Information Sciences 472 (2019) 77–93

Contents lists available at ScienceDirect

Information Sciences

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

Collaborative block compressed sensing reconstruction with dual-domain sparse representation

Yu Zhou[a], Hainan Guo[b,*]

[a] College of Computer Science and Software Engineering, Shenzhen University, Shenzhen 518060, China
[b] Research Institute of Business Analytics and Supply Chain Management, College of Management, Shenzhen University, 518060, China

ARTICLE INFO

Article history:
Received 29 April 2018
Revised 23 August 2018
Accepted 26 August 2018
Available online 11 September 2018

Keywords:
Block compressed sensing
Kernel regression
Perceptual
Non-local similarity
Dual-domain sparse representation

ABSTRACT

In the past decade, image reconstruction based on compressed sensing (CS) has attracted great interest from researchers in signal processing. Due to the tremendous amount of information that an image contains, block compressed sensing (BCS) is often applied to divide an entire image into non-overlapping sub-blocks, treating all sub-blocks separately. However, an independent reconstruction ignores the correlation between adjacent sub-blocks and results in quality degradation, both in objective and subjective assessments. To obtain a satisfactory reconstructed image, this paper proposes a collaborative BCS (CBCS) framework with dual-domain sparse representation, where local structural information (LSI) and non-local pixel similarity are jointly considered. During a reconstruction, a local data-adaptive kernel regressor is introduced to extract the local image structure, which helps build a correlation of pixels between adjacent sub-blocks and preserves the details of an image. At the same time, a perceptually non-local similarity (PNLS), based on the human visual system, is used to improve visual quality. In addition, we employed both an analysis model and a synthesis model to further enhance sparseness and to formulate a dual-domain sparse representation based BCS reconstruction problem. Finally, an efficient, iterative approach, based on the multi-criteria Nash equilibrium technique, is proposed to solve this problem. Experimental results on benchmark images demonstrate that the proposed method can achieve competitive results both in both numerical and visual comparisons with some state-of-the-art BCS algorithms.

1. Introduction

In recent years, due to the paradigm of simultaneous acquisition and dimension reduction of signals, compressed sensing (CS) [15] has been widely applied in different areas, such as Dynamic MRI [30,37], wireless networks [3,43], image or video coding [26,28] and signal processing [52]. CS states that a sparse or compressive signal can be exactly reconstructed from a small number of highly incomplete linear measurements, as long as the Restricted Isometry Property (RIP) [8] condition is satisfied. Currently, due to the huge amount of information that multidimensional signals (images or video) contain, the primary challenge for image reconstruction involves low computational cost for the algorithm and easy storage for memory, when implemented. To address this problem, block compressed sensing (BCS), which divides the image signal into several non-overlapping image sub-blocks was developed [20,21].

* Corresponding author. Fax: +86 755 26054111.
E-mail addresses: zhouyu_1022@126.com (Y. Zhou), guohn403@126.com, hainaguo-c@my.cityu.edu.hk (H. Guo).

https://doi.org/10.1016/j.ins.2018.08.064
0020-0255/

Although a block-by-block method is able to achieve competitive performances in CS reconstruction, each sub-block is recovered independently and lacks cooperation from sub-blocks in the neighborhood area during the reconstruction process. The most straightforward outcome would be possible artifacts between adjacent sub-blocks, which not only decrease the Peak Signal-Noise Ratio (PSNR) but also degrade the visual quality. One solution is to extract some overlapped sub-blocks instead, with the recovered image finally being obtained by averaging the overlapped region. However, the average alone does not capture image details well. Whats worse, this operation may cause some details to blur.

To better characterize the different structures and to maintain smoothness between pixels in a CS reconstruction, some local priors are adopted. In [40], a piecewise autoregressive (PAR) method is introduced to build a model that estimates local structures effectively. However, the reconstruction is largely dependent on the model's accuracy, which may be affected by inaccurate estimates of the original image. In [35], a local kernel regressor is proposed, to estimate local structures by introducing a data-adaptive kernel function. This local kernel regression method, which can be implemented iteratively to improve the quality of the entire image, has been proven effective in the application of image inpainting, denoising, fusion, and interpolation. In addition, inspired by the fact that natural images often contain repetitive image structures, non-local self-similarities [6],[7] are also considered as constraints. In [42], a non-local similarity was introduced into the process of patch aggregation in term of l_2 norm, which preserved the sharpness of edge well and improved the image quality. In [51], a perceptually non-local similarity (PNLS) constraint in BCS was proposed, which improved the perceived visual quality of the reconstructed image. However, these options either consider modeling the pixel relationship in local structures or taking non-local similarity into consideration, which ignores the collaboration between them.

It is also well known that sparsity plays an important role in CS reconstruction. Once sparsity is well explored, a signal can be recovered perfectly with high probability. Because an image is not sparse in a spatial domain, an exploration should be done using the sparse representation technique. Conventional BCS methods employ a transform basis, such as discrete cosine transform (DCT), discrete wavelets transform (DWT), and curvelets. Thus, a sparse signal can be obtained by this forward transformation, which is regarded as the analysis model for sparse representation. With the development of machine learning techniques, the adaptive dictionary learned from samples, known as a synthesis model [1,2,17], has been widely applied in the area of image processing and computer vision, such as image superresolution [22,49,50,53], image fusion [54], 3D human pose recovery [25], image reranking [44] and classification [48]. The idea of incorporating dictionary learning-based sparse representation into image reconstruction was introduced in [14], where local sparsity constraints were taken into consideration, and an l_1 norm-based non-local regularizer was proposed to exploit pixel redundancies. Although these methods improve reconstruction quality significantly, image sparsity is still not fully explored; therefore, the quality of the reconstruction can be improved.

In this paper, to obtain a better-reconstructed image, a collaborative BCS (CBCS) reconstruction framework with dual-domain sparse representation is developed. In this framework, both local structure information (LSI) and perceptually non-local similarity (PNLS) are employed. Specifically, the block-based, locally data-adaptive kernel regressor is introduced, which provides a good approximation for LSI across different sub-blocks. The relationship between adjacent sub-blocks is built intrinsically. Simultaneously, PNLS constraints based on a structural similarity (SSIM) index [38] are used to enhance the perceived visual quality of a reconstructed image. In addition, we employ both analysis and synthesis models to further enhance sparseness and to formulate a dual-domain sparse representation based on the BCS reconstruction problem. An efficient, iterative approach, using a multi-criteria Nash equilibrium technique, is proposed to solve this problem and to obtain a final, recovered image. Experimental simulations are taken when testing natural images from benchmark datasets. Results demonstrate that the proposed method achieved competitive results both numerically and visually, compared with some state-of-the-art BCS algorithms. In summary, the contributions of this paper are threefold as follows:

- A collaborative block compressed sensing (CBCS) framework is proposed, where the LSI and PNLS better characterize structural details and maintain pixel smoothness.
- Combining synthesis with an analysis sparse coding model is applied in the formulated CBCS, which better explores signal sparsity.
- An efficient, iterative approach, based on a multi-criteria Nash equilibrium technique, is proposed to solve the reconstruction problem. This results in better performance than comparative state-of-the-art BCS methods.

The remainder of this paper is organized as follows. Related work is introduced in Section 2. In Section 3, a detailed description of our proposed method is presented. Numerical and visual results from benchmark images are shown in Section 4. Finally, Section 5 offers a conclusion and suggests future work.

2. Related work

Most sparsity-based approaches can be divided into two categories, analysis-based and synthesis-based sparse regularization [18]. Natural images are known to be approximately sparse in analytical transform domains. In [31,32] and [20], the discrete wavelet transform (DWT), discrete cosine transform (DCT), and dual-tree DWT (DDWT) are applied, respectively, in BCS reconstruction after a sampling in the spatial domain. Coefficients in the transformed domain are updated by soft threshold shrinkage to constrain sparsity for the entire image. A smoothed, projected Landweber recovery algorithm is proposed to reconstruct each sub-block in an iterative way, and wiener filtering is also applied to reduce the block artifact. A multi-scale sampling technique in an analysis-based transform domain is also developed. In [23] and [24], based on a