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Collective noise model for focal plane modulated single-pixel imaging

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ABSTRACT

Single-pixel imaging, also known as computational ghost imaging, provides an alternative method to perform imaging in various applications which are difficult for conventional cameras with pixelated detectors, such as multi-wavelength imaging, three-dimensional imaging, and imaging through turbulence. In recent years, many improvements have successfully increased the signal-to-noise ratio of single-pixel imaging systems, showing promise for the engineering feasibility of this technique. However, many of these improvements are based on empirical findings. In this work we perform an investigation of the noise from each system component that affects the quality of the reconstructed image in a single-pixel imaging system based on focal plane modulation. A collective noise model is built to describe the resultant influence of these different noise sources, and numerical simulations are performed to quantify the effect. Experiments have been conducted to verify the model, and the results agree well with the simulations. This work provides a simple yet accurate method for evaluating the performance of a single-pixel imaging system, without having to carry out actual experimental tests.

1. Introduction

Since a major part of the information processed in our daily life is in graphic form, imaging technology is one of the most important tools in the development of society. Conventional digital imaging uses a lens to map the spatial information from a scene onto the focal plane, where a pixelated array records the light intensity. Over the past two decades, an alternative way to perform imaging known as ghost imaging [1–3] or single-pixel imaging [4–6] has aroused much interest in the scientific community. Single-pixel imaging (SPI) reconstructs an image by measuring the correlations between the scene and a series of masks. It enables various applications, such as multi-wavelength imaging [7,8], three-dimensional imaging [9,10] and imaging through turbulence under certain circumstances [11–13], all of which pose difficulties for conventional imaging.

Besides environmental effects, internal noise of the imaging system is an important factor that determines the image quality for both conventional and SPI approaches. In conventional digital imaging systems, the noise originates from the electronic readout of the pixel array, which has a direct additive effect on the corresponding image. In SPI, however, several different components contribute to the noise, such as the light source and the bucket detector, and their effects on image quality are less straightforward due to the image reconstruction mechanism. As a matter of fact, the signal-to-noise ratio (SNR) issue is one of the major obstacles facing widespread application of SPI.

Many promising schemes have been proposed to improve the SNR in the last decade. Computational ghost imaging [14] uses a spatial light modulator (SLM) to replace the reference arm in the original second-order intensity correlation imaging systems, simplifying the setup and improving the performance. Differential ghost imaging [15] normalizes the total intensity of each measurement, minimizing the effect of intensity instabilities of the source. Compressive sensing [16,17] takes advantage of sparsity in the scene and improves the reconstructed image by minimizing a certain measure of the sparsity. High-order ghost imaging [18,19] exploits higher-order correlation to increase the SNR. Positive–negative ghost imaging [20,21] utilizes the symmetry of noise in positive and negative fluctuations, partially canceling the noise in the system. Single-pixel imaging based on different orthonormal bases [5–7,22,23] maintains the orthogonality within a series of sampling masks, leading to theoretically perfect reconstruction and a much smaller number of measurements. Digital microscanning [24] applies a super-resolution technique [25, 26] to achieve a better SNR and higher resolution. However, many of these improvements are obtained after the measurements have been performed, and the noise evaluations were based on the specific system configurations, which might pose certain difficulties for starting researchers not familiar with the area to understand the roles of the different noise sources and to decide what devices to choose in order to set up their own SPI systems with the desired performance.

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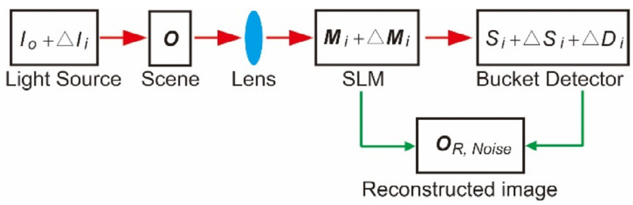

Fig. 1. Schematic diagram of an SPI system based on focal plane modulation.

In two SPI schemes which are essentially the same, one scheme uses structured light illumination [5, 14], and the other uses focal plane modulation [4,24]. In this work we investigate the noise transmitted from the system components to the resulting reconstructed image for an SPI setup based on focal plane modulation. Digitization electronics is a common source of noise and is a topic that has been widely discussed. The main understanding is that the higher the digitization resolution, the less noise there will be, and the improvement approaches its limit as the resolution increases. However, higher resolution means slower sampling rates and larger amount of data transfer and computing, therefore a more practical question for setting up an SPI system is which digitizer would be best for the application. For example, a high resolution digitizer would be preferable for static imaging, and a low resolution but fast sampling rate digitizer for real-time motion detection, but this issue will not be discussed here. In this work, noises from the light source, SLM and detector are analyzed separately, their overall effect on image quality is investigated, and a collective noise model is built. Numerical simulations at different noise levels are performed based on this model to visualize the effect of each noise component on the reconstructed image. Measurements on an experimental setup agree well with the numerical simulation, demonstrating that our model is effective in predicting the performance of SPI systems. Our work provides a simple yet accurate noise model for researchers who are interested in SPI to understand and evaluate the system performance of their own SPI configuration before having to actually set up the system.

2. Collective noise model

In an SPI system based on focal plane modulation, as illustrated in Fig. 1, light of intensity I_0 emitted from a source illuminates a scene $\boldsymbol{O}$. The spatial information of the scene is imaged by an imaging lens onto its focal plane, where an SLM generates intensity modulation masks $\boldsymbol{M}_i$, for up to $i = 1, 2, \ldots, N$ measurements. The transmitted or reflected light is then collected, and its total intensity signal S_i measured by a bucket detector is

$$S_i = \sum_m \sum_n \left(I_0 M_{i,mn} \cdot O_{mn}\right), \tag{1}$$

where m and n indicate the horizontal and vertical coordinates of the mask, respectively. If the masks $\boldsymbol{M}_i$ are orthonormal such that their transpose is the same as their inverse, by performing N independent SLM mask exposures, the image O_R can be perfectly reconstructed as [24]

$$\boldsymbol{O}_R = \sum_{i=1}^{N} \left(\boldsymbol{M}_i \cdot S_i\right) = \sum_{i=1}^{N} \left(\boldsymbol{M}_i \cdot \sum_m \sum_n \left(I_0 M_{i,mn} \cdot O_{mn}\right)\right). \tag{2}$$

During the imaging process, if the focusing lens has zero aberration, we only have to consider the noise due to the light source, the SLM, and the bucket detector (digitization electronics is not included in the scope of this work). The contribution from each of these components will now be analyzed below to formulate a collective noise model.

2.1. Light source noise

For a laser operating well above threshold we can ignore its quantum fluctuations, so the chief source of noise in its emission is caused by driving current fluctuations. The characterization of laser noise has been widely investigated and is quite complicated if all aspects were considered [27,28]. For our purposes, we measured the output of a typical continuous wave diode laser with a low noise PIN detector (Thorlabs DET10A), and from 100,000 measured points determined that the random fluctuations exhibit an approximate Gaussian dependence on current. Modeling the light intensity as $I_0 + \triangle I_i$, from Eqs. (1) and (2) the reconstructed image $\boldsymbol{O}_{R,\ Light}$ can be expressed as

$$\boldsymbol{O}_{R,Light} = \sum_{i=1}^{N} \left(\boldsymbol{M}_i \cdot \sum_m \sum_n \left(\left(I_0 + \triangle I_i\right) M_{i,mn} \cdot O_{mn}\right)\right). \tag{3}$$

Subtracting Eq. (2) from Eq. (3), the noise introduced into the resulting image is

$$\triangle \boldsymbol{O}_{R,Light} = \sum_{i=1}^{N} \left(\triangle I_i \cdot \boldsymbol{M}_i \cdot S_i / I_0\right). \tag{4}$$

2.2. Spatial light modulator noise

The SLM noise arises from aberrations in surface curvature, comprising low order Zernike polynomials if the SLM is liquid crystal based, or from fluctuations in the tilt angles of the micromirrors if it is a digital micromirror device (DMD). In both cases, the masks generated by the SLM are $\boldsymbol{M}_i + \triangle \boldsymbol{M}_i$, where $\triangle \boldsymbol{M}_i$ is an error function of i, m and n. The reconstructed image $\boldsymbol{O}_{R,\ SLM}$ can be expressed as

$$\boldsymbol{O}_{R,SLM} = \sum_{i=1}^{N} \left(\boldsymbol{M}_i \cdot \sum_m \sum_n \left(I_0\left(M_{i,mn} + \triangle M_{i,mn}\right) \cdot O_{mn}\right)\right). \tag{5}$$

Subtracting Eq. (2) from Eq. (5), the noise introduced into the image is

$$\triangle \boldsymbol{O}_{R,SLM} = \sum_{i=1}^{N} \left(I_0 \cdot \boldsymbol{M}_i \cdot \sum_m \sum_n \left(\triangle M_{i,mn} \cdot O_{mn}\right)\right). \tag{6}$$

If the error caused by each pixel is due to imperfect manufacturing of the device, then $\triangle \boldsymbol{M}_i$ can be viewed as a constant $\triangle \boldsymbol{M}$ during N measurements. In this case, $\triangle \boldsymbol{O}_{R,\ SLM}$ adds only a constant to the reconstructed images, which can be reduced by normalization and so is inconsequential.

If the error arises from the instability of the device voltage, then $\triangle \boldsymbol{M}$ follows a similar Gaussian distribution to that of the device current fluctuations.

2.3. Detector noise

There are two kinds of noise in a bucket detector. One is dark current $\triangle D_i$, which exists in the readouts of the detector when there is no incident light and can be considered to have a Gaussian distribution with a mean value of D [29]. The other type of noise $\triangle S_i$ is induced by incident light, and its level is proportional to the detected signal S_i. The measured signal is $S_i + \triangle S_i + \triangle D_i$ when light is present, and the reconstructed image $\boldsymbol{O}_{R,\ Det}$ can be expressed as

$$\boldsymbol{O}_{R,Det} = \sum_{i=1}^{N} \left(\boldsymbol{M}_i \cdot \left(\sum_m \sum_n \left(I_0 M_{i,mn} \cdot O_{mn}\right) + \triangle S_i + \triangle D_i\right)\right). \tag{7}$$

Subtracting Eq. (2) from Eq. (7), the noise introduced is

$$\triangle \boldsymbol{O}_{R,Det} = \sum_{i=1}^{N} \left(\left(\triangle S_i + \triangle D_i\right) \cdot \boldsymbol{M}_i\right). \tag{8}$$

We can further separate the detector induced noise into the signal-related noise $\triangle \boldsymbol{O}_{R,\ Det,\ S}$ and signal-unrelated noise $\triangle \boldsymbol{O}_{R,\ Det,\ D}$, as follows:

$$\triangle \boldsymbol{O}_{R,Det,S} = \sum_{i=1}^{N} \left(\triangle S_i \cdot \boldsymbol{M}_i\right), \tag{9}$$

$$\triangle \boldsymbol{O}_{R,Det,D} = \sum_{i=1}^{N} \left(\triangle D_i \cdot \boldsymbol{M}_i\right). \tag{10}$$