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Geometric structure based intelligent collaborative compressive sensing for image reconstruction by l_0 minimization

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ABSTRACT

Image reconstruction by l_0 minimization is an NP-hard problem with high computational complexity and the results are sometimes not accurate enough due to the down-sampled measurements. In this paper, we propose a novel geometric structure based intelligent collaborative compressive sensing (G-ICCS) method for image reconstruction by l_0 minimization. Firstly, the local geometric structures of image are exploited to establish the geometric structure based sparsity models based on the geometric over-completed dictionaries, which aims to enhance the reconstruction accuracy of image structures. To reduce the computational complexity and achieve the better reconstruction accuracy, we utilize the nonlocal self-similarity property to obtain the geometric sparsity prior to guide the reconstruction for each geometric structure based sparsity model, respectively. Considering intelligent optimization algorithm has superior performance in solving combinatorial optimization problems and global searching and greedy algorithm performs well in reconstruction speed, we make a hybrid use of them to solve the l_0 minimization essentially by designing the intelligent searching strategies. Finally, the image patches are estimated by the designed intelligent searching strategies under the guidance of the geometric sparsity prior to improve the reconstruction accuracy significantly especially when the measurement rate is relatively small. Some experiments test the proposed method G-ICCS on natural images, and the results demonstrate that G-ICCS outperforms its counterparts in both numerical measures and visual quality.

1. Introduction

Image reconstruction by sparse coding [1,2,3,4] has attracted increasing interests based on the fact that the over-completed dictionary supplies more sparse, flexible and adaptive representation for signals compared to the orthogonal bases. In such a model, the image reconstruction problem turns to estimate the sparse representation of each image patch on the over-completed dictionary. Suppose the original image is $X \in R^{n*n}$, which can be divided into L nonoverlapped image patches $x_i \in R^{\sqrt{B}*\sqrt{B}}, i = 1, 2, \ldots, L$. The down-sampled measurements can be obtained by Eq. (1), where $\phi \in R^{m*B}$ is the measurement matrix, $\psi \in R^{B*N}$ is the over-completed dictionary and $s_i \in R^{N*1}$ is the sparse representation of x_i.

$$y_i = \phi * x_i = \phi * \psi * s_i, \quad i = 1, 2, \ldots, L. \tag{1}$$

Based on Eq. (1), the image reconstruction problem by sparse coding can be modelled as the unconstrained optimization problem, which is given by Eq. (2) and composed of L subproblems.

$$s_i^* = argmin_{s_i} \parallel s_i \parallel_0 + \lambda * \parallel y - \phi * \psi * s_i \parallel_2^2, \quad i = 1, 2, \ldots, L. \tag{2}$$

where $\|s_i\|_0$ counts for the number of the nonzero elements of s_i and λ is a regularization parameter.

As we can see, Eq. (2) is the l_0 minimization problem, which is NP-hard and has a high computational complexity. As l_1 norm is a good approximation to l_0 norm under some certain conditions, l_1 minimization is often utilized to replace l_0 minimization to implement the reconstruction, which can be modelled by Eq. (3). The l_1 minimization problem in Eq. (3) is convex, so the convex optimization algorithms, such as linear programming algorithm [5] and basis pursuit algorithm [6] are available to solve it effectively. However, a fact that is often neglected is the conditions guaranteeing the equivalence of l_0 minimization and l_1 minimization are not necessarily satisfied. If the conditions can not be satisfied successfully, the convex optimization algorithm can not obtain the optimal solution of reconstruction. So the l_0 minimization in Eq. (2) is the essential problem for reconstruction.

$$s_i^* = argmin_{s_i} \parallel s_i \parallel_1 + \lambda * \parallel y - \phi * \psi * s_i \parallel_2^2, \quad i = 1, 2, \ldots, L. \tag{3}$$

Up to now, the methods for solving the l_0 minimization can be mainly divided into two categories: greedy algorithm and heuristic

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algorithm. However, greedy algorithm, such as orthogonal matching pursuit (OMP) algorithm [7], subspace pursuit (SP) algorithm [8] and compressive sampling matching pursuit (CoSaMP) algorithm [9], adopts the fast sub-optimal searching strategies, which is easy to fall into a sub-optimal solution. Also, greedy algorithm always needs more measurements to obtain a relatively accurate reconstruction result. In recent years, intelligent optimization algorithm [10,11] is widely utilized to solve the l_0 minimization as it has superior performance in solving combinatorial optimization problems and global searching. In our previous works [12,13], the GA-BFO based reconstruction algorithm and AIA based reconstruction algorithm were proposed to solve the l_0 minimization directly, which achieved the state-of-the-art reconstruction accuracy but slow reconstruction speed. Three heuristic algorithms, including simulated annealing algorithm for sparse reconstruction (SASR) [14], hybrid simulated annealing thresholding (HSAT) algorithm [15] and heuristic search algorithm for multiple measurement vectors problem [16], which were all based on simulated annealing (SA) algorithm [17–19], were proposed for the reconstruction by l_0 minimization. However, the searching strategies of the single-cycle algorithm in those three heuristic algorithms sometimes made them easy to find a local sub-optimal solution when the measurement rate is relatively small. To solve this problem, we proposed an intelligent greedy pursuit model [20] and a two-cycle optimization algorithm by combining the superiorities of intelligent optimization algorithm and greedy algorithm, which can not only solve the l_0 minimization essentially but also improve the reconstruction accuracy significantly especially when the measurement rate is relatively small. Nevertheless, the heuristic algorithms mentioned above, which were based on the intelligent searching strategies, performs more superiorly when the length of the original signal is relatively small. As the over-completed dictionary has a large amount of columns and leads to a more illness reconstruction problem, both the greedy algorithm and the heuristic algorithm can not bring their superiorities into full play. Therefore, one should turn to improve the illness reconstruction problem and shrink the searching area by extracting some prior information to reduce the computational complexity.

The geometric information of image [21,22], which can significantly influence the image perception quality, has been successfully used in many image applications, such as denoising [23,24], restoration [25,26] and super-resolution [27,28]. In the process of image reconstruction, the geometric structures such as the edges, textures and contours, can be derived as the supervised prior to reduce the computational complexity and remarkably improve the reconstruction accuracy of image structures especially when the measurement rate is relatively small. In [29] and [30], the dictionary generation method was proposed by sampling the raw patches randomly based on the similar statistical geometric structures and achieved a superior result. A novel reconstruction algorithm based on geometric structures of image was proposed in [31] to reduce the computational complexity and improve the reconstruction accuracy of image structures. In our previous work [32], we extracted the prior information by using the multi-variable scheme and edge information of image to guide the sampling and reconstruction, which achieved the state-of-the-art reconstruction accuracy with a relatively small measurement rate for medical images. We then extended the method [32] and developed as a predicted reconstruction algorithm using the guidance of prior information for medical image sequences in [33]. In [34], the self-similarity property was exploited to cluster the image patches into different classes, which was beneficial to utilizing the joint sparsity to improve the reconstruction accuracy. Also, we utilized the nonlocal self-similarity property and the property that image patches spatially nearby share the similar structures to obtain the prior information to guide the reconstruction in our previous work [35]. In [35], the method can not only reduce the computational complexity but also improve the reconstruction accuracy significantly for natural images.

In this paper, we propose a novel geometric structure based intelligent collaborative compressive sensing (G-ICCS) for image reconstruction by l_0 minimization, which aims to reduce the computational complexity and improve the image reconstruction accuracy when the measurement rate is relatively small. First of all, all the image patches are clustered into three types of geometric patterns: smooth patches, oriented patches and stochastic patches, based on the geometric structures of image and the down-sampled measurements. As the over-completed dictionary is utilized to introduce the sparsity for image patches, it is also clustered into different geometric dictionaries. Based on the corresponding geometric dictionaries, we establish three geometric structure based sparsity models for the smooth patches, oriented patches and stochastic patches, respectively. In this case, the proposed method G-ICCS can not only reduce the computational complexity significantly but also contribute a lot to improve the reconstruction accuracy of image structures. Then the nonlocal self-similarity property and the property that image patches spatially nearby share the similar structures are used to extract the geometric sparsity prior for each geometric structured sparsity model respectively to guide the reconstruction, which contributes a lot to reduce the computational complexity. Thirdly, we design the intelligent searching strategies by taking advantage of intelligent optimization algorithm in solving combinatorial optimization problems and global searching and utilizing the fast searching strategies in greedy algorithm to solve the l_0 minimization essentially. Finally, the sparse representation of each image patch is estimated by the designed intelligent searching strategies under the guidance of the geometric sparsity prior. By means of establishing the geometric structure based sparsity models based on geometric structures of image and solving the l_0 minimization essentially based on intelligent searching strategies, G-ICCS can achieve the state-of-the-art reconstruction accuracy and improve the reconstruction accuracy of image structures significantly. Also, the clustering of geometric dictionaries and the guidance of the geometric sparsity prior both can reduce the computational complexity remarkably. Experimental results on several natural images demonstrate that the proposed method G-ICCS outperforms the compared state-of-the-art algorithms in both the numerical measures and visual quality.

The major contributions of this paper is threefold:

(1) We establish the geometric structure based sparsity models based on the geometric structures of image and the geometric dictionaries, which is beneficial to enhancing the reconstruction accuracy of image structures and reducing the computational complexity.
(2) We exploit the nonlocal self-similarity property and the property that image patches spatially nearby share the similar structures to extract the geometric sparsity prior to guide the reconstruction for each geometric structured sparsity model respectively, which contributes a lot to reducing the computational complexity.
(3) We design the intelligent searching strategies by taking advantage of intelligent optimization algorithms and greedy algorithms to solve the l_0 minimization essentially and find the global optimal solution, which can remarkably improve the reconstruction accuracy especially when the measurement rate is relatively small.

The reminder of this paper is organized as follows: In Section 2, the three main stages of the proposed G-ICCS and the computational complexity analysis are provided. Experimental results and analysis are given in Section 3 to verify the superior performance of G-ICCS. Section 4 concludes this paper.