Digital Signal Processing 79 (2018) 23–33

Contents lists available at ScienceDirect

Digital Signal Processing

www.elsevier.com/locate/dsp

Coded diffraction imaging via double sparse regularization model

Baoshun Shi, Qiusheng Lian*, Shuzhen Chen, Ye Tian, Xiaoyu Fan

School of Information Science and Engineering, Yanshan University, Qinhuang Dao, 066004, Hebei province, China

ARTICLE INFO

Article history:
Available online 22 April 2018

Keywords:
Phase retrieval
Coded diffraction imaging
Poisson noise
Low rank
Total variation

ABSTRACT

Coded diffraction patterns (CDPs) recorded by optical detectors are often affected by Poisson noise in optical applications. How to recover the image of interest from few noisy CDPs is a challenge. In this paper, a double sparse regularization (DSR) model that exploits both the gradient sparsity and the structured sparsity is proposed to recover the image of interest from the recorded CDPs corrupted with Poisson noise. An image patch group matrix is formed by stacking similar image patches one by one. Owing to the similar structure of these image patches, the formed image patch group matrix is low rank. Based on this fact, a group low rank (GLR) regularization model is formulated. Combining the GLR model and the total variation (TV) model, we propose the so-called DSR model. The DSR model is utilized to formulate a phase retrieval optimization problem that consists of two terms: (i) the Poisson likelihood fidelity term, (ii) the proposed DSR model of utilizing TV and GLR. The accelerated gradient descent method that utilizes the adjustable gradient clipping technique is presented to solve the corresponding problem. Experimental results demonstrate that the proposed algorithm can recover the image with high quality from few CDPs, and can be robust to Poisson noise.

© 2018 Elsevier Inc. All rights reserved.

1. Introduction

In the past several decades, phase retrieval (PR), i.e., recovery of the object or image from the recorded magnitudes or intensities of its linear transform, is an old, but hot topic. The PR technique arises in various science and engineering fields, including optics [1], X-ray crystallography [2], astronomy [3], and signal processing [4]. Since limited information about the image of interest is recorded by the charge-coupled-device (CCD) detector in optical systems, recovering the image of interest from the non-linear measurements is a challenging task. To acquire more information about the image compared to the traditional PR sampling systems, a coded diffraction imaging system that acquires the diffraction patterns of the modulated signal was designed by Candes [5]. The recorded diffraction pattern is called a coded diffraction pattern (CDP), which carries more image information compared to the Fourier intensity under the same scenario. Subsequently, various PR algorithms based on the CDP model were developed.

The first class of approaches to solve the PR problem is the PR technique based on a semidefinite program (SDP) method [5,6]. In general, this class of PR algorithms first formulates a low-rank PR optimization problem via the PhaseLift technique, and then translates the resulting non-convex problem into a convex one, which we expect. However, the SDP-based PR algorithms that replace the signal vector with a higher-dimensional matrix are not suitable for large-scale problems.

Recently, according to the maximum posterior probablity (MAP) rule, a non-convex but smooth least-squares estimation problem was formulated. The corresponding problem is usually solved by gradient-based methods, examples of which include Wirtinger flow (WF) [7], truncated Wirtinger flow (TWF) [8], reweighted Wirtinger flow [9], sparse truncated Wirtinger flow [10], and median truncated Wirtinger flow [11]. The provable convergence of these algorithms leads them to popular ones. However, image inherent priors are ignored in these algorithms. As a result, they often suffer from bad reconstructions in the case of a few CDPs. An alternative strategy is to exploit the regularization model, which imposes a certain desirable property on the recovered image. The most popular regularization model is the sparse regularization model. This regularization model has been utilized to develop effective PR algorithms. Tillmann *et. al.* [12] exploited the sparse representation model under an adaptive synthesis dictionary to construct the regularization term, and proposed the so-called DOLPHIn (DictiOnary Learning for PHase retrIeval) algorithm. Experiments for real-valued images validated that higher reconstruction quality was achieved by DOLPHIn, compared with the WF algorithm. Katkovnik [13] derived a sparse phase amplitude reconstruction (SPAR) algorithm based on sparse models of magnitude and absolute phase of the

* Corresponding author.
E-mail addresses: shibaoshun@ysu.edu.cn (B. Shi), lianqs@ysu.edu.cn (Q. Lian), chensz@ysu.edu.cn (S. Chen), tianye@ysu.edu.cn (Y. Tian), fxy50210@163.com (X. Fan).

https://doi.org/10.1016/j.dsp.2018.04.010
1051-2004/© 2018 Elsevier Inc. All rights reserved.

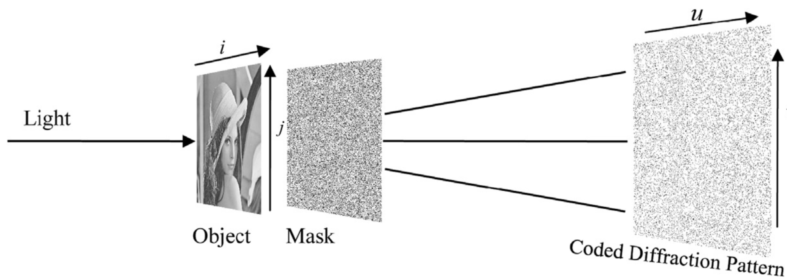

Fig. 1. Illustration of realistic CDP model.

complex-valued object. In the SPAR algorithm, block-matching and three-dimensional (3D) filtering (BM3D) frames [14] were utilized for sparse models. Compared to the TWF algorithm, experimental results indicated that the SPAR algorithm could achieve higher reconstruction quality. More recently, Chang et al. [15] exploited the total variation (TV) regularization model for PR, and developed an effective algorithm by using orthogonal dictionary learning in their following work [16]. Numerical experiments [12,13,15,16] demonstrated that the regularized PR algorithms out-performed the PR algorithms without regularization.

Many PR algorithms for recovering the image from the recorded CDPs corrupted with Gaussian noise were developed. However, for realistic applications, the measurements are often contaminated by Poisson noise. How to recover the high-quality image from Poisson-noisy CDPs is an important issue. To improve the reconstruction quality, we exploit the structured sparsity and the gradient sparsity (sparse in gradient domain) for PR. The similar image patches are grouped to form a data matrix, and we call this formed matrix as image patch group. Each patch in the image patch group contains similar structures, which implies the structured sparsity. The structured sparsity has been utilized for solving image inverse problems. The algorithms of exploiting the structured sparsity for image restoration have been proposed, such as the adaptive iterative singular-value thresholding (SAIST) algorithm [17], the weighted nuclear norm minimization (WNNM) algorithm [18], and the compressed sensing via non-local low-rank regularization (NLR-CS) algorithm [19]. Moreover, the BM3D image denoising with shape-adaptive principal component analysis (BM3D-SAPCA) algorithm that exploits non-local similarity was proposed [20]. Differ from these works, we exploit the structured sparsity for diffraction imaging, i.e., recovering the image only from the intensities of its linear transform. Based on the fact that the image patch group is low rank, we formulate the group low-rank (GLR) model to characterize the low-rank property of the image patch group. The TV model and the GLR model are fused to formulate a double sparse regularization (DSR) model. The main contributions of the current paper are as follows:

(1) Based on the fact that the image patch group is low rank, we formulate a GLR regularization model that exploits the structured sparsity. The GLR model is a general sparse model, and it is suitable for any image inverse problem, not just limits in phase retrieval.

(2) We propose a double sparse regularization model that exploits both the TV model and the GLR model. In fact, the DSR model characterizes not only the sparsity of the underlying image in the gradient domain, but also the low-rank property of the image patch group.

(3) According to the Poisson data model and the MAP rule, we derive a regularized PR model under the Poisson case. The DSR model that can characterize multiple image priors is utilized to formulate a PR optimization problem. The accelerated gradient descent method that exploits the adjustable gradient clipping technique is proposed to solve the formulated non-convex problem. Experimental results show that the proposed algorithm out-performs the previous PR algorithms in terms of the reconstruction quality for the case of a few CDPs. Most importantly, the proposed algorithm is robust to Poisson noise.

The structure of this paper is as follows. In Section 2, we review previous PR models and algorithms. Then, in Section 3, we introduce the GLR model. In Section 4, we firstly formulate the PR problem of exploiting the DSR model, and then describe the proposed numerical method for solving the corresponding optimization problem in detail. We present our experimental simulations in Section 5. Finally, concluding remarks and directions for future research are presented in Section 6.

2. Phase retrieval models and algorithms

In various optical applications, the measurements acquired by detectors are often affected by noise; therefore, it is important to study robust PR algorithms. The CDP model has gained popularity in the PR field in recent years. Fig. 1 presents an illustration of the realistic setup of the CDP model. In the figure, i and j represent the index values of the horizontal direction and the vertical direction in the object plane, respectively. u and v represent the index values in the sensor plane. A light or X ray illuminates the object (signal or image) of interest, and a random mask is placed behind the object to modulate the signal. The measurement device records the diffraction pattern of the modulated signal, and the recorded diffraction pattern is called the CDP. Mathematically, given a real image $\mathbf{x} \in \mathbb{R}^N$, the CDP model under the noise case can be described as

$$\mathbf{y} \approx |\mathbf{\Phi x}|^2, \tag{1}$$

where $|\cdot|$ is the magnitude operator, and $\mathbf{y} \in \mathbb{R}^M$ represents the CDP acquired by the detector. In model (1), $\mathbf{\Phi x}$ is defined as follows:

$$\mathbf{\Phi x} = [\mathbf{F I}_1 \odot \mathbf{x}, \ldots, \mathbf{F I}_L \odot \mathbf{x}]^{\mathrm{T}}, \tag{2}$$

where $[\mathbf{I}_1, \ldots, \mathbf{I}_L]$ represents the illumination mask, L is the number of the illumination masks, and $\mathbf{F}$ represents a Fourier-transform matrix. $\odot$ denotes the element-wise product. Recovering the image $\mathbf{x}$ from the CDP $\mathbf{y}$ is the goal of PR algorithms. Recently, Candes [7] proposed the WF algorithm, and constructed the following non-convex optimization model

$$\min_{\mathbf{x}} \ ||\mathbf{y} - |\mathbf{\Phi x}|^2||_2^2. \tag{3}$$

The above problem is solved by a gradient descent scheme in the WF method. The WF method often starts with an elaborate initialization that is obtained by means of the spectral method. Experimental results showed that the WF method could recover the image perfectly from sufficient noiseless measurements. On the theoretical side, the WF algorithm was shown to allow the exact

Download English Version:

https://daneshyari.com/en/article/6951668

Download Persian Version:

https://daneshyari.com/article/6951668

Daneshyari.com