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Survey for Image Representation Using Block Compressive Sensing For Compression Applications

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Abstract
Compressing sensing theory have been favourable in evolving data compression techniques, though it was put forward with objective to achieve dimension reduced sampling for saving data sampling cost. In this paper two sampling methods are explored for block CS (BCS) with discrete cosine transform (DCT) based image representation for compression applications - (a) coefficient random permutation (b) adaptive sampling. CRP method has the potency to balance the sparsity of sampled vectors in DCT field of image, and then in improving the CS sampling efficiency. To attain AS we design an adaptive measurement matrix used in CS based on the energy distribution characteristics of image in DCT domain, which has a good impact in magnifying the CS performance. It has been revealed in our experimental results that our proposed methods are efficacious in reducing the dimension of the BCS-based image representation and/or improving the recovered image quality. The planned BCS based image representation scheme could be an efficient alternative for applications of encrypted image compression and/or robust image compression.
Keywords—Block compressive sensing, Coefficient random permutation, compressive sensing, random sampling**,** Image representation,

I. INTRODUCTION

Recent years have seen important interest in the paradigm of compressed sensing (CS) which permit, in certain conditions, signals to be sampled at sub-Nyquist rates via linear projection onto a random basis while still enabling exact reconstruction of the original signal. As applied to 2D images, though, CS faces some challenges including a computationally expensive reconstruction process and huge memory required to store the random sampling operator. in recent times, numerous fast algorithms have been developed for CS rebuilding, while the latter challenge was addressed in [1] using a block-based sampling operation. Additionally in projection- based Landweber iterations were planned to achieve fast CS reconstruction while simultaneously imposing smoothing with the goal of improving the reconstructed-image quality by eliminating blocking artifacts. Sparse representation and compressive sensing establishes a more rigorous mathematical framework for studying high-dimensional data and ways to discover the structures of the data, giving rise to a large range of efficient algorithms. When transmitting data over insecure bandwidth-limited channels, data compression and encryption is for all time needed. An encryption algorithm converts the data from comprehensible to incomprehensible structure, thus making the encrypted data difficult to compress using any of the classical compression algorithms, which relies on intelligence embedded in the data. Hence, traditionally the encryption always follows compression. While such a scheme is suitable for most of the applications, there are some applications which need encryption to be carried out before compression [2]. Consider for example, an information owner and a network operator who does not trust each other. In such a case, to protect his content, the information owner encrypts his data before giving it to network operator. Due to the bandwidth limitation the network operator is forced to compress this encrypted data stream [3]-[5].

II. PROBLEM FORMULATION

The idea of CS is to represent the signal by non adaptive random projections to reduce the sampling rate, which is considered as an advantage of CS. However, the main challenges existed in CS for practical applications include how to reduce efficiently measurement rate with preserving good recovered image quality and decreasing the implementation complexity. To address these

problems, many researches [6] have reported to use the prior knowledge of the sampled signal to enhance the performance of CS. Although most of them focused on decoder-based reconstruction optimization, encoder-based sampling optimization may have important sense for addressing these problems. Block-based sampling for fast CS of

natural images, where the original image is divided into small blocks and each block is sampled independently using the same measurement operator. The possibility of exploiting block CS is motivated
by the great success of block DCT coding systems which are widely used in the JPEG and the MPEG standards[7]. The main advantages of our proposed system include: (a) Measurement operator can be easily stored and implemented through a random under sampled filter bank. Block-based measurement is more advantageous for real-time applications as the encoder does not need to send the sampled data until the whole image is measured; (b) Since each block is processed independently, the initial solution can be easily obtained and the reconstruction process can be substantially speeded up; For natural images, our preliminary results show that block CS systems offer comparable performances to existing CS schemes with much lower implementation cost.

III. IMAGE REPRESENTATION

The objective is to signify and express the resulting aggregate of segmented pixels in a form suitable for further computer processing after segmenting an image into regions.

• Two choice for representing a region:

External characteristics: its boundary.

Internal characteristics: the pixels comprise the region. For example, a region may be represented by (a) its boundary with the boundary describe by features such as its length, (b) the orientation of the straight line joining the extreme points, and (c) the number of concavities in the boundary.

• An external representation is chosen while the primary focus is on shape characteristics.

• An internal representation is chosen when the primary focus is on reflectivity properties, such as color and texture. The segmentation techniques yield raw data in the form of pixels along a boundary or pixels contained in a region. Although these data are sometimes used directly to obtain descriptors (as in determining the texture of a region), standard practice is to use schemes that compact the data into representations that are considerably more useful in the computation of descriptors. This section introduces some basic representation schemes for this purpose. To represent a boundary by a connected sequence of straight line segments of specified length and direction.

IV. IMAGE REPRESENTATION TECHNIQUES

Over the last two decades, great improvements have been made in image and video compression techniques driven by a growing demand for storage and transmission of visual information. By far, many image and video compression standards, such as JPEG, JPEG2000 and MPEG-4 AVC/H.264 etc., have been proposed. However, these mainstream compression coding techniques still may be not very efficiency in some special compression applications, for examples of robust image coding and encrypted image compression. Robust coding is very important in digital multimedia transmission over internet and wireless networks, where the image codec needs to have not only excellent compression performance to reduce data rate, but also high robustness performance to resist transmission error due to channel noise and/or packet loss.

A) CRP Based Block Compressive Sensing

As mentioned above, the theory foundation of CS is that the signal sampled is sparse or compressible, and the required minimal number of measurement dimension for perfect recovery is determined by the sparsity of the sampled signal. When an image is represented by a BCS scheme, it will be inefficient to assign the same number of measurement dimension to each sampled vector corresponding to the different image block, 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 rich edge or texture region. The method of bits random permutations has been used in channel coding in communication system for design of interleaved, which can maximally scatter the burst error generated in the process of data channel transmission, thus plays a very important role in increasing the reliability of data transmission. Motivated by the above fact, 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 in this Section, which is followed by a CRP based BCS scheme. The proposed CRP can be at the same time used to achieve encrypting image in transform domain at information owner side. In traditional BCS, the CS sampling does not exploit the inter coefficient correlation within a sampled signal vector, so coefficient permutations across signal vectors will not adversely affect encoding performance. On the other hand, because the random Permutations make the distribution of coefficients become randomization and homogenization, such random permutations will make sparsity of all the sampled vectors nearly identical, which improves reconstruction performance since it is likely that before CRP some less sparse vectors will not be reconstructed well [8].

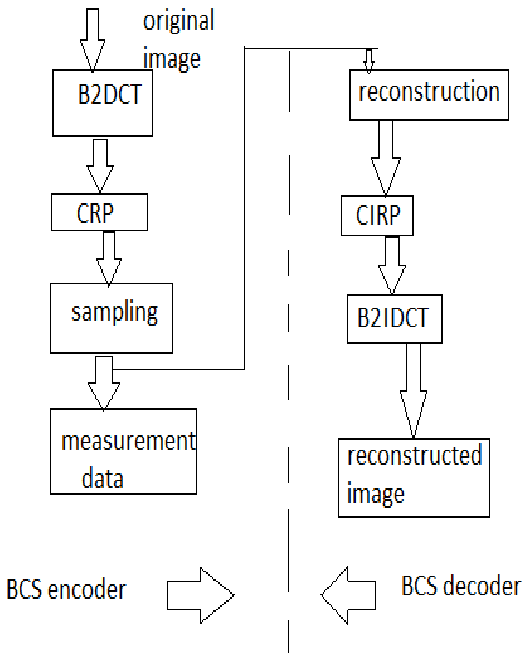

Figure 1: The architecture of BCS scheme with CRP

B) AS Based Block Compressive Sensing

In conventional CS scheme, a fixed measurement matrix is used to achieve non-adaptively sampling signal. This scheme is simple but not high efficiency, because it identically samples all signals with different feature, and non-distinctively extracts all information components of a signal that maybe have different importance to recovery signal quality [9]. In this Section, a novel method of developing adaptive measurement matrix is proposed to achieve adaptive Sampling (AS) in our BCS in DCT domain. As what we have known, image signals are bandwidth limited, and their energy are mostly distributed in the low-frequency components. In addition, the human eyes have certain masking effect on some parts of the frequency spectrum of image signals, which like low-pass filters that makes them more sensitive to low frequency components than high frequency ones. So, the low frequency components occupying large part of energy of image signals are more important to image quality than the high frequency components occupying less part of energy. Considering these facts, we propose to develop an adaptive measurement matrix in BCS framework based on the energy distribution characteristic of the sampled image signal in DCT domain to enhance the performance of BCS. The key idea is to adaptively extract more information of the important frequency components than that of the relatively non-important frequency components in sampling stage to reduce recovery error. It is implemented by adaptively scaling the coefficients of measurement matrix according to the sampled image's characteristic, i.e. unequally measuring the different frequency components based on their importance to image quality.

C) Compressed Sensing

Compressed sensing is a signal processing technique for ably acquire and reconstructing a signal, by finding solution to underdetermined linear systems. This takes profit of signal's sparseness or compressibility in particular domain, we design compressed data acquisition protocols which perform as if it were possible to directly acquire just allowing the entire signal to be determined from relatively few measurements. The important information about the signals/images in effect, not acquiring that part of the data that would eventually just be "thrown away" by lossy compression[10]. Moreover, the protocols are non adaptive and parallelizable; they do not require knowledge of the signal/image to be acquired in advance other than knowledge that the data will be compressible and do not attempt any "understanding" of the underlying object to guide an active or adaptive sensing strategy. The measurements ended in the compressed sensing protocol are holographic thus, not easy pixel samples and must be process nonlinearly. In specific applications, this principle might enable dramatically reduced measurement time, dramatically reduced sampling rates, or reduced utilize of analog-to digital converter resources [10].

Shuffling the class attribute values belonging to heterogeneous leaves of a decision tree. If a leaf corresponds to a group of records having different class attribute values, then the leaf is identified to be a heterogeneous leaf.

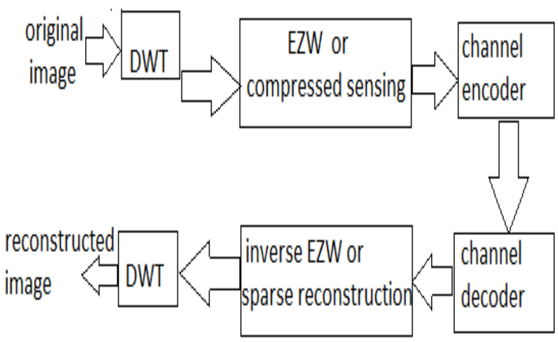

Figure2: Overall joint source-channel coding system block diagram [11]

Recently, we developed an interactive and adaptive joint source-channel coding algorithm by which the centre and size of the image are specified by the user after receiving the low-resolution background image.

D) Random Permutations Based Block Bompressive Sensing

Compressive sensing (CS) is a novel theory framework for signal acquisition, which has been widely concerned in many application fields. A new block CS scheme for image compression applications, in which a method of coefficients random permutations (CRP) in transform domain is exploited for optimal sampling of CS, considering the fact that the image blocks with different spatial characteristics have different sparsity or compressibility [12]. The proposed random permutations technique makes the sparsity of all the sampled coefficients vectors more evenly, which results in requiring approximate equal number of measurement for well restoration. New results show that our proposed scheme can efficiently enhance the CS performance in increasing reconstructed image quality or reduce the measurement ratio.

(a) (b)

Figure 2: Visual quality comparisons with measurement rate equaling to 0.4 and block size of 8×8. “(a) Original image, (b) reconstruction image by CRP-based CS method.

A novel scheme of image compressive sensing for compression applications is proposed in this paper. By employing the coefficients random permutations technique in sampling process, the sparsity of all sampled vectors could be balanced efficiently, which can considerably increase the utilization of sensing resources. The simulation results illustrate that our proposed sampling scheme can enhance the performance of compressive sensing efficiently in both objective and subjective assessment manners with little increasing the complexity.

E) Reweighted Compressive Sampling For Image Compression

Shannon sampling theory tells us that if we want to reconstruct a band limited signal without distortion, then sampling the original signal at a rate which is at least twice of its highest frequency is necessary. However, a newly emerged theory called Compressive Sampling (CS), also known as Compressive Sensing proves that this is not always true. It tells that as long as the signal is sparse or compressible, then we can exactly recover the original signals through only a few measurements, namely, we can achieve data sampling and compression at the same time for designing highly efficient data compression techniques while the performance of existing ones seem to reach the bottleneck. Some initial exploration about applying CS theory in data compression has been made; however, the performance is limited. The main problem that prevents CS framework from being applied in real data compression system is the efficiency decrease for complex signals which are Usually hard to be perfectly sparsely represented. One major reason causing this efficiency dropping is that conventional CS framework samples data randomly without showing discrimination to different components, in other words, it does not consider about the characteristics of the signals. However, this may not be the best way to sample when it comes to the complex signals, resembling images. A lot of efforts have been made trying to improve the performance of the CS signal recovery algorithms by adjusting the behavior of the decoder adaptively to the signal characteristics. However, usually their methods are based on the blind estimation of the signal magnitudes and iterative refining process in the decoding side. For instance, in, the authors propose an iterative reweighting scheme to enhance the sparsity of the reconstruction results. In their work, the solution of an unweighted minimization reconstruction is used as the initial guess, and then the weighting coefficients are refined iteratively, until the convergence is reached. However, the complexity for these iterative processing schemes is too high for the methods to be practical, and they are often guaranteed only to converge to a local (not necessarily) optimum. In this paper, we propose a reweighted Compressive Sampling for CS based image compression by introducing a weighting scheme into the encoding procedure. This method works on the block-based processing mechanism. First the images will be divided into small blocks, and then the weighting coefficients are determined by taking advantage of the statistical characteristics of natural images and subsequently sent together with the CS measurements to help the decoder to achieve better reconstruction results. The main advantage of our proposed method is that it can sufficiently utilize image characteristics to achieve considerable performance gain without notably increasing the complexity of the system structure or the computation procedures [13].

G) Robust Image Compression Based On Compressing Sensing

The existing image compression methods (e.g., JPEG2000, etc.) are vulnerable to bit-loss, and this is generally tackle by channel coding that follow. Though, source coding and channel coding have contradictory requirement. In this paper, we deal with the problem with an alternative paradigm, and a novel compressive sensing (CS) based compression scheme is therefore pro- posed [14]. Discrete wavelet transform (DWT) is applied for sparse representation, and base on the property of 2-D DWT, a fast CS measurements captivating technique is presented. Unlike the un- equally important discrete wavelet coefficients, the resultant CS measurements hold nearly the same amount of information and have minimal effects for bit-loss. At the decoder side, one can merely recreate the image via minimization. New-results show that the proposed CS-based image codec with- out resorting to error protection is more robust compared with existing CS technique and relevant joint source channel coding (JSCC) schemes.

V. CONCLUSION

With the help of compressive sensing using the recently developed HALS algorithm based on nonlinear thresholding a progressive transmission system has been introduced in this paper. The main contributions of this effort are on *a*. selection and coding of a small number of samples (sampled below Nyquist rate) and *b*. introducing an adaptive thresholding technique for selection and reconstruction of those samples. Keep the inferences that disclose private information about organizations or individuals at a minimum.Compression of encrypted image is not possible by using any of the classical compression techniques. We proposed a system and showed that lossy compression of encrypted image data is indeed possible by using compressive sensing techniques. The basis pursuit algorithm was appropriately modified to enable joint decompression and decryption. Simulation results were provided to demonstrate the compression results of the proposed method.

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