Software Impacts 9 (2021) 100081

Contents lists available at ScienceDirect

Software Impacts

journal homepage: www.journals.elsevier.com/software-impacts

Original software publication

OpenICS: Open image compressive sensing toolbox and benchmark

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ARTICLE INFO

Keywords:
Compressive sensing
Computer vision
Machine learning
Signal processing
Image processing

ABSTRACT

The real-world application of image compressive sensing is largely limited by the lack of standardization in implementation and evaluation. To address this limitation, we present OpenICS, an image compressive sensing toolbox that implements multiple popular image compressive sensing algorithms into a unified framework with a standardized user interface. Furthermore, a corresponding benchmark is also proposed to provide a fair and complete evaluation of the implemented algorithms. We hope this work can serve the growing research community of compressive sensing and the industry to facilitate the development and application of image compressive sensing.

Code metadata

Current code version	v1
Permanent link to code/repository used for this code version	https://github.com/SoftwareImpacts/SIMPAC-2021-52
Permanent link to Reproducible Capsule	https://codeocean.com/capsule/6184610/tree/v1
Legal Code License	Mixed. Refer to https://github.com/PSCLab-ASU/OpenICS/blob/master/LICENSE for details.
Code versioning system used	git
Software code languages, tools, and services used	Python, MATLAB, Pytorch, Tensorflow
Compilation requirements, operating environments & dependencies	https://github.com/PSCLab-ASU/OpenICS/blob/master/README.md
If available Link to developer documentation/manual	https://github.com/PSCLab-ASU/OpenICS/blob/master/README.md
Support email for questions	zzhan362@asu.edu

Software metadata

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Permanent link to executables of this version	https://github.com/PSCLab-ASU/OpenICS
Permanent link to Reproducible Capsule	https://codeocean.com/capsule/6184610/tree/v1
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Computing platforms/Operating Systems	Linux, OS X, Microsoft Windows, Unix-like
Installation requirements & dependencies	https://github.com/PSCLab-ASU/OpenICS/blob/master/README.md
If available, link to user manual–if formally published include a reference to the publication in the reference list	https://github.com/PSCLab-ASU/OpenICS/blob/master/README.md
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1. Introduction

Compressive sensing is a signal sensing technique that simultaneously performs sensing and compression of signals in order to reduce the transmission cost of sensor devices. A wide variety of image compressive sensing reconstruction algorithms has been proposed over the years with a prominent performance in terms of reconstruction speed and accuracy. However, the application of image compressive sensing in real world is largely limited by the lack of standardization in implementation and evaluation.

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https://doi.org/10.1016/j.simpa.2021.100081
Received 8 May 2021; Received in revised form 11 May 2021; Accepted 11 May 2021

To address this limitation, we present OpenICS, an image compressive sensing toolbox with multiple image compressive sensing reconstruction algorithms implemented into a unified framework to greatly improve the usability of various image compressive sensing algorithms. We also propose a corresponding benchmark to provide a comprehensive and fair evaluation of all the implemented algorithms as well as the future proposed algorithms.

We hope this toolbox and benchmark can serve the research community and the industry to facilitate the development of new image compressive sensing algorithms and the application of image compressive sensing in real-world problems.

2. Toolbox functionality and benchmark

2.1. Toolbox functionality

OpenICS has ten image compressive sensing algorithms implemented. Based on whether the method is data-dependent, we divide implemented methods into two categories: Model-based methods and data-driven methods. Model-based methods include L1[1], NLR-CS [2], TVAL-3[3] and D-AMP [4]. Data-driven methods include ReconNet [5], LDAMP [6], ISTA-Net [7], LAPRAN [8], CSGM [9], CSGAN [10]. Each method is reimplemented with a standard interface, same parameter definitions, and similar program structures to provide high usability and readability for users. The common parameters of all the methods are 1. dataset: the name of the dataset to be used; 2. input_channel: number of color channels in images; 3. m: dimensionality of measurements; 4. n: dimensionality of input images.

In addition to the unified interface, each implemented algorithm can also be used separately with no dependency on other algorithms, which provides high extensibility and customizability for developers. In addition, the pre-trained models of data-driven methods are also provided. Users can easily apply existing algorithms to new problems or datasets by further fine-tuning pre-trained models. Developers can easily build new algorithms on top of existing algorithms by reusing the implementations as well as the pre-trained models as the starting point.

2.2. Benchmark

We conduct the benchmark experiments on six datasets: MNIST [11], CIFAR10[12], CIFAR10(grayscaled), CELEBA [13], Bigset, Bigset (grayscaled). Bigset stands for a manually composed dataset used in LAPRAN [8]. For MNIST, CIFAR10, CIFAR10(gray), the image size of samples is 32×32. For CELEBA, Bigset(gray) and Bigset, the image size of samples is 64×64. We take five different compression ratios: 2, 4, 8, 16, 32. The reconstruction accuracy is quantified with two metrics: PSNR(0-48) and SSIM(0-1) between reconstructed images and original images on average. The reconstruction speed is quantified with the number of images reconstructed per second on average.

3. Impact overview

OpenICS is an open-source image compressive sensing toolbox that provides a unified framework with a modularized design for multiple popular image compressive sensing reconstruction algorithms out-of-box. To the best of our knowledge, OpenICS is the first image compressive sensing toolbox so far that has the above features and implemented up to ten different image compressive sensing algorithms. We will continue to add new image compressive sensing algorithms to the toolbox in the future when new algorithms are proposed.

We also present a corresponding benchmark for a comprehensive and fair comparison of all the implemented algorithms. To the best of our knowledge, OpenICS is by far the most comprehensive performance benchmark in the domain of image compressive sensing in terms of the diversity of datasets, the scale of the tested compression ratios, and the number of tested methods.

This toolbox was initially privately developed and used within the lab for research purposes. The relevant academic publications include [8] and [14]. In [8], the LDAMP and LAPRAN methods from the toolbox are used to benchmark each method's reconstruction accuracy and time on different datasets and compression ratios. In [14], the OpenICS implementations of ReconNet and LAPRAN are used as the initial and main reconstruction networks to quickly demonstrate the performance of the proposed compression ratio adaptor. We very recently made the toolbox publicly available and drafted a corresponding technical report [15]. We hope our work can help to advance the research and application of image compressive sensing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work is supported by the Research Experiences for Undergraduates (REU) funding of an National Science Foundation, USA grant (IIS/CPS-1652038) and the Fulton Undergraduate Research Initiative (FURI) program at Arizona State University, USA. Part of the NVIDIA GPUs used for this work were donated by NVIDIA Corporation. The CPU servers used for this work were donated by Intel Corporation.

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