A Low-Cost and Portable Single-Pixel Camera

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***Abstract*—This paper proposes an architecture for a lensless single-pixel camera composed of a pico-projector, luminosity sensor, and a single-board computer. The compressive sensing matrix is projected onto the scene from the pico-projector. For each projected matrix the single element sensor receives a summation of the reflected light from the scene and acquires a luminosity measurement. Differential detection is used to minimize the effects of noise on measurement integrity. The single-board computer coordinates forming compressive sensing matrices, projecting them, acquiring luminosity measurements, and storing data. The platform is both highly affordable and highly portable, lending itself to be attractive in education and research applications. Reconstruction of the image occurs outside of the acquisition platform, using the optimization technique of ℓ_1 minimization. Both monochromatic and full color images can be reconstructed from this architecture. Color imaging is further compressed by the use of a projected Bayer pattern, and color imaging efficiency is improved through use of a color sensor.**

I. Introduction

Compressive sensing (CS) is an emerging field that deals with sparse signal recovery, based on the idea that sparse signals can be sampled under the Nyquist rate while still preserving the salient information in the signal. As the name suggests, in CS the compression occurs at the time of data acquisition, often in the form of a summation of information into a single measurement value. While typical imaging systems acquire a large quantity of information only to discard a sizeable portion of it later in compression, CS imaging aims to apply compression at the time of data acquisition. CS imaging allows for an acceptable reconstruction of an image using a number of measurements that is a small percentage of the number of pixels in the image. This allows for the possibility of faster acquisition time and lower data bandwidth requirements, at the expense of added complexity in the reconstruction phase. A CS reconstructed image is said to be sub-Nyquist when the number of measurements taken to reconstruct it is below the number of image pixels in the reconstructed image.

The application of CS imaging was pioneered by Rice University [1]. The Rice single-pixel camera (SPC) uses a lens to form an image of a scene onto a digital micromirror device (DMD). The DMD is a tiny array of micromirrors that can be individually modulated at two different angles. The DMD is loaded with a random binary matrix that subsamples the image plane formed at the mirrors, reflecting a subset of the image toward a second lens that focuses this light onto a single photodiode. The photodiode acquires a measurement value for each random matrix loaded onto the DMD. While the Rice SPC does an impressive job reconstructing monochromatic and color images of scenes, it has several drawbacks. The architecture is prohibitively expensive, mainly due to its use of a high end DMD development tool. Its use of lenses results in the camera system being large and spread out on an optical breadboard. Lenses also bring with them a need for accurate alignment, added costs, and constraints on the geometric mapping of the scene to an image [2].

To reduce both cost and complexity, the lensless SPC has recently become a focus of research and development. The use of a transmissive LCD panel to pass the randomly subsampled light of a scene into a box with a photodiode was shown by [3] to be capable of forming accurately reconstructed color images. The use of digital light projector (DLP) technology by [4-6] to project random patterns of light onto a dark scene and sensing the reflected light intensity from the scene to reconstruct an image has proven to allow for a more portable and accessible SPC architecture. This approach is taken in this paper's design of an ultra-portable and affordable single-pixel camera platform.

II. Data Acquisition and Reconstruction

To take a CS measurement for an image $\underline{x}$ of a scene of dimensions $R \times C$, a random binary measurement matrix φ of dimensions $R \times C$ is projected onto the scene. For m measurements, there are m measurement matrices formed. Each measurement matrix φ_{i} in the acquisition

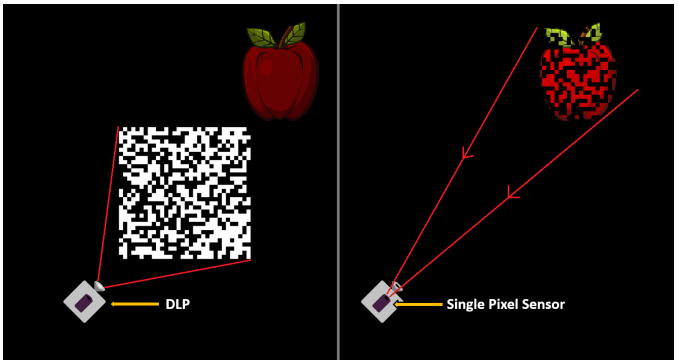

Fig. 1: The DLP projects random light patterns onto the scene (left) and a summation of reflected light from the subsampled scene is sensed by the single-pixel sensor as a luminosity measurement (right).

set is flattened into a 1D vector of length RC and placed in matrix ϕ as a row vector. We have

$$\phi = \begin{bmatrix} - & \varphi_1 & - \\ - & \vdots & - \\ - & \varphi_{\mathrm{m}} & - \end{bmatrix}_{m \times RC} . \tag{1}$$

Since $m < RC$ for compression, $\underline{y} = \phi \underline{x}$ is an underdetermined system in the canonical basis. However, in the DCT domain the image is sparse, i.e. $\mathrm{DCT}(\underline{x}) = \underline{s}$ is sparse, and thus $m < RC$ measurements can be used to represent the image in the DCT domain. To represent the system in the DCT domain, we first post-multiply ϕ by the $RC \times RC$ inverse DCT Transformation matrix Ψ_{dct}^{-1}. This multiplication results in the discrete cosine transform (DCT) of each row of ϕ being taken.

$$\phi_{\mathrm{dct}} = \begin{bmatrix} - & \mathrm{DCT}\left(\varphi_1\right) & - \\ & \vdots & \\ - & \mathrm{DCT}\left(\varphi_{\mathrm{m}}\right) & - \end{bmatrix}_{m \times RC} . \tag{2}$$

For each φ_{i} matrix projected, a luminosity measurement y_{i} is taken. The CS reconstruction problem can be stated as

$$\underline{y} = \phi \underline{x} = \phi \Psi_{\mathrm{dct}}^{-1} \Psi_{\mathrm{dct}} \underline{x} = \phi \Psi_{\mathrm{dct}}^{-1} \underline{s} = \phi_{\mathrm{dct}} \underline{s} \tag{3}$$

where $\underline{y}$ is the column vector of CS measurements, $\Psi_{\mathrm{dct}}^{-1} \phi_{dct} = \phi$ is the measurement matrix in DCT space, and $\underline{s}$ is the column vector of unknowns in DCT space. The unknown vector $\underline{s}$ can be solved for using convex optimization techniques such as ℓ_1 minimization (4). The reconstructed $\underline{s}$ is then taken out of DCT space by taking the inverse discrete cosine transform (IDCT) of the vector, and the reconstructed image is formed by reshaping the vector to the image dimensions.

$$\underline{s} = \operatorname{argmin} \|\underline{s}\|_1 \quad \text{subject to} \quad \underline{y} = \phi_{\mathrm{dct}} \underline{s} \tag{4}$$

In this paper, $\underline{s}$ is solved for by two methods: ℓ_1 minimization using CVX, a package for specifying and solving convex programs [7-8], and the Gradient Projection for Sparse Reconstruction (GPSR) algorithm [9].

III. Experimental Camera Setup

To build a single-pixel camera that uses this projection-based method of imaging, only three main components are required: a digital light projector (≈$100), a single-board computer (≈$50), and a luminosity sensor (≥ $5). These components can be found at most major electronic component vendors, and at least some can be purchased from more general retailers such as Amazon. The single-pixel camera used in this paper is shown in Fig. 2. It consists of a TI DLP LightCrafter 2000 360x640 projector evaluation module ($99), Beaglebone Black single-board computer ($62), and a TSL2591 luminosity sensor on an Adafruit Industries breakout PCB ($7). The secondary setup substitutes a TCS34725 RGB sensor on a similar Adafruit Industries breakout PCB ($8). Other minor required components include a micro SD card for data and program storage, several jumper wires to connect the sensor to the single-board computer, and a 5V power supply for the projector. These components are likely cheap, already owned by a lab and/or reusable for or from other projects, so we do not consider them to contribute to the cost of this setup. In our case, the single-pixel camera′s base is fabricated from an acrylic panel, and a 3D printed mounting piece is used to attach the sensor. The main drawback of this projection-based setup is that imaging must occur in a dark room, where ambient light as a possible contaminant of measurement values is minimized, which may overwhelm the relevant data even when using differential measurements.

Performing the CS imaging requires running a Python script from the Linux OS of the Beaglebone Black. Sensor parameters such as integration time and gain are set for each imaging session to maximize signal while avoiding sensor saturation. Image resolution is set in each script and determines the pixel size of each CS matrix element on the projected image. In this paper a constant image resolution of 90x160 is used, and image reconstruction occurs on a PC using MATLAB

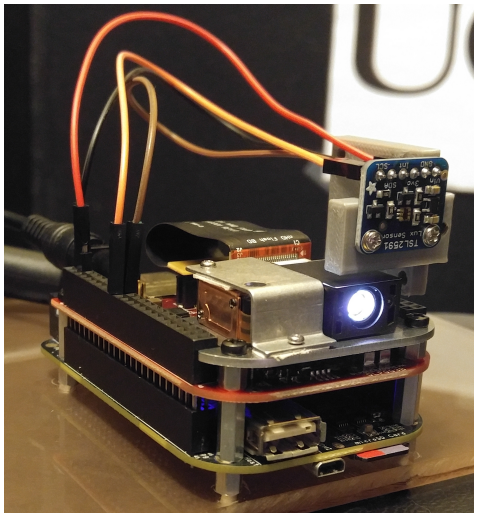

Fig. 2: Single-pixel camera composed of DLP 2000 projector, Beaglebone Black single-board computer, and TSL2591 sensor.

to preprocess, then Python to reconstruct and form the final image result.

To validate the hardware, an image is directly acquired by scanning a 4-pixel square across a scene in row-major order, taking a luminosity measurement at each step during the scan. Since only light from a single small square is reflected from the scene during any measurement, the image formed is the absolute best possible image given the projection and sensing hardware and is therefore referred to as the ground truth image.

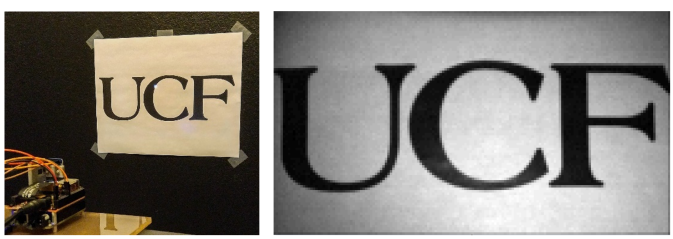

Fig. 3: Single-pixel camera directly scanning ground truth image (left) and resulting 90x160 ground truth image (right).

IV. Reconstruction of Monochrome Images

To validate the reconstruction algorithm using ℓ_1 minimization, 3600 simulated CS measurements are formed by multiplying the ground truth image element-wise by random binary measurement matrices and summing the non-zero image values into an individual measurement value. Since each pixel in the ground truth image is a measurement of the luminosity reflected from the scene by only one projected pixel square, the summation of

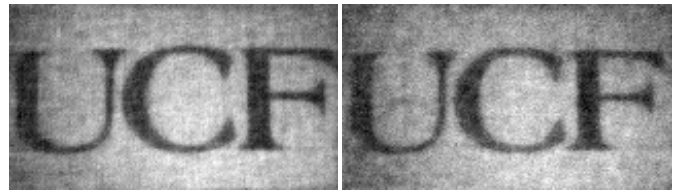

Fig. 4: Reconstructed image of UCF from $m = 3600$ (25% Nyquist) simulated measurements (left), and reconstructed image from $m = 3600$ CS experimental measurements (right).

random ground truth pixel values from the measurement matrix form a good approximation of the luminosity measurement that would result from projecting the same pattern onto the scene. The random binary measurement matrices in this paper have a 50-50 split between ones and zeros.

Next, the same random binary matrices are used to acquire 3600 real CS measurements from the single-pixel camera. To help improve the dynamic range and signal-to-noise ratio (SNR) of the luminosity sensor, four consecutive luminosity samples are summed for each pattern projected onto the scene. The results of ℓ_1 reconstruction for the simulated and real CS measurements are shown in Fig. 4.

V. Single Versus Differential Measurement

Random noise components such as fluctuating ambient light and sensor dark current can cause a long-term drift of the measurement mean in the form of a time-varying bias that is added to luminosity measurements. A method known as differential CS detection overcomes this noise by acquiring two measurements, one using a random binary matrix and one using its inverse (ones and zeros swapped), each 50% ones and 50% zeros. The difference of the two measurements is taken to cancel out the common bias [4-5]. Ambient light is assumed to have a uniform effect on the scene, and sensor dark current is assumed to be constant between differential measurements. Thus the bias is guaranteed to be cancelled out. For reconstruction, the differential CS measurements and corresponding differential measurement matrices φ_{i} are used.

To compare between the use of single and differential CS measurements, 10,800 single CS measurements are taken of a scene, and 10,800 differential CS measurements are taken of the same scene. These measurements are used to reconstruct images for both single and differential CS measurements for various sub-Nyquist percentages, as shown in Fig. 5.

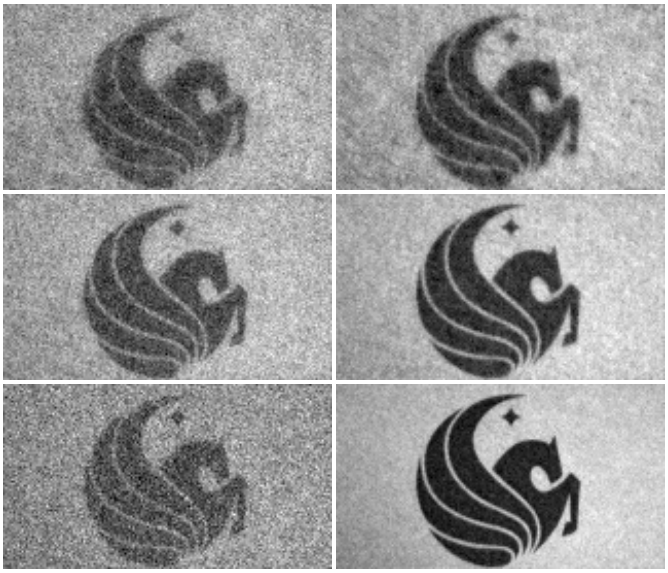

Fig. 5: Left column top to bottom: single CS measurement reconstructed images, 25%, 50%, 68% Nyquist. Right column top to bottom: differential CS measurement reconstructed images, 25%, 50%, 75% Nyquist. Note that 68% Nyquist is the highest percentage for single CS measurements where reconstruction was successful.

The single CS measurements taken contain a time varying bias that causes the mean of the measurements to drift, while the differential CS measurements have had the time varying bias cancelled out by virtue of differential detection. The advantage of differential detection is evident when comparing between reconstructed images of the same Nyquist percentage, and of the same number of raw measurements. Differential CS measurement results show less noise, better detail recovery, and higher contrast, while the time varying bias in the single CS measurements cause the reconstruction results to be less optimal. The time varying bias has caused reconstruction from the sets of single CS measurements above 68% to fail.

VI. CS Imaging of Color Scenes With Depth

To acquire and reconstruct a color image using the single-pixel camera, a random binary measurement matrix is sequentially projected in red, green, and blue, and separate measurements are taken for each colored projection. Reconstruction is performed separately on each set of measurements to obtain each color channel of the final RGB image. Due to the varying intensities of the projectors color LEDs and the responsivity of the broadband photodiode not being uniform with respect to wavelength, a white balance adjustment is used to balance the color channels to produce accurate color reconstruction.

The scene to be imaged in color consists of a pot of faux flowers. Differential CS measurements are taken, acquiring 10,800 measurements for each color channel.

The grayscale scenes that have been reconstructed thus far have been flat and have had the projected measurement matrix focused at the plane of the piece of paper being imaged. When imaging 3D objects in a scene, the focus point of the projector determines at which depth in the scene the measurement matrix will have the sharpest focus, and therefore the most detail when imaged. In order to image detail throughout the depth of a 3D object shown in Fig. 6, the measurement matrix is focused near the center of the objects depth along the optical axis, which allows the measurement matrix to be only slightly out of focus before and after this point.

VII. Efficient CS Imaging of Color Scenes

Single-pixel cameras have been shown to be capable of color imaging by acquiring separate color channel CS measurements, either by using three detectors as in [4], or by projecting separate colored φ matrices. The cost of acquiring a color image versus a monochrome image in both cases is triple the number of measurements. Similar to a monochromatic digital image sensor acquiring color images using a Bayer filter array [10] in front of the detector, the single-pixel camera in this paper can make use of a statically projected Bayer pattern coupled with random φ matrices to reconstruct color images without increasing the number of measurements.

The projection of a Bayer patternis coupled with random φ matrices where ones correspond to projecting the Bayer colors and zeros correspond to no color being projected. The monochromatic luminosity sensor collects a measurement for each φ that is the summation of the reflected luminosity from the scene. While color information would normally be lost by the use of a monochromatic sensor, the static Bayer pattern on the scene is used to correlate pixel intensity in the final image with color intensity. Gradient-corrected linear interpolation is then used in a debayer (demosaic) algorithm to fill in the missing color information for each pixel in the image and form a final RGB image.

The use of interpolation in the debayering phase results in a loss of spatial resolution and introduction of some color artifacting. The image in Fig. 7b, resulting from $m = 10800$ measurements, certainly exhibits a loss of spatial detail when compared to the RGB image

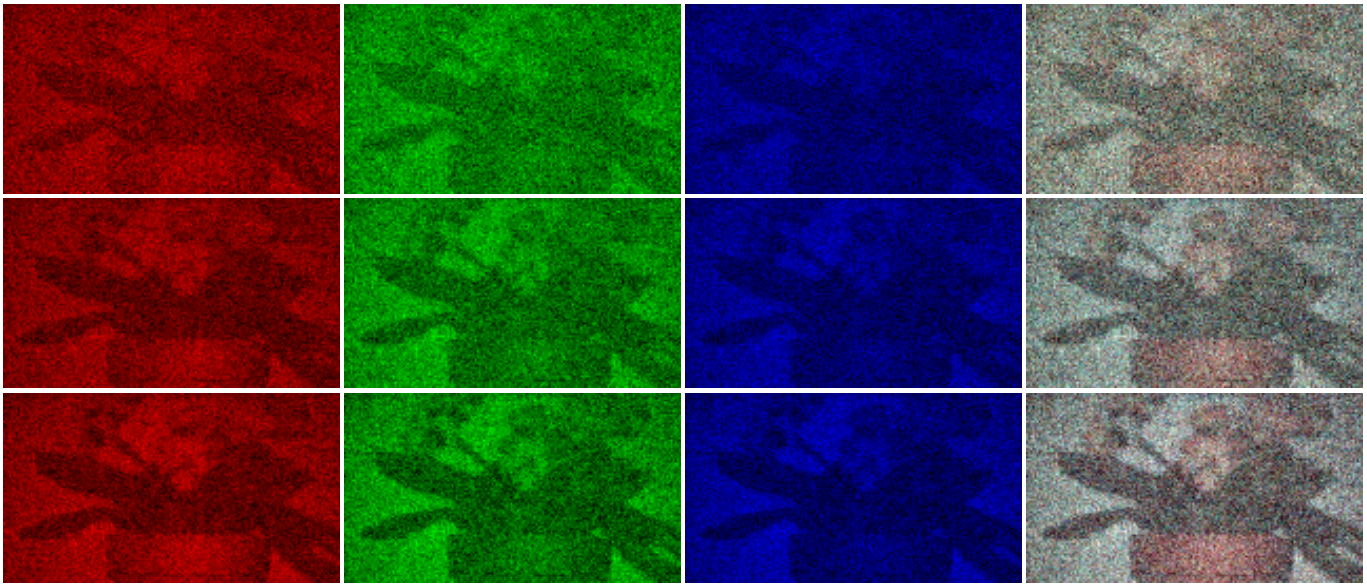

Fig. 6: Reconstructed color channels and corresponding RGB images. Columns from left to right: Red, Green, Blue, RGB. Rows from top to bottom: 25%, 50%, 75% Nyquist ($m = 3600, 7200, 10800$ for each color channel).

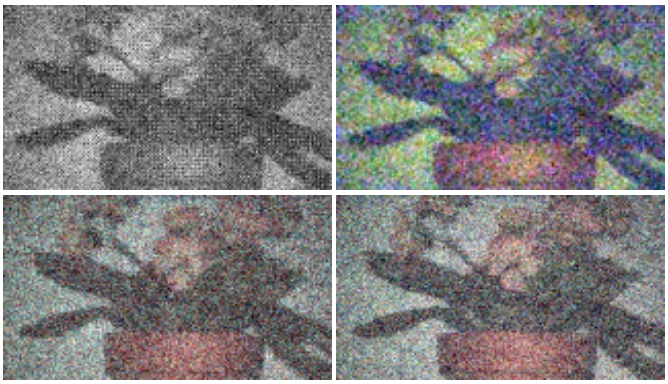

Fig. 7: Reconstructed image with color information encoded from Bayer Pattern (top left). Debayered (demosaiced) image with the color information restored (top right). Reconstructed image from individual channel measurements (bottom left). Reconstructed image using simultaneous measurements from TCS24725 color sensor (bottom right). All reconstructions are based on 10800 measurements per channel, or 10800 measurements total for the Bayer encoded images.

in Fig. 7c resulting from $m = 10800$ measurements for each color channel. However, considering that the result in Fig. 7b is formed entirely from $m = 10800$ measurements, then comparing it against the RGB image in Fig. 6 (top right) resulting from a total of $m = 3600 \times 3 = 10800$ measurements shows that the Bayer projection method of capturing color images has a clear advantage in terms of image quality versus number of total measurements. Thus this method may be preferred when memory limitations are a concern either during the sensing or the reconstruction phases. When memory is not a concern but sensing time is, a color sensor can be used to measure each color channel simultaneously while projecting a white sensing matrix. Thus the time spent taking measurements is 1/3 that used for the images in Fig. 6, while the number of measurements taken remains the same. A TCS34725 color sensor was substituted for the TSL2591 ambient light sensor as it was a similar cost, had an available Python library, and used an I2C interface like the TSL2591 sensor. As seen in Fig. 7, the image quality is comparable to that of the restoration from individual measurements using the more highly sensitive full-spectrum sensor, being slightly noisier but with more accurate colors. Similar differences in noise level were observed for black and white imaging, but with no improvement in color the original TSL2591 sensor is preferable for grayscale imaging.

VIII. Conclusion

The lensless single-pixel camera proposed in this paper shows promise as being a compact and affordable platform for education and research purposes. It is capable of acquiring CS measurements that can be reconstructed into monochromatic and color images. Differential detection has been shown to remove the noise components of ambient light and sensor dark current, which results in higher reconstructed image quality. Color imaging can be performed by seperate

color channel reconstruction, by using a projected Bayer pattern, or by using a color sensor with receptors for each of the three digital color channels.

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