Lensless imaging by coded image sensors

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Abstract This paper presents a novel architecture of the lensless camera using coded image sensors, which equip spatially-randomized holes in pixels. In the system, the two coded image sensors are placed facing each other. The image reconstruction from sparse coded image was confirmed by simulations using a mask-based lensless camera.

Keywords: lensless camera, compressive sensing, CMOS image sensor

1. Introduction

Recently the lensless camera is an attractive topic for realizing ultra-thin imaging systems [1]. The lensless camera is basically composed of an optical encoder and computational decoder. The encoder is implemented by a coded aperture placed in front of an image sensor, whereas the decoder is realized by a digital signal processor. Interestingly, the function of image formation is virtualized in the lensless camera; therefore, it enables the ultra-thin optical hardware for imaging and the flexible digital re-imaging such as digital refocusing [2].

Another advantage of lensless imaging is the extended freedom of optical design for imaging. In lens-based cameras, the perpendicular arrangement of a lens system and an image sensor is mandatory. In contrast, the lensless imaging potentially breaks through such restriction on hardware construction. As long as the linear forward model can be implemented, the optical design can be freer than that in conventional lens-based imagers.

Based on the above idea, we propose a novel lensless camera architecture. The schematic diagram is shown in Fig. 1. In the optical system, randomly-drilled image sensors referred as *coded image sensors* are arranged whose photodetectors face with each other. In a coded image sensor, some pixels in the whole pixels are replaced with air holes by drilling. The drilled pixels are chosen randomly. Since the image sensor is opaque, the sensor simultaneously works not only as a sparse image sampler but also as a coded aperture. Exploiting this symmetry, the sensors detects coded images of multiple field-of-views (FOVs) simultaneously, which contributes the extension of the FOV in lensless camera maintaining its compactness. Unlike the conventional lensless cameras, the coded optical image is sampled sparsely by an image sensor due to the coded structure. The lack of sampling is computationally restored by image decoding based on compressive-sensing (CS) framework [3].

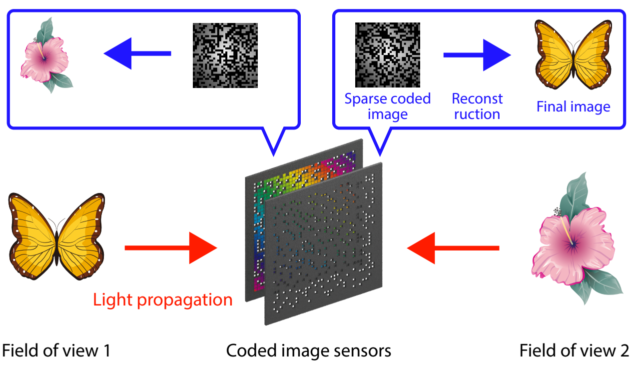

Fig. 1. Concept of proposed architecture on lensless camera.

2. Proposed method

We denote terms of the *sampling sensor* which is the image sensor used for image sampling, and the *aperture sensor* which is for masking-based image encoding, respectively. Note that the two sensors are interchangeable. The forward model of the coded-image capture by a sampling sensor is described as follows:

$$\boldsymbol{g} = \boldsymbol{M}_2(\boldsymbol{W}_z\boldsymbol{m}_1 * \boldsymbol{b} * \boldsymbol{f}) + \boldsymbol{n}, \tag{1}$$

where $\boldsymbol{g} \in \mathbb{R}^{N_g\times 1}$ is the captured image, $\boldsymbol{M}_2 \in \mathbb{R}^{N_g\times N_f}$ is the matrix expressing the sparse sampling by a sampling sensor, $\boldsymbol{W}_z \in \mathbb{R}^{N_f\times N_f}$ is the depth-dependent scaling function for a geometrical shadow of the aperture sensor, $\boldsymbol{m}_1 \in \mathbb{R}^{N_f\times 1}$ is the amplitude transmittance of the aperture sensor, $\boldsymbol{b} \in \mathbb{R}^{N_f\times 1}$ is the blur kernel by diffraction, $\boldsymbol{f} \in \mathbb{R}^{N_f\times 1}$ is the object, and $\boldsymbol{n} \in \mathbb{R}^{N_f\times 1}$ is noise, respectively. In Eq. (1), the geometrical shadow of the aperture sensor is scaled with object depth, blurred by diffraction, convolved with the object image, and sparsified by the sampling sensor, respectively. Since $N_g < N_f$, the inverse problem of Eq. (1) is ill-posed. Therefore, we solve the inverse problem based on CS framework as follows:

$$\hat{\boldsymbol{f}} = \mathrm{argmin}\|\boldsymbol{g} - \boldsymbol{M}_2(\boldsymbol{W}_z\boldsymbol{m}_1 * \boldsymbol{b} * \boldsymbol{f})\|_{\ell 2} + \tau\Psi(\boldsymbol{f}), \tag{2}$$

where $\hat{\boldsymbol{f}} \in \mathbb{R}^{N_f\times 1}$ is the decoded image, $\|\cdot\|_{\ell 2}$ is the ℓ_2 norm, τ is a coefficient, $\Psi(\cdot)$ is the regularizer function, respectively. To decrease mutual coherence in CS, the spatial pattern of the air-holes in both sensors is designed as the random pattern.

3. Simulation with numerical data

We verified the possibility of imaging with our proposed architecture by numerical simulations. We assumed two coded image sensors whose pixels are randomly drilled into air holes. We obtained 8 bit monochromatic captured data by calculating Eq. (1) with additional white Gauss noise at 40 dB. We chose 50% as the ratio between pixel and air holes, and set margins at surrounding pixel region. The distance between two sensors was set as 2 mm. Reconstruction was performed by solving the inverse problem of Eq. (2) with the TwIST algorithm with total variation

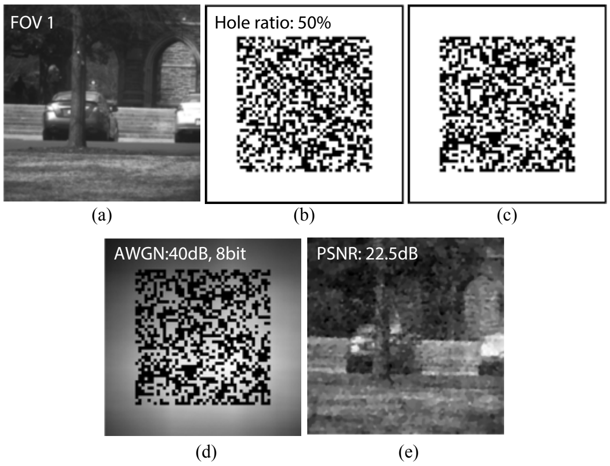

Fig. 2. Simulation results. (a) Original object, (b) structures of an aperture sensor and (c) a sampling sensor, (d) captured image, and (e) reconstructed image.

regularizer [4].

Figure 2 shows the results. As shown in the figure, an object of natural scene was successfully reconstructed even with sparse sampling of the sensor. The peak signal-to-noise ratio between original and reconstructed images was 22.5 dB.

4. Simulation with a mask-based lensless camera

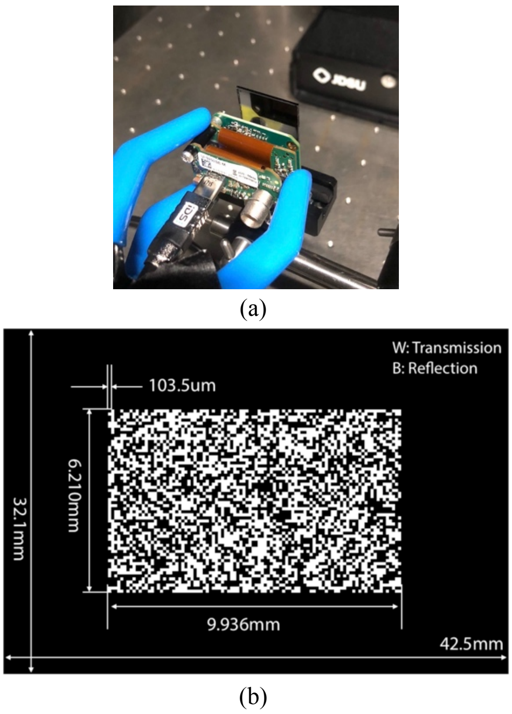

Fig. 3. Setup of a lensless camera. (a) Overview and (b) the amplitude transmission of an amplitude mask.

We also simulated the proposed imaging by using captured data by a prototype of the random-mask-based lensless camera. In the experiment, coded image capture was performed experimentally, and the sparse sampling of the image was implemented numerically. The overview of the experimental setup of a lensless camera is shown in Fig. 3 (a). We placed a randomized amplitude mask of Fig. 3 (b) in front of a monochromatic image sensor (UI-3202SE-M by IDS Imaging Development Systems GmbH). The distance between the sensor and the mask was 10 mm, and that between the mask and a subject was 40 cm, respectively. As a subject, we set a liquid-crystal display showing a standard image ‘Cameraman’.

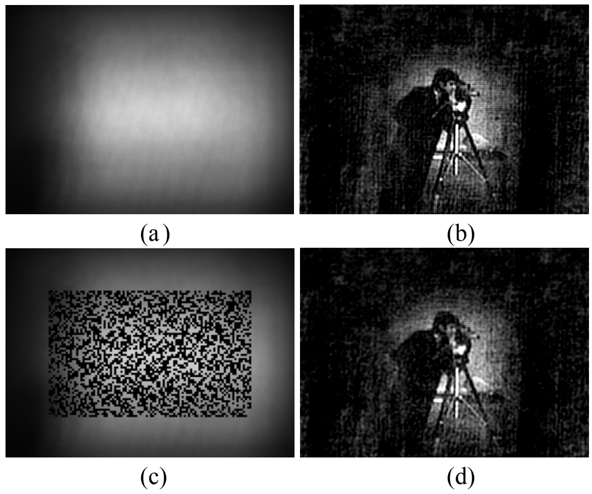

Fig. 4. (a) Original captured image and (b) reconstructed image. (c) Sparsified captured image and (d) reconstructed image via CS framework.

Captured and reconstructed images by the conventional method with the lensless camera are shown in Figs. 4 (a)-(b). For reconstruction, we also used TwIST algorithm. The numerically-sparsified captured image and the reconstructed images via CS framework are shown in Figs. 4 (c)-(d). We confirmed that we can reconstruct a similar image even from a sparsified captured image, though the image was slightly smoothed by sparsity constraint in reconstruction. Note that the background component in a captured image was subtracted before reconstruction. The computational time for a monochromatic image reconstruction with 684 x 500 pixels was 317.1 seconds using Matlab and a 2.9GHz Intel Core i9 CPU.

5. Conclusions

We proposed a novel lensless camera architecture by coded image sensors, and confirmed the validity of the concept by simulations with numerical and real coded image. As a next step, we will design and implement coded image sensors, and verify the concept using prototype of the proposed architecture described in Fig. 1.

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