Optics Communications 417 (2018) 1–13

Contents lists available at ScienceDirect

Optics Communications

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

Adaptive single-pixel imaging with aggregated sampling and continuous differential measurements

Yaoran Huo [a], Hongjie He [a], Fan Chen [a,*], Heng-Ming Tai [b]

[a] Sichuan Key Laboratory of Signal and Information Processing, Southwest Jiaotong University, Sichuan, Chengdu 611756, China

[b] Department of Electrical and Computer Engineering, University of Tulsa, Tulsa, OK 74104, USA

ARTICLE INFO

Keywords:
Adaptive imaging
Single-pixel imaging
Aggregated sampling
Continuous differential measurement

ABSTRACT

This paper proposes an adaptive compressive imaging technique with one single-pixel detector and single arm. The aggregated sampling (AS) method enables the reduction of resolutions of the reconstructed images. It aims to reduce the time and space consumption. The target image with a resolution up to 1024×1024 can be reconstructed successfully at the 20% sampling rate. The continuous differential measurement (CDM) method combined with a ratio factor of significant coefficient (RFSC) improves the imaging quality. Moreover, RFSC reduces the human intervention in parameter setting. This technique enhances the practicability of single-pixel imaging with the benefits from less time and space consumption, better imaging quality and less human intervention.

1. Introduction

Compressive-sensing-based single-pixel imaging (CS-SPI) [1,2] introduces compressive sensing [3,4] into the imaging technology for a better imaging quality with less sampling resource. CS-SPI can sense an n dimensional sparse signal with m ($<n$) measurements to reconstruct the original signal with the optimization strategies. Single-pixel imaging (SPI) has attracted more attentions in recent years [5–9]. It has been applied to three-dimensional imaging [10–12], terahertz imaging [13,14], microscopy [15,16], and the secure key distribution [17,18].

CS-SPI intends to provide superior imaging quality with low time and space complexity. Conventional SPIs [1,7–9] detect the target with the random 0/1 binary speckle patterns loaded onto a digital micro-mirror devices (DMD) and reconstruct the image with the convex optimization strategy [19]. However, these 0/1 measurement matrices do not satisfy the restricted isometry property (RIP) condition [20,21]. To address this problem, the differential strategies [21–25] have been proposed, which use the random -1/1/0 ternary measurement matrices. The differential measurement matrix with a mean of ∼0 satisfy the RIP with a great probability and provides a higher-quality image. Since the resolution is large for the target image with a larger resolution than 256×256, CS-SPI [7–9,21–25] suffers from severe time and space consumption [26].

To reduce the computational complexity in CS reconstruction, the adaptive single-pixel imaging schemes have been proposed to adaptively sample the significant regions at multi-scales. The schemes utilize the structural sampling [5,26–28] and random sampling [29–31]. The random sampling strategies only samples the significant regions at the finer scales localized by the results at the coarser scales [29,30]. These strategies lower the reconstruction resolution so as to reduce the time and space complexity. However, a waste of sampling resource occurs in that the sampled data at the coarser scales are not used for the final reconstruction. Adaptive compressive ghost imaging (ACGI), which utilizes all the sampled significant wavelet coefficients for the final reconstruction, was proposed to overcome this problem [31]. However, the time and space consumption of CS-based adaptive strategies can be further reduced [32]. Moreover, the imaging quality under the noisy environments is unsatisfactory since the random 0/1 binary measurement matrix cannot achieve a good performance with respect to the RIP condition.

In this paper, we propose an adaptive single-pixel imaging (ASPI) strategy that enables high imaging quality and reduces the computational consumption. The low computational complexity goal is achieved by the aggregated sampling (AS) and the continuous differential measurement (CDM) reconstruction methods. The significant wavelet bands with fewer errors are sensed by AS and reconstructed by CDM. A ratio factor of significant coefficient (RFSC) is used to optimally allocate the ratio of significant coefficients at each scale with less human intervention. In addition, the proposed ASPI method can be used in the weak light condition. This is a significant improvement for the practicability of SPI.

This paper is organized as follows. Section 2 describes the ASPI model based on the AS and CDM methods with the non-square speckle patterns (NSPs) and the aggregated square speckle patterns (ASSPs). Section 3 analyzes the optimal choice of RFSC via statistical results of

* Corresponding author.
E-mail addresses: yrhuo_swjtu@my.swjtu.edu.cn (Y. Huo), hjhe@home.swjtu.edu.cn (H. He), fchen@home.swjtu.edu.cn (F. Chen), tai@utulsa.edu (H.-M. Tai).

https://doi.org/10.1016/j.optcom.2018.02.021
Received 7 November 2017; Received in revised form 25 January 2018; Accepted 8 February 2018

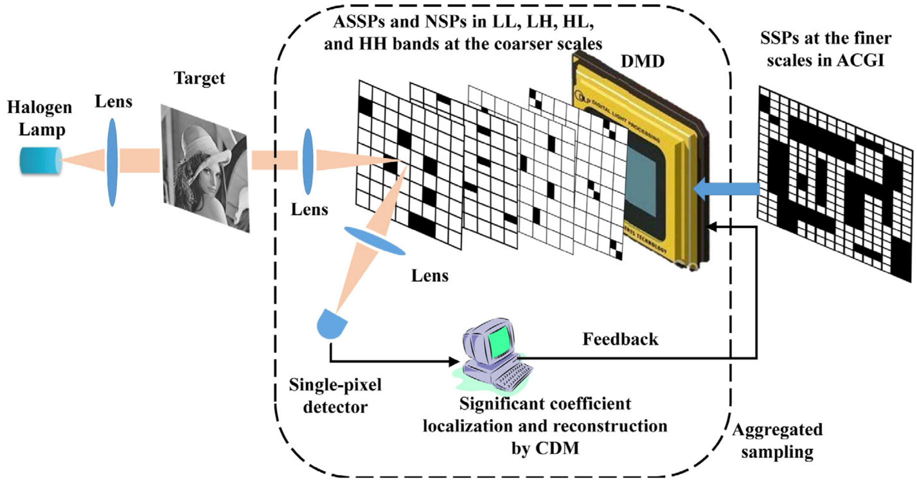

Fig. 1. Schematic of ASPI based on the AS and CDM methods.

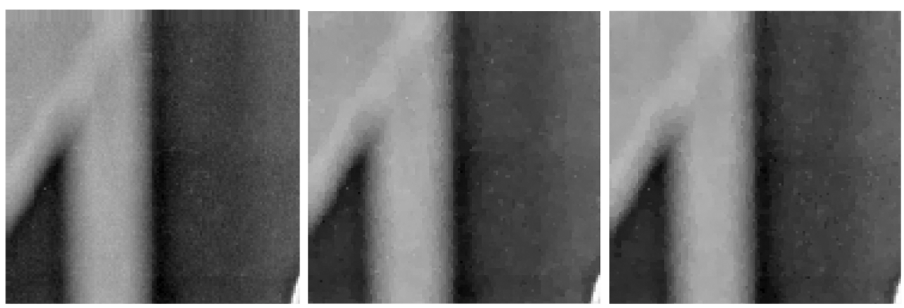

Fig. 2. Reconstruction results with different reconstruction resolutions (a) Original image with the resolution of 128×128 (b) Reconstruction result with reconstruction resolution of 128×128 (c) Reconstruction result formed by the reconstructed sub-images.

the images with different resolutions. Simulation results on the imaging quality, time and space complexity are given in Section 4. Finally, a brief summary is presented in Section 5.

2. Adaptive single-pixel imaging based on AS and CDM

In this section, the proposed ASPI technique adopting AS and CDM is described in detail. Fig. 1 is the schematic of the proposed ASPI method with one single-pixel detector and single-arm. The target object illuminated by a Halogen Lamp is modulated by a DMD. The signal light is collected by a detector and transmitted to the computer. A digital image is used as the target object for simulation. ASPI is based on the wavelet transformation theory [33]. Firstly, a coarse image is retrieved with a series of random 0/1 binary full screen ASSPs, of which the speckles are of the largest pixel size. Then, the significant coefficients at the finer scale are localized by the sampled coefficients at the coarser scale and a threshold based on the parent–children relationship. This threshold is generated by RFSC. The significant coefficients are sensed with a series of NSPs and ASSPs, and reconstructed by CDM. The steps of prediction, sensing and reconstruction in AS iterate until all the sampling resources are used up or the size of speckles is 1×1 the same as the resolution of DMD. The final image is reconstructed by the inverse wavelet transform using the sampled significant coefficients.

2.1. Sampling method in ACGI

ACGI first retrieves the LL band at finer scale $j-1$ with the sparse random 0/1 binary speckle patterns and obtain the significant coefficients at scale j by one-level wavelet decomposition. According to the wavelet tree, the resolution of significant coefficients at scale $j-1$ is larger than the resolution at scale j. Fig. 2 shows the reconstruction result with different reconstruction resolutions for the same image. TVAL3 (TV minimization scheme based on augmented Lagrangian and alternating direction algorithms) is used in CS reconstruction [32]. In each pattern, the ratio of the number of pixel 1 to the number of all the pixels is 0.005. The original image with the resolution of 128×128 selected from the 8-bit grayscale digital image Lena shown in Fig. 2(a) is used for simulation. The reconstruction result at 40% sampling rate is shown in Fig. 2(b). On the other hand, the original image is divided into four sub-images with the resolution of 64×64, which are sampled at 40% sampling rate. The final reconstruction result is shown in Fig. 2(c). The time consumption of the CS reconstruction is evaluated by the sum of time consumption for reconstructing these four sub-images.

Fig. 2(b) and 2(c) show that similar reconstruction quality in terms of Peak Signal to Noise Ratio (PSNR) of 38 dB and 38.3 dB, respectively, are obtained. PSNR for the 8-bit grayscale image is calculated by

$$\mathrm{PSNR} = 10\log_{10}\left(255^2 / \sum_{x,y}\left(I_{(x,y)} - I'_{(x,y)}\right)^2\right), \tag{1}$$

Where $\log_{10}$ represents the base-10 logarithm. $I_{(x,y)}$ and $I'_{(x,y)}$ are the pixel values at the coordinate (x,y) in the original image I and retrieved image I', respectively. However, the time and peak space consumption of Fig. 2(b) in CS reconstruction is 21 s and 2568 kb, respectively. The storage space of the measurement matrix is 1741 kb. In Fig. 2(c), the total time consumption and peak space consumption for four sub-images are 6 s and 936 kb, respectively. The storage space of all the speckle patterns is 428 kb. We can see that the time consumption, peak space consumption and storage space are reduced if the original image is divided into several sub-images with lower resolution. In summary,