IJMTST is UGC Approved Journal with Journal Id: 43137

International Journal for Modern Trends in Science and Technology, 8(S05):06-10, 2022

ISSN: 2455-3778 online
DOI: https://doi.org/10.46501/IJMTST08S0502
Available online at: https://www.ijmtst.com/vol8si05.html

Study on Single-pixel Image Acquisition Using Compressive Sensing Framework

Dr.A.V.Bharadwaja | P.S.L.S.Pranathi | R.Ganesh | S.Teja

Department of Electronics and Communication Engineering, Godavari Institute of Engineering and Technology(A), JNTUK, Kakinada.

To Cite this Article
Dr.A.V.Bharadwaja, P.S.L.S.Pranathi, R.Ganesh and S.Teja. Study on Single-pixel Image Acquisition Using Compressive Sensing Framework. International Journal for Modern Trends in Science and Technology 2022, 8(S05), pp. 06-10. https://doi.org/10.46501/IJMTST08S0502

Article Info
Received: 26 April 2022; Accepted: 24 May 2022; Published: 30 May 2022.

ABSTRACT

A digital image is acquired on digital detectors like Charge Coupling Devices (CCD)/ Complementary Metal Oxide Semiconductor (CMOS) sensors. These digital camera sensors consist of thousands or millions of pixels in sensor array. The number of pixels constituting the digital image must satisfy the Nyquist-Shannon sampling theorem with respect to sensor arrays. Therefore, the cost of the digital cameras dramatically increases with the number of pixels in the sensor. Nevertheless, it is possible to make a camera that only needs one pixel. The principle of compressed sensing then allows an image to be generated. In the present work, the single-pixel imaging using compressive sensing (CS) framework is proposed with sampling the object information of interest using proper sampling operator before being detected by a photodetector. The numerical experiments are presented to verify the proposed single-pixel compressive framework. The results shows that single pixel camera is really efficient for good quality image reconstruction than the conventional imaging and provides good resolution at low cost.

Keywords:—Digitalimage,single-pixelimaging,Compressivesensing,Samplingmask

1.INTRODUCTION

Modern digital image cameras and video cameras requires thousands or millions of pixels to sense the object information of interest [1-6]. Development of computational methods including compressedsensing, compressive sensing, allow us to reconstruct full object image with a good quality from sub-Nyquist sampling measurements [7-9]. CS has been widely used in many image processing applications such as tomography [10-12], magnetic resonance [13-15], radar imaging [16-18], satellite imaging [19-21], SAR image [22-24], encryption [25-28]. The development of photodetector or bucket detector has given an idea for new sensing methodologies, that allowing the cost-effective imaging systems. A modest method of acquiring a digital image using a single-pixel detector is to sequentially obtain each pixel inraster-scan method. To sample the scene of interest, a light modulator is used to compress the scene before being detected by the photodetector. To compress the scene of interest various sampling mask or spatial patterns are used with various sample ratios through required computations. It implies that CS aims to carry compression during acquisition procedure itself. Moreover, the arrangement of CS based single-pixel imaging relies on reconstructing a high-resolution image from a lesser number of pixels or measurements with a cost-effective hardware and fastreconstruction computational software.

The concept and principle of photodetector and single-pixel imaging was first demonstrated braunik et.

al. [7,9]. In the recent literatures [7-9], the single-pixel imaging is employed to carry out recovery of image by using inverse problem principle of CS framework. To achieve this the image or signal acquisition procedure is considered as linearity by considering object as spare in nature. A signal is said to be sparse if it has very few numbers of pixels or high number of zeros. If signal is not enough for sparse thenthe signal transformed into othertransform domains such as Fast Fourier Transforms (FFT), Discrete Cosine Transform (DCT), Wavelet, etc. Li et. al. has proposed a low-cost acquisition for sensing using visible spectrum. This research paper mainly concentrates on imaging static or dynamic objects for real time scenario using single-pixel compressive imaging approach. Later, the protentional of CS with single-pixel imaging is explained in detail in the cited references [29-32].

In the present paper, we have demonstrated the use of single-pixel acquisition and CS approach for imaging the two-dimensional objects from a sub-Nyquist sampling principle. This methodology consists of two steps. In first step, the light modulator such as digital micromirror device (DMD) or spatial light modulators (SLM) are used to sample or compress the object information. In the second step, the modulated projections from the light modulator are acquired by single-pixel detector. This procedure permits us to acquire samples beyond Nyquist sampling theorem than the conventional pixelated sensor array. We have performed numerical experiments to show the proof of the proposed concept. The results from numerical computations show that the image reconstruction from a various sample ratio can be accuracy recovered with good resolution. The present paper is organized as follows: We have given a brief review on CS, single-pixel imaging and related priory literature survey methods. The detail mathematical framework for the proposed single-pixel compressive imaging explained in section 2. In section 3, we illustrated the numerical experiments, results and discussion. Finally, the conclusions and future scope are presented in the section 4.

2. METHODOLOGY

Let us consider a two-dimensional object information as $I(x,y)$ with pixel resolution of M=NxN pixels. Generally, the conventional cameras record the binary or greyscale image as real-valued 2D matrix or array. In this scenario, each pixel value in image is related to the scene under recording with spatial location $I = \begin{bmatrix} i1 & \cdots & in \\ \vdots & \ddots & \vdots \\ i2 & \cdots & in \end{bmatrix}$. In the present paper, a single-pixel imaging principle is used to obtain the image. Therefore, in this scenario a 2D array is transformed into one-dimensional vector, then I = [i1, i2, . . . , i_M]^T. Then the acquired image consists of M pixels. Fig.1 show the illustration of proposed single-pixel acquisition used for the numerical experiments. The proposed single-pixel imaging is combined with compressive sensing framework (CS) to record the incomplete image measurements of the object under scene by using a DMD device. The measurement matrix or sensing matrix in the DMD is used to sample the object using various sampling masks. Among those masks, the random sampling is the best one used in the literature [29-32]. The proposed concept allows us to compression in the acquisition stage itself using the sensing matrix in the DMD.

The DMD samples of the input image $I(x,y)$ is done with random sensing or measurement matrix with a different sample ratioto sense the incomplete measurements ($K \ll M$) and is recorded by the single-pixel detector or photo detector. Let X be the incomplete linear measurements ($X \in R^{K\times 1}$) obtained from the modulated light field reflected from a DMD measured by a single-pixel detector. This is computed by taking the inner product of the interference field $I(x,y)(I \in R^{N\times 1})$ and the measurement matrix A generated ($\mathrm{A} \in R^{M\times N}$) in the DMD. The X measurements of the single-pixel detector are obtained sequentially through K computations of the measurement matrix in the DMD.

$$X_{K\times 1} = \mathrm{A}_{M\times N} \cdot I_{N\times 1} \qquad (1)$$

The sample ratio in the DMD plane is defined as the ratio of number of pixel measurements (K) used in the compression to the total number of pixels of the original image(M), *i.e.*,$(K/M) * 100$. The lesser the sample ratio, more will be the data compression.In the present paper, the image is sampled using random measurement matrix approach. The acquired X vector consists of only K pixels from originally image having of $I = M = N \times N\ pixels$. The pixels are far less than the Nyquist sampling criteria.

The original image I is reconstructed from X incomplete linear measurements, which is ruled by solving the optimization problem as given in equation (2). In the present paper, TVAL3 [33] algorithm is implemented with l_1-norm to reconstruct the original image from a few samples.

$$\underbrace{min}_{I} \sum_{i=1}^{N} ||H_i I||_1 \text{ subject to } X = AI \quad (2)$$

where H_i denotes discrete gradient of the vector I at position N, μ is non-negative parameter for recovering using CS framework. To validate the results MSE along with additive noise is calculated between reconstructed image from CS approach and original image considered for the simulation.

3. COMPUTER SIMULATIONS AND RESULTS

To validate the proposed CS approach and single-pixel imaging, computer simulations are executed using GIET gray scale image of pixel size 128×128 pixels ($M = 16834$ pixels in the input image). Let us consider an image show in in Figure 1 is on the DMD plane with 128×128 pixels for compression.

Fig.1. input image considered for the simulation

The single-pixel intensity measurements X ($K << M$) are obtained by numerically simulating equation (2). Only fewer image pixels are used for the recovery of original image using single pixel imaging. To evaluate the performance of our method of image reconstruction , three various sample ratios such as 25%, 50%, 70%, 99% measurements are accomplished in the DMD plane with additive noise standard deviation of 0.2 (20% of noise). The reconstruction of image using TVAL3 algorithm was carried out by minimizing the equation (2).

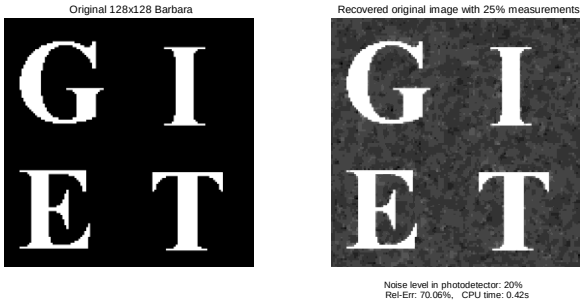

Fig.2. Reconstructed image using CS approach with 25%-pixel measurements of input image considered for the simulation

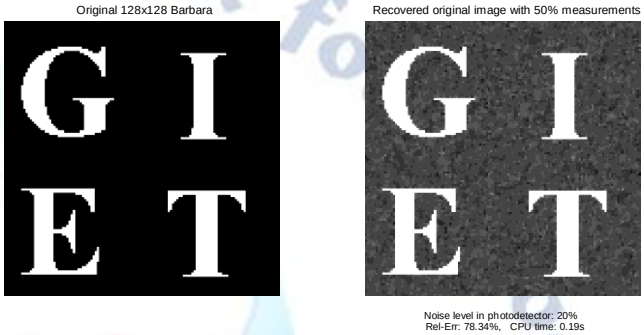

Fig.3. Reconstructed image using CS approach with 50%-pixel measurements of input image considered for the simulation

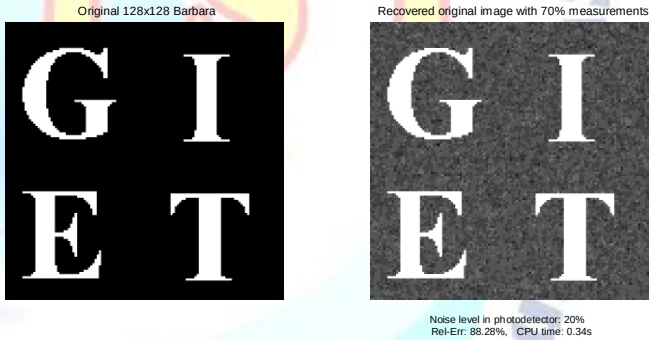

Fig.4. Reconstructed image using CS approach with 70%-pixel measurements of input image considered for the simulation

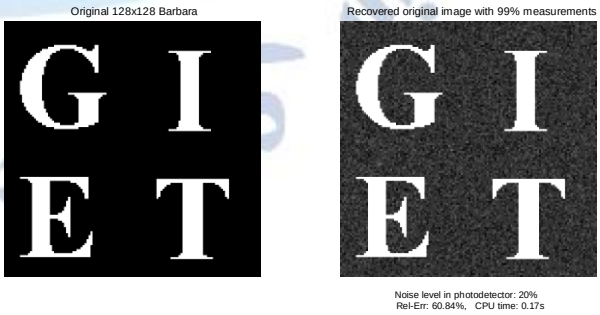

Fig.5. Reconstructed image using CS approach with 99%-pixel measurements of input image considered for the simulation

Figure (4-5) show the reconstructed image using TVAL3 approach by considering 25%, 50% ,70% and 99% pixels. An accurate and best quality reconstruction achieved with a least MSE obtained for all cases. It can be observed seen that, the reconstructed GIET using even 25%, 50% and 70% sample ratios in measurement matrix results in a greater quality and a less MSE deviation when compared to 99% cases. The MSE values of the recovered images using TVAL3 approach with random sensing matrix have shown the best quality reconstruction. From these figures, it can be inferred that the random sensing matrix in the DMD stands good because of its better superior image reconstruction quality from a sub-Nyquist sampling approach.

.4.CONCLUSIONS

We have implemented the numerical simulations of the image that to be compressed based on single-pixel imaging and compressive sensing framework. In this paper, the reconstruction quality of the image from beyond Nyquist sampling criteria is done compared to the conventional imaging. The proposed method has advantage it needs only fewer pixels in the image that will intensely reduce the reconstruction time and cost of the sensor as compared to conventional cameras and image processing techniques. The computer results of the proposed work for the four different sample ratio cases are performed with random sensing matrix. The CS minimization problem is done with TVAL3 The results from the numerical simulations show that the reconstructed image obtained by CS algorithm from single-pixel measurements is satisfactory to reconstruct a good quality image

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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