Optics & Laser Technology 63 (2014) 83–89

Contents lists available at ScienceDirect

Optics & Laser Technology

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

Innovative remote sensing imaging method based on compressed sensing

Li Sheng-liang [1], Liu Kun *, Zhang Feng, Zhang Li, Xiao Long-long, Han Da-peng

Institute of Space Technology, College of Aerospace Science and Engineering, National University of Defense Technology, Deya Road, Changsha, China

A R T I C L E I N F O

Article history:
Received 9 December 2013
Received in revised form
27 March 2014
Accepted 29 March 2014
Available online 23 April 2014

Keywords:
Compressed sensing
Remote sensing video
Phase modulator and subframe

A B S T R A C T

Compressed sensing (CS) has good application prospects in remote sensing imagery. In particular, CS theory can be used to alleviate the burden for remote sensing data transmission and recover scenes at high resolution. However, the application of CS theory to practical remote sensing imaging systems involves some key challenges: (i) Many random projections cannot be implemented in practical systems. (ii) These random projections cannot change after the linear optical system is fixed. (iii) Some traditional imaging systems, such as single-pixel cameras, are unfit for spacecraft. Therefore, innovative imaging systems must be designed for remote sensing imaging. In this paper, we review CS theory, and present a remote sensing (RS) imagery system based on CS. The video sequence measurement model is introduced. Three CS optical architectures, namely, single-pixel, coded aperture, and photon-superimposition, are presented. We then design a new imaging architecture that uses a phase modulator and subframe superimposition, and introduce phase modulator matrix in correspondence. A coupled reconstruction model for recovering video is proposed. Through numerical simulations, we demonstrate the effectiveness of the optical architectures and compare it with two traditional architectures (coded aperture, and photon-superimposition). The effectiveness of coupled models is compared with traditional single models. We can conclude that, the proposed imaging architecture can precisely assess resolution and increase field of view. Furthermore, the presented coupled model can easily improve accuracy and speed of video reconstruction.

1. Introduction

Compressed sensing (CS), which captures and represents compressible signals at a sampling rate significantly below the Nyquist rate, serves as a framework for signal sampling and reconstruction based on signal sparsity or compressibility [1,2]. CS has good application prospects in remote sensing (RS) imagery [3,4]. RS data need to be transmitted back to Earth. To transmit the data collected by satellites back to Earth, conventional imaging principles require high compression ratios, which introduce inevitable distortions and mosaic artifacts. CS-based RS directly records one or few pixels to improve transmission problems. CS-based RS includes two stages: onboard encoding imaging and offline decoding recovery [3]. Offline decoding recovery has long been investigated [5–8] as an inverse problem, but theoretical support for onboard encoding imaging is lacking. Two main challenges are encountered in onboard encoding. First, the field of vision (FOV) of RS imaging is restricted by a focal plane array on spacecraft. Second, many CS reconstruction algorithms are accelerated by exploiting key properties of the sensing matrix. Once the algorithms are changed, the sensing matrices must be adjusted accordingly. However, the sensing matrices cannot be changed because the linear optical architectures are fixed.

In this paper, we review several practical systems for measuring a varying scene and explore practical systems to address the above challenges in the context of phase modulator and subframe superimposition optical architecture. Accordingly, a multi-frame difference reconstruction model is proposed for RS video systems. This architecture can precisely assess resolution by using a phase modulator and increase FOV by using subframe superimposition optical architecture.

The rest of the paper is organized as follows: Section 2 reviews CS, a signal processing theory, and presents an RS imagery system based on CS. In Section 3, we introduce the video sequence measurement model. Three CS optical architectures, namely, single-pixel, coded aperture, and photon-superimposition, are presented. We then design the CS imaging system based on a phase modulator and subframe superimposition. The phase modulator matrix is designed in correspondence with this system based on a

* Corresponding author. Tel.:13308491272; fax: +86 07318457194.
E-mail addresses: lishengliang@nudt.edu.cn, lishengliang@163.com (L. Sheng-liang), liukun_open@163.com (L. Kun).
[1] Tel.: +86 13469428395; fax: +86 07318457194.

http://dx.doi.org/10.1016/j.optlastec.2014.03.019
0030-3992/© 2014 Elsevier Ltd. All rights reserved.

converse principle. A coupled reconstruction model for recovering video is proposed in Section 4. Section 5 reports numerical results and performance comparison results of the three imaging systems and two reconstruction models. The final section concludes this paper.

2. Remote sensing imaging system based on compressed sensing

CS is an efficient and fast-growing signal recovery framework. The basic principle of CS theory is that when the image of interest is very sparse or highly compressible, relatively few well-chosen observations are sufficient for reconstructing the most significant non-zero components. The CS model is described as

$$(P_0)\ \hat{x} = \min ||x||_0\ s.t.\ y = \Phi \times f = \Phi \times \Psi \times x = \Theta \times x, \tag{1}$$

where $Y \in Z^M$ is an M-dimensional observation vector. $f \in R^N$ is an N-dimensional unknown signal that can be sparsely represented as $f = \Psi \times x$ on an orthonormal basis Ψ. If only K ($K < < N$) non-zero components of x are observed, f is defined as K-sparse. Φ denotes a $M \times N$ ($K < < N$) matrix called the measurement matrix. Θ is a sensing matrix compounded by Φ and Ψ.

To successfully reconstruct a signal with incomplete measurements, Θ must satisfy a special property called the restricted isometry property (RIP) [9,10], that is, for all K-sparse $x \in R^N$, a constant $\delta_k \in (0,1)$ exists so that

$$1 - \delta_k \le \frac{||\Theta x||_2^2}{||x||_2^2} \le 1 + \delta_k. \tag{2}$$

The problem (P_0) is a combinatorial feature that is generally difficult to solve. To solve the problem (P_0), it can be transformed into a linear programming problem

$$(P_1)\ \hat{x} = \min ||x||_1\ s.t.\ y = \Phi \cdot f, \tag{3}$$

where $||x||_1 = \sum_{i=1}^{N} |x_i|$. We call (P_0) L_0 regularization and (P_1) L_1 regularization. L_1 regularization is widely used.

RS imagery calls for more stringent imaging resolution requirements. High-resolution imaging systems require large pixel arrays and small pixel pitch. Such a system produces a large amount of data, which causes considerable burden on data storage and real-time transmission. CS-based RS imaging directly records very limited pixels to improve transmission problems, as presented in the next section. A spacecraft RS video system performs compressed measurement, remote transmission, and reconstruction, as shown in Fig. 1. We consider compressed measurement and video reconstruction in the following sections.

3. Compressed measurement

The process of recording limited pixels is called compressed measurement, which is beneficial to remote transmission. Recent studies investigated the theoretical and practical aspects of

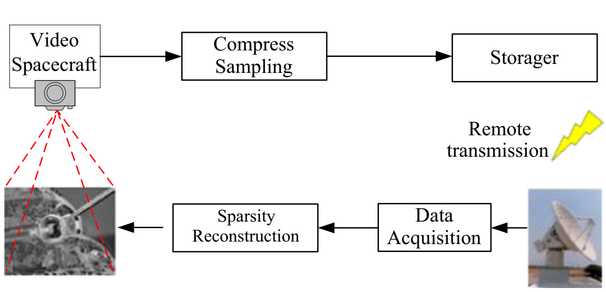

Fig. 1. Remote sensing imaging based on CS.

compressed measurement. For the theoretical aspect, selection of optimal measurement matrices is widely studied in literature. However, the practical aspects of optical system design make this infeasible in our setting.

We present a measurement model for CS-based RS video, review several practical imaging systems, and outline some challenges in this section. A CS imaging system is designed to be incorporated into theoretical measurement matrices and practical architectures.

3.1. Measurement model

In general, the transmission data collected through imaging are represented as

$$y = \Phi f + w, \tag{4}$$

where $y \in R^M$ is the observed data, $w \in R^M$ is the noise, $f \in R^N$ is the image, and $\Phi \in R^{M \times N}$ is the linearly projected matrices. If $M \ll N$, the data can be compressed directly.

For the constituent images of a video sequence f_i, where i represents the time, the data are described as

$$y_i = \Phi_i f_i + w_i. \tag{5}$$

The measurement matrix Φ_i can correspond to various video imaging systems.

3.2. Conventional CS optical architectures

In this section, three architectures for CS are given, which allows us to have complete control over the types of measurements we make: (i) single-pixel, in which measurements are taken a different random projection at each time; (ii) coded aperture, in which multiple measurements are taken simultaneously by using a fixed mask; and (iii) photon superimposition, in which beam splitters and micromirror arrays are used to collect measurements. Here, we describe the three optical architectures with these measurement matrices that have been recently investigated in literature.

3.2.1. Single-pixel for CS imaging systems

Sensors that take the linear measurements in (4) have to be built. A well-known example of this is the “single-pixel” of [3,11]. This system uses only a single detector element to image a scene. The measurement matrix operation can be modeled as

$$y = \Phi^{(\text{pinhole})} f + w, \tag{6}$$

where $\Phi^{(\text{pinhole})}$ is usually a Bernoulli matrix because the “0” and “1” elements can be realized by a proper physical mask design that blocks or passes light, respectively.

This system has the following advantages: the architecture requires only one detector element, and any Bernoulli projection matrix can be implemented in this system. However, this system requires the camera to remain focused on the scene for a long time, that is, the scene has to remain static. Thus, the single-pixel camera is unsuitable for RS video on dynamic spacecraft.

3.2.2. Coded aperture for CS imaging systems

Coded aperture imaging is introduced to construct a mask pattern that introduces a more complicated point spread function than that associated with a pinhole. The measurement matrix operation can be expressed as

$$y = \Phi^{(CCA)} f + w, \tag{7}$$

where the measurement matrix $\Phi^{(CCA)} = D(h^{(CCA)} \otimes \tilde{h}^{(CCA)})$ approximately equals the Kronecker δ function multiplied by a downsampling operator. If a coded aperture imaging mask $h^{(CCA)}$ is designed by