J. Vis. Commun. Image R. 30 (2015) 94–105

Contents lists available at ScienceDirect

J. Vis. Commun. Image R.

journal homepage: www.elsevier.com/locate/jvci

Adaptive sampling for compressed sensing based image compression ☆

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ARTICLE INFO

Article history:
Received 7 November 2014
Accepted 19 March 2015
Available online 26 March 2015

Keywords:
Sparsity
Compressed sensing (CS)
Block-based compressed sensing (BCS)
Image compression
Image coding
Adaptive sampling
Sampling efficiency
Measurement allocation

ABSTRACT

The compressed sensing (CS) theory has been successfully applied to image compression in the past few years as most image signals are sparse in a certain domain. In this paper, we focus on how to improve the sampling efficiency for CS-based image compression by using our proposed adaptive sampling mechanism on the block-based CS (BCS), especially the reweighted one. To achieve this goal, two solutions are developed at the sampling side and reconstruction side, respectively. The proposed sampling mechanism allocates the CS-measurements to image blocks according to the statistical information of each block so as to sample the image more efficiently. A generic allocation algorithm is developed to help assign CS-measurements and several allocation factors derived in the transform domain are used to control the overall allocation in both solutions. Experimental results demonstrate that our adaptive sampling scheme offers a very significant quality improvement as compared with traditional non-adaptive ones.

1. Introduction

The compressed sensing (CS) theory [1,2] has been demonstrated to be a very significant breakthrough in signal processing over the past few years, in which the data acquisition and compression are accomplished simultaneously, leading to an efficient way for signal processing. The CS theory tells that a sparse signal can be recovered exactly from a few sampling measurements via solving a convex problem although the sampling rate is (much) lower than the Nyquist rate. However, there still exist two important challenges within the CS theory [3]. The first one is how to design the sampling mechanism to achieve an optimal sampling efficiency. This includes how many samples to take; how to formulate these samples (i.e., using what kind of sampling matrix); single pass or multiple passes for sampling; adaptive sampling; etc. The second one is how to perform the reconstruction to get the highest quality to achieve an optimal signal recovery. It includes various efficient reconstruction algorithms, such as the basis pursuit (BP) algorithm [4], the gradient projection for sparse reconstruction (GPSR) algorithm [5], the iterative thresholding (IT) algorithm [6], etc.

Most image signals are sparse in a certain domain. Therefore, the CS theory has been successfully applied to image compression in the past few years. One of the well-known CS-based image compression schemes is the block-based CS (BCS) [7,8] in which an image is divided into blocks and the CS reconstruction is performed on each block after the sampling on individual blocks with a fixed sampling rate. The BCS scheme saves the memory storage (for the sampling matrix) and computational complexity (for the signal recovery) very significantly. Both advantages make the application of the CS theory in image compression more practical. Current efforts on the BCS-based image compression are focusing on how to improve the quality for the recovered image with a smaller number of sampled data. One potential way to achieve this goal is to optimize the reconstruction algorithm used for the image recovery. Besides the most popular methods (including their improved versions) we mentioned above, the iterative reweighting algorithm [9–12] now becomes a more efficient way to enhance the recovery quality for image signals. In the iterative reweighting scheme, an iterative reweighted minimization strategy is used to help reconstruct the signal and the weighting factors used in this algorithm make the signal highly sparse in a certain domain so that a better reconstruction may be achieved more easily. However, each weighting factor in the reweighted minimization algorithm must be iteratively updated, which makes the reconstruction more complicated. Alternatively, such a reweighting may be carried out during the sampling to acquire the CS-measurements instead of

☆ This paper has been recommended for acceptance by M.T. Sun.

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http://dx.doi.org/10.1016/j.jvcir.2015.03.006
1047-3203/

when the signal reconstruction is performed, leading to the so-called reweighted sampling. This sampling scheme tries to get a better reconstruction through improving the sampling efficiency. To implement such a reweighted sampling, an additional weighting matrix must be applied to image signals during the data acquisition. There are various ways to construct such a weighting matrix, such as using the first order moment [13] or the second order moment [14,15] of the frequency component in the transform domain to determine its elements.

In the traditional BCS schemes, including the non-reweighted and reweighted ones, a fixed sampling rate is always used to determine the number of sampled CS-measurements for each block. In fact, a natural image normally consists of various contents, and therefore it is necessary to represent different image portions with different numbers of CS-measurements in order to achieve a higher sampling efficiency. Obviously, the uniform measurement allocation used in the traditional BCS ignores the diversities of blocks – which will affect the sampling efficiency and eventually limit the overall quality of the whole recovered image. In this paper, we focus on the design of an adaptive sampling mechanism for BCS, especially for the reweighted BCS. In our proposed adaptive sampling mechanism, the number of assigned CS-measurements to each block is determined by the specific statistical characteristics and all measurements are allocated non-uniformly to image blocks with diversified contents. In order to achieve this goal, two solutions are proposed to perform the statistical analysis on each individual block and to control the measurement allocation at the encoder side and decoder side, respectively. In the first solution (*Solution-1*), the analysis is performed directly on the original image block at the encoder side and the extracted information is used to lead a dynamic measurement allocation, i.e., to control the number of CS-measurements assigned to each block. In this way, some additional information which will be used for the signal reconstruction at the decoder side are required to represent the number of assigned CS-measurements for each block and we can control these additional information in an acceptable range. In the second solution (*Solution-2*), the statistical analysis is carried out at the decoder side and a feedback connects the decoder side and the encoder side to help allocate measurements in the CS-sampling. In this solution, the sampling procedure is divided into two phases. In the first phase, a fixed but lower (than the required rate) sampling rate is applied to all image blocks and a coarse image with a lower quality will be recovered firstly. In the second phase, the remaining measurements are adaptively allocated to image blocks to perform a re-sampling according to the statistical information of the corresponding initially-recovered blocks from the previous phase. In order to implement the adaptive sampling in both solutions, we develop a generic allocation algorithm to control the overall measurements assignment on the whole image. In our proposed allocation algorithm, an allocation factor correlated to the statistical information of each individual block is used to determine the number of assigned CS-measurements and several different ways are tried to generate such an allocation factor based on different statistical parameters in the transform domain.

The rest of this paper is organized as follows. We present an overview of the CS theory for image compression in Section 2 and develop a jointly-reweighted BCS after the comparison between two traditional reweighted BCS schemes in Section 3. Then, we propose a generic measurement allocation algorithm which is controlled by the allocation factor to implement the adaptive sampling in Section 4. In Section 5, we describe how to calculate the allocation factor used in the measurement allocation algorithm according to the statistical information in the transform domain. After that, we implement the adaptive sampling on the reweighted BCS with two different solutions in Section 6. The experimental results are presented in Section 7 to compare our proposed adaptive (reweighted) BCS with the traditional non-adaptive BCS schemes. Finally, some conclusions are drawn in Section 8.

2. Overview of compressed sensing

2.1. Traditional compressed sensing

The CS theory tells that a signal may be exactly recovered from a few of its linear measurements as long as it is sparse enough in a certain domain. Let's consider a 1-D sparse signal $\boldsymbol{x} \in \mathbb{R}^L$ and it is assumed to be K-sparse ($K \ll L$), i.e., containing only K non-zero or significant elements in a certain domain. The CS-sampling of $\boldsymbol{x}$ means to apply a random matrix to $\boldsymbol{x}$ to acquire a sampled vector $\boldsymbol{y} \in \mathbb{R}^M$ ($M \ll L$). The general representation for the CS-sampling may be formulated as follows:

$$\boldsymbol{y} = \boldsymbol{\Phi}\boldsymbol{x} \tag{1}$$

where $\boldsymbol{\Phi}$ is an $M \times L$ random sampling matrix. The elements of $\boldsymbol{y}$ are called measurements of $\boldsymbol{x}$ and according to the CS theory, $\boldsymbol{x}$ can be perfectly recovered from $M = \mathcal{O}(K\log L/K)$ measurements by solving an optimization problem via minimizing the ℓ^0-norm as follows:

$$\boldsymbol{x} = \arg\min_{\boldsymbol{x}:\boldsymbol{y}=\boldsymbol{\Phi}\cdot\boldsymbol{x}} \|\boldsymbol{x}\|_0 \tag{2}$$

To make the signal reconstruction easier, the above problem is converted into a convex one through minimizing the ℓ^1-norm of $\boldsymbol{x}$ as:

$$\boldsymbol{x} = \arg\min_{\boldsymbol{x}:\boldsymbol{y}=\boldsymbol{\Phi}\cdot\boldsymbol{x}} \|\boldsymbol{x}\|_1 \tag{3}$$

The 2-D image signal can be converted into a 1-D signal by the lexicographic re-ordering, and then it may be sparsely (or approximately sparsely) represented in a transform domain, such as the DCT or wavelet domain. Suppose that there exists an $L \times L$ basis matrix $\boldsymbol{\Psi}$ which makes $\boldsymbol{x} = \boldsymbol{\Psi}\boldsymbol{X}$ and $\boldsymbol{X}$ contains only K non-zero or significant elements. Then, the CS-sampling may be rewritten as:

$$\boldsymbol{y} = \boldsymbol{\Phi}\boldsymbol{x} = \boldsymbol{\Phi}(\boldsymbol{\Psi}\boldsymbol{X}) = \boldsymbol{\Omega}\boldsymbol{X}. \tag{4}$$

2.2. Block-based compressed sensing for image compression

Although the CS framework has been very successful in image compression, there are still two problems in the practical application. The first one is how to reconstruct a large-sized image with a lower computation complexity. The second one is how to store a big sampling matrix when the CS-sampling and signal reconstructing are performed on a large-sized image.

The BCS scheme is proposed to solve above problems. In the BCS, a 2-D image signal is first divided into $B \times B$ image blocks and each block is converted to a 1-D signal, denoted as $\boldsymbol{x}_i$. Then, a fixed sampling rate r (for the whole image) is performed on each block to acquire the sampled $\boldsymbol{y}_i$ as:

$$\boldsymbol{y}_i = \boldsymbol{\Phi}^{(B)}\boldsymbol{x}_i = \boldsymbol{\Phi}^{(B)}(\boldsymbol{\Psi}^{(B)}\boldsymbol{X}_i) = \boldsymbol{\Omega}^{(B)}\boldsymbol{X}_i, \tag{5}$$

where $\boldsymbol{\Phi}^{(B)}$ is the $n^{(B)} \times B^2$ matrix by selecting $n^{(B)} = \lfloor r \cdot B^2 \rfloor$ rows from a $B^2 \times B^2$ random matrix $\boldsymbol{S}$, and $\boldsymbol{\Psi}^{(B)}$ is the $B^2 \times B^2$ basis matrix which makes $\boldsymbol{x}_i = \boldsymbol{\Psi}^{(B)} \boldsymbol{X}_i$. Obviously, reconstructing a separated image block and saving a sampling matrix for it are much easier than performing the same operations on the whole image.