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Predicted multi-variable intelligent matching pursuit algorithm for image sequences reconstruction based on l_0 minimization

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A B S T R A C T

In this paper, we study the problem of reconstructing image sequences which satisfy the conditions that (a) the sparsity level is high in the wavelet domain and (b) the sparsity pattern of adjacent images changes very slowly. The idea of the proposed method predicted multi-variable intelligent matching pursuit (PMIMP) algorithm is to use the estimated support collection of the previous image as prior information and then utilize the prior information to guide the current image reconstruction by solving l_0 minimization. Multi-variable scheme is used to sample image sequences to enhance the guidance of prior information and improve the reconstruction accuracy with fewer measurements. l_0 minimization is an NP-hard problem that requires exhaustively listing all possibilities of the original signal and is difficult to be achieved by traditional algorithms. To solve it, we take advantage of the intelligent optimization algorithm which is famous for its global searching ability and superior performance in solving combinatorial optimization problems. To improve the reconstruction speed, matching strategies of greedy algorithm, which performs quite well in reconstruction speed, are utilized to design the updating mechanism of PMIMP. As the sparsity level is hard to be estimated in image sequences reconstruction, we propose a novel optimization function which does not need the sparsity level known as a prior. We illustrate the reconstruction performance of our proposed method PMIMP on several image sequences and compare it with the state-of-the-art algorithms. The experimental results demonstrate that PMIMP achieves the best reconstruction performance in both PSNR, SSIM and visual quality with fewer measurements.

1. Introduction

Image sequences, such as computed tomography (CT) image sequences and magnetic resonance (MR) image sequences, satisfy the conditions that (a) the sparsity level of each image is high in the wavelet domain and (b) the sparsity pattern of adjacent images changes very slowly. So compressive sensing (CS) [1–3] can be used to reconstruct the original sequences from a much smaller number of measurements. One kind of the existing methods [4–6] for image sequences reconstruction treats all the frames in the sequences as a single spatiotemporal signal, which leads to a very high computational complexity. An alternative kind of methods would apply compressive sensing reconstruction to each frame separately, which has a low computational complexity but needs more measurements to achieve the accurate reconstruction.

Image sequences reconstruction based on l_0 minimization is an NP-hard problem which is difficult to be achieved by traditional algorithms. Methods available for solving the l_0 minimization directly are greedy algorithms [7], such as orthogonal matching pursuit (OMP) algorithm [8], subspace pursuit (SP) algorithm [9], stagewise orthogonal matching pursuit (StOMP) algorithm [10], polytope faces pursuit (PFP) algorithm [11], backtracking-based matching pursuit (BAOMP) algorithm [12], sparsity adaptive matching pursuit (SAMP) algorithm [13] and compressive sampling matching pursuit (CoSaMP) algorithm [14]. Suppose the sparsity level is known as a prior, the purpose of greedy algorithm is to estimate the support collection and its corresponding coefficients using the least square method based on the residual correlation. However, the residual correlation just can reflect the correlative degree between the coefficients and the measurement signal, but cannot indicate that the larger the residual correlation is, the larger the coefficient should be. Another common shortcoming of greedy algorithm is that it is more likely to fall into a sub-optimal solution. While intelligent optimization algorithm [15–17] is famous for its global searching ability and superior performance in solving combinatorial optimization problems, it is deserved to be used to solve l_0 minimization essentially. Simulated annealing algorithm is widely used for CS reconstruction by l_0 minimization, such as

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hybrid simulated annealing thresholding (HSAT) algorithm [18], simulated annealing algorithm for sparse reconstruction (SASR) [19] and heuristic search algorithm for multiple measurement vectors problem (HSAMMV) [20]. The proposed methods in [18–20] are both single-cycle, which are time-consuming and easy to find a sub-optimal solution when the measurement number is relatively small. Also, the precondition of [18–20] is that the sparsity level must be known as a prior. However, the sparsity level is hard to be estimated in many reconstruction problems. In our previous work [21,22], we propose two reconstruction methods based on the combination of genetic algorithm and bacterial foraging optimization (GA-BFO) algorithm and artificial immune algorithm (AIA), which perform quite well in reconstruction accuracy. Nevertheless, the computational complexity of the two methods are high, which leads to the slow reconstruction speed.

Prior information, which plays an important role in image processing, can not only improve the efficiency of the reconstruction algorithms but also reduce the computational complexity to accelerate the reconstruction speed. Many methods using image structures as the prior information were proposed. Sajjad et al. [23] proposed a novel framework for image super-resolution using an over-complete dictionary based on effective image-representation, such as edges, contours and high-order structures. A new framework for single image and video super-resolution is proposed in [24], which aims to employ the geometric details of the image as the prior information to minimize the possible artifacts. Mehmood et al. [25] also used some image structures to calculate the image priority, such as the novel features derived from an integral-image and the integral-image-based temporal gradients, which can extracts semantically important frames from the video to reduce the bandwidth requirement. If the sparsity pattern of adjacent images in the image sequences changes very slowly, it is natural to apply some information of the previous image as the prior information to guide the current image reconstruction. In [26], the authors proposed a method called Kalman Filtered compressive sensing (KF-CS), which runs a reduced order Kalman filter with the current estimated support and estimates new additions to the support set by applying CS to the Kalman innovations or filtering error. Vaswani [27] proposed a least square method (LS-CS) for image sequences reconstruction by using compressive sensing on the least square residual computed by the estimated support collection of the previous image instead of using compressive sensing on the measurement data. The modified compressive sensing method (modified-CS) was proposed for image sequences reconstruction with partially known support in [28]. The purpose of the modified-CS is to solve a convex relaxation of the problem that find the signal which satisfies the data constraint and is the sparsest outside the known support. Afterwards, some more powerful methods such as modified-CS-residual [29,30] and regularized modified-CS [31,32] were developed. Other recent work which applies compressive sensing to measure the difference signal and then reconstructs the difference signal was proposed in [33]. Also, the weighted-CS proposed in[34] used the estimated previous frame to extract an estimated probability model and then used the model to guide the reconstruction process.

In this paper, we propose a novel method called predicted multi-variable intelligent matching pursuit (PMIMP) for image sequences reconstruction. PMIMP, which aims to estimate the support collection of the current original image intelligently and accurately based on the limited number of measurements and the prior information, addresses the l_0 minimization problem essentially. First of all, based on the fact that the sparsity pattern of adjacent images is correlative and changes slowly, we set the estimated support collection of the previous image as the prior information. After that, we use the prior information to guide the current image reconstruction, which can not only reduce the computational complexity but also reconstruct the current image accurately using fewer measurements. Also, multi-variable scheme, which takes advantage of the statistic dependency among the wavelet coefficients, is used to sample the original image to enhance the guidance of the prior information and improve the reconstruction performance significantly. Then, as the sparsity level is hard to be estimated in image sequences reconstruction, we propose a novel optimization function which does not need the sparsity level known as a prior. In addition, we utilize the advantage of intelligent optimization algorithm in solving combinatorial optimization problems to solve the l_0 minimization essentially, which is also beneficial to finding the global optimal solution (support collection). To improve the reconstruction speed, matching strategies of greedy algorithm, which performs quite well in reconstruction speed, are introduced to design the updating mechanism of PMIMP. As PMIMP can solve l_0 minimization essentially and find the global optimal solution, it improves the reconstruction accuracy significantly for image sequences. By means of setting the estimated support collection as the prior information and introducing matching strategies to design the updating mechanism, PMIMP also has a reasonable reconstruction speed, especially when the sparsity pattern changes slowly. Experiments on phantom image sequence, brain CT image sequence and brain MR image sequence based on PMIMP and other state-of-the-art algorithms, including OMP, CoSaMP, edge based matching pursuit algorithm (EMPA) [35], Kalman Filtered compressive sensing (KF-CS) method, least square residual compressive sensing (LS-CS) method, KFLS-CS and Modified-CS, are used to illustrate the superiorities of the proposed method PMIMP.

In accordance with the process of CS, the major contributions of this paper are fourfold:

1. We use the estimated support collection of the precious image as the prior information to guide the current image reconstruction, which can not only reduce the computational complexity but also reconstruct the current image accurately using fewer measurements.
2. We use multi-variable scheme to sample each frame of the original image sequences, which is beneficial to enhancing the guidance of prior information and improving the reconstruction performance significantly.
3. As the sparsity level of image sequences is hard to be estimated, we develop a novel optimization function for image sequences reconstruction when the sparsity level is unknown as a prior.
4. We solve the l_0 minimization problem essentially by taking advantage of intelligent optimization algorithm in combinatorial optimization problems and improve the reconstruction speed by introducing matching strategies of greedy algorithm.

The reminder of this paper is organized as follows: In Section 2, the related works are provided for an easy understanding of our proposed method. In Section 3, the framework of PMIMP and the computational complexity analysis are provided. Experimental results are given in Section 4 to illustrate the performance of the proposed method PMIMP. Section 5 concludes this paper.

2. Related works

2.1. Image sequences reconstruction

Suppose the original image sequence is represented by $X := [x_1, x_2, \ldots, x_n]$, where $x_i,\ i = 1, 2, \ldots, n$ represents the ith frame of the original image sequence. In compressive sensing