Signal Processing: *Image Communication* 40 (2016) 16–25

Contents lists available at ScienceDirect

Signal Processing: *Image Communication*

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

Geometric structure guided collaborative compressed sensing ☆

Leping Lin [a,b,*], Fang Liu [a,b], Licheng Jiao [b]

[a] *School of Computer Science and Technology, Xidian University, Xi'an 710071, China*

[b] *Key Laboratory of Intelligent Perception and Image Understanding of Ministry of Education, International Research Center for Intelligent Perception and Computation, Xidian University, Xi'an 710071, China*

ARTICLE INFO

Article history:
Received 12 November 2014
Received in revised form
14 October 2015
Accepted 14 October 2015
Available online 7 November 2015

Keywords:
Geometric structure
Collaborative reconstruction
Overcomplete dictionary
Self-similarity
Structured sparsity

ABSTRACT

Employing overcomplete dictionaries for applications captures the great interest, but the problem of recovering a signal from its random compressed measurements by taking advantage of the sparsity prior introduced by an overcomplete dictionary is very ill-posed, due to the compressed sampling operator and the redundancy of the dictionary. To achieve accurate and stable estimation, we exploit the local geometric structures of an image, and make a hybrid use of them and the self-similarity property of natural images. In the proposed geometric structure guided collaborative compressed sensing reconstruction (GS_CR) method, the geometric structured sparsity models are established and imposed to the sparse representation coefficients of the image blocks, which are designed to enhance the estimation accuracy of the local structures of an image. In the two reconstruction processes of GS_CR, the collaborative reconstruction patterns adapted to the geometric structures are established, where an image block is estimated by the collaboration of its local and nonlocal neighbors of different geometric types. By the experimental results, GS_CR is shown to outperform the previously proposed collaborative reconstruction scheme in reconstruction accuracy and speed.

1. Introduction

Compressed Sensing (CS) has been making a big impact on signal acquisition, representation and processing. The CS theory [1–4] shows that a signal $\mathbf{x} \in \mathbb{R}^n$ can be accurately recovered from its very few nonadaptive compressive samples $\mathbf{y} = \Phi\mathbf{x} \in \mathbb{R}^m$ $(\Phi \in \mathbb{R}^{m\times n}, m << n)$. One of the reconstruction models can be cast as

$$\mathfrak{s}^* = \arg\min_{\mathfrak{s}} \|\mathbf{y} - \Phi\mathfrak{D}\mathfrak{s}\|^2, \quad \text{s.t. } \|\mathfrak{s}\|_0 \le K, \tag{1}$$

where the overcomplete dictionary $\mathfrak{D} \in \mathbb{R}^{n\times N}(N >> n)$ introduces the sparsity for $\mathbf{x}: \mathbf{x} = \mathfrak{D}s(\mathfrak{s} \in \mathbb{R}^N, \|\mathfrak{s}\|_0 << n)$. The l_0 norm $\|\cdot\|_0$ counts the number of nonzero components of a vector. The parameter K is called the sparsity of $\mathfrak{s}$. After $\mathfrak{s}$ is estimated, $\mathbf{x}$ is estimated by $\mathfrak{D}\mathfrak{s}^*$. In such a model, the reconstruction of an image is transformed into the problem of estimating the sparse representation coefficient of the image on the overcomplete dictionary. Moreover, the dictionary plays an important role in the problem. It supply more sparse, adaptive and flexible representations for the signals compared to orthogonal bases and frames [5–7],

☆ The work was carried out with the part-supports of the National Basic Research Program (973 Program) of China (No. 2013CB329402), the Fund for Foreign Scholars in University Research and Teaching Programs (the 111 Project) (No. B07048), the Major Research Plan of the National Natural Science Foundation of China (Nos. 91438201 and 91438103), the Program for Cheung Kong Scholars and Innovative Research Team in University (No. IRT1170), the National Natural Science Foundation of China (Nos. 61173090, 61573267 and 61362021), and in part by Guangxi Natural Science Foundation (Grant nos. 2013GXNSFDA019030 and 2014GXNSFDA118035).

* Corresponding author at: School of Computer Science and Technology, Xidian University, Xi'an 710071, China.
E-mail addresses: lin_leping@163.com (L. Lin), f63liu@163.com (F. Liu), LCHJiao@mail.xidian.edu.cn (L. Jiao).

http://dx.doi.org/10.1016/j.image.2015.10.006
0923-5965/

while contributes to the illness of the reconstruction problems. The reconstructions are ill-posed [8], multi-modal [5], and NP-hard problems [9]. To accurately estimate the signals from their measurements, constrains beyond classic sparsity must be imposed on the signals, the dictionary, or both of them [10,11].

In our previous work [9], the self-similarity property of natural images [12–14] are made use to impose constrains on the sparse representations of image blocks. In the proposed two-process collaborative reconstruction scheme (CR_CS), an image block is estimated by the collaboration of its local and nonlocal neighbors. Thus more information is made use for individual blocks than their own measurements, and the reconstruction accuracy is significantly improved. Though the results of CR_CS are inspiring, its running time are long and the local structures of the images failed to be accurately captured. To improve CR_CS, in this paper, the local geometric structures of images are estimated and introduced to guide the collaborative processes, and a geometric structure guided collaborative reconstruction scheme (GS_CR) is proposed. Compared to CR_CS, GS_CR incorporates more image prior knowledge and imposes more constrains on the signals and dictionary, hence better and faster reconstruction results could be expected.

In GS_CR, an image block will be estimated as one of the three geometric types based on the analysis of their measurements: *smooth block*, *oriented block* and *stochastic block*. Then, each image block will be estimated by the collaboration a group of blocks, which are chosen according to not only the local and nonlocal similarity as in CR_CS, but also the geometric types. Besides, the geometric structured sparsity models will be imposed on the sparse representation coefficients of the blocks of different types, which will benefit the estimation of local directional structures and yield various collaborative patterns. By the experimental results, GS_CR is shown to outperform CR_CS in both visual effects and numerical measures.

The remainder of the paper is organized as follows. Section 2 introduces the overall GS_CR scheme. Section 3 establishes the geometric structured sparsity on the parametric Ridgelet overcomplete dictionary. In Section 4, the proposed GS_CR scheme and its greedy realization are presented. In Section 5, the experimental results and theoretical analysis are presented. The last section makes a conclusion of the paper.

2. Collaborative reconstruction scheme guided by geometric structure

Fig. 1 depicts the GS_CR scheme. The scheme comprises two successive collaborative processes as in CR_CS. But all the steps and operators of GS_CR, such as the collaborative reconstruction patterns, the local and nonlocal block matching, are instructed by the geometric structures estimated on the measurements.

In the first process, an image block will be estimated by the measurements of its nonlocal neighbors of the same type, which is designed for making use of more information than the measurement of the block. At the same time, the imposed sparsity models related to the geometric structure types will limit the ranges of the nonzero-valued components of the coefficients. The joint of the above actions will simplify and fasten the reconstruction of CR_CS.

In the second process, the acquired estimation in the first process will be exchanged between the local and nonlocal similar blocks of different types by the collaborative patterns, and the errors occurred in labeling and the previous process will be compensated and corrected. In this process, we designed various collaborative patterns adapted to different geometric types. The new patterns are the special and simplified cases of that in CR_CS, which leads to faster refinement algorithm without the loss of accuracy.

3. Geometric structured sparsity on overcomplete dictionary

3.1. Block CS reconstruction

This work is carried out in the scenario of block CS of natural images [15,9]. The block-wise measurements of an image $I \in \mathbb{R}^{\sqrt{n}\times\sqrt{n}}$ is obtained by compressed sampling its non-overlapped vectorizing blocks $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_L)$ by the operator $\Phi \in \mathbb{R}^{m_b \times B} (\sqrt{B} = 16)$: $\mathbf{Y} = \Phi\mathbf{X} = (\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_L)$, where $\mathbf{y}_i = \Phi\mathbf{x}_i$. The block-based CS reconstruction model

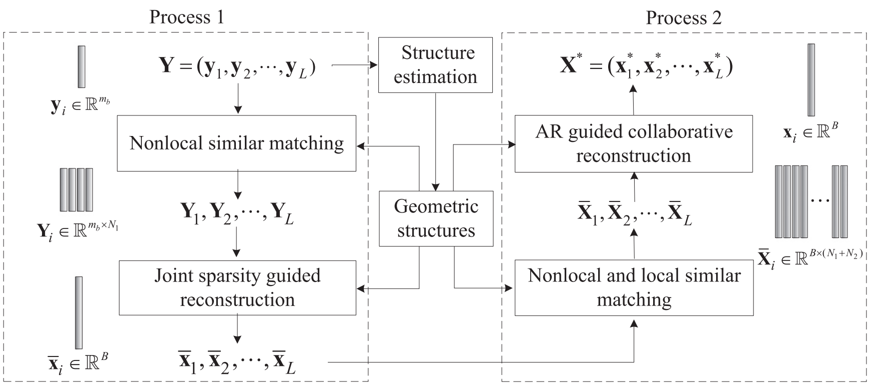

Fig. 1. The diagram of GS_CR scheme.