256 x 256 gray-level .bmp compression test images for our experiments, and then set block size as 16 x 16. The i.i.d Gaussian matrix is used as the conventional CS measurement Matrix Ø, and the CS reconstruction is done by OMP [17] algorithm which is fast but highly efficient. The magnitude values are expressed in logarithm format as 20 log 10(.) for clearly shown. Experimental results shows that the CRP is efficient in order to make the distribution of coefficients magnitude decay curves of all the sampled vectors, which could, when the measurement dimension are equally allocated to different sampled vectors will considerately enhance the sampling efficiency. The stability and efficiency of CRP in equalizing the sparsity of the sampled vectors is verified 10 - 100-tries with different randomly generated permutation matrix.

V. Conclusions

This paper analyses the Image representation using BCS in DCT domain for compression applications usually suited for encrypted image compression. To enhance the BCS performance two efficient techniques are used in the stage of encoding. The proposed CRP not only can efficiently equalize the sparsity of the sampled coefficients vectors for improving CS encoding efficiency, but also can provides an efficient method to implement image encryption before compression. The results show that some less sparse blocks will not be reconstructed well without CRP when the same numbers of measurement dimension are assigned to all blocks. The random permutations across blocks do not harmfully affect encoding of CS that does not exploit inter-coefficient correlation within a block. Such permutations make all vectors to be measured nearly equally sparse, therefore CRP can enhance measurement efficiency. This is efficient in enhancing CS encoding performance and/or improving the reconstructed image quality. Alternative to encrypted image compression our proposed scheme is efficient.

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