Three-Dimensional Photon Counting Integral Imaging Reconstruction using Merging Reconstruction Method

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***Abstract*— In this paper, we propose a new three-dimensional (3D) photon counting integral imaging reconstruction method using elemental image merging process for the effective use of the extracted photons under severely photon starved conditions. In previous methods, the photons are extracted from elemental images using Poisson random process and 3D images are reconstructed by Maximum Likelihood Estimation (MLE). However, 3D integral imaging with photon counting do not use the photons effectively in reconstruction. Thus, it may not visualize 3D objects in severely low light level conditions. In addition, it may not generate high-quality reconstructed 3D images when the number of the recorded elemental images is insufficient. Therefore, to solve these problems, we propose a new 3D reconstruction method for photon counting integral imaging, which can generate high-quality 3D images without photon loss in the reconstruction process. To prove our method, we carry out the simulation experiments.**

Keywords—3D reconstruction, 3D visualization, Integral imaging, Photon Counting

I. INTRODUCTION

Recently, three-dimensional (3D) imaging has been used in many industries. Integral imaging is one of the popular passive 3D imaging techniques [1-3]. It can provide full-parallax without special glasses and coherent light sources. It records multiple two-dimensional (2D) images which have different perspectives of 3D scene using camera array or lenslet array [4]. These images are referred to as elemental images. In general, Volumetric Computational Reconstruction (VCR) [3] is used to reconstruct 3D images digitally. However, VCR has a critical problem. It may not generate high-resolution 3D images using low-resolution elemental images or the insufficient number of elemental images.

It is a big challenge to visualize the object under the photon starved conditions. Photon counting can visualize the object under low light level conditions. It can detect photons using Poisson random process and statistical estimation such as maximum-likelihood estimation (MLE) [5]. To generate the 3D image of the object, photon counting integral imaging has been proposed [6-10]. The conventional photon counting integral imaging technique can detect photons of the object and generate the 3D image of the object in the dark scene by MLE and VCR. However, the conventional photon counting integral imaging has the same critical problems as in the VCR method.To solve these critical problems, we propose a new reconstruction method that can generate high visual quality 3D images. Our proposed method can visualize the object under severely photon-starved conditions with a small number of photons. In addition, it is an effective method to visualize the object with a few elemental images.

This paper organized as follows. In Section 2, we mention the conventional photon counting integral imaging and describe our proposed reconstruction method for visualization. In Section 3, we show the simulation setup and results to prove better performance of our proposed method. Finally, we present the conclusion in Section 4.

II. PHOTON COUNTING INTEGRAL IMAGING SYSTEM

A. Conventional Photon counting Integral Imaging

Photon detector is modelled mathematically by statistical distribution such as a Poisson distribution, since the photons are rarely detected in unit time and space. We extract the photons from the normalized elemental images to set a specified number of photons. We normalized the elemental images as following;

$$\lambda(\mathrm{x}) = \frac{I(x)}{\sum_{x=1}^{Ex} I(x)} \tag{1}$$

$I(\mathrm{x})$ is the original elemental image without normalization. Ex is the number of pixels in the elemental image. Finally, we can get normalized irradiance of the detected image $\lambda(\mathrm{x})$. Equation 2 shows how to detect the photons from the normalized image using Poisson distribution.

$$\mathrm{C(x)} \mid \lambda(\mathrm{x}) \sim \mathrm{Poisson}[N_p\, \lambda(\mathrm{x})] \tag{2}$$

$\mathrm{C(x)}$ is a photon-limited image which has an expected number of photons N_p. We illustrate these processes in Fig. 1.

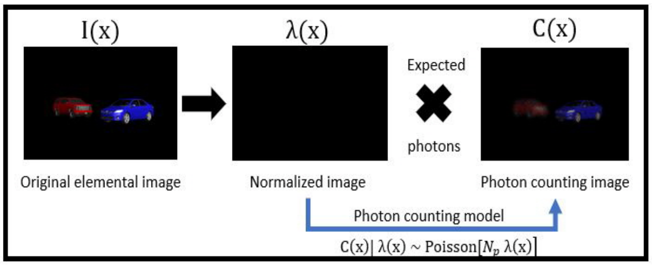

Fig. 1. Photon counting system for detecting the photons from elemental image.

To generate a color photon counting image, we consider red, green, and blue channels for each image. Each channel has different optical frequency and carries different photon energy. Therefore, we can define the expected number of photons for each color channel as the following.

$$\bar{N}c = \Gamma_c W = \frac{\eta W}{h\bar{\upsilon}_c} \tag{3}$$

$$\Gamma_c = \frac{\eta}{h\bar{\upsilon}_c} \tag{4}$$

$\bar{N}c$ is the expected number of photons in each color channel, and h is a Planck constant. W is the energy that occurs on the photo surface during the observation. $\overline{\upsilon_c}$ represents the mean optical frequency of the radiation in each color channel, and η is the quantum efficiency which represents the average number of photo events produced by each incident photon.

To generate 3D images from photon counting 2D images, we use integral imaging. Integral imaging technique has two processes; pickup and reconstruction processes. Fig. 2 represents the principle of integral imaging.

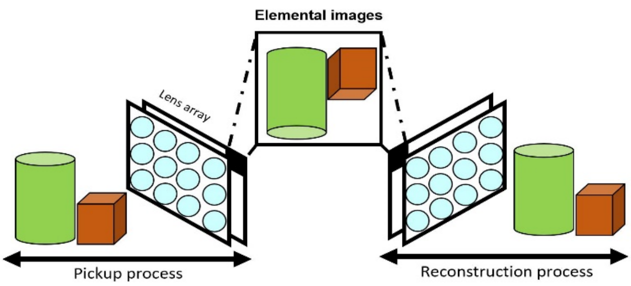

Fig. 2. Principle of Integral imaging.

When the lenslet array is used to record elemental images, the resolution of elemental images is degraded. To overcome this problem, Synthetic Aperture Integral Imaging (SAII) [4] can be used. In SAII, since camera array is used, high-resolution elemental images can be obtained. To generate the photon-limited elemental images, elemental images are normalized using Eq. (1) and photons are extracted from them using Eq. (2). In addition, MLE is used to estimate the original image from the photon-limited elemental images described as the following:

$$\mathrm{L}(\lambda) = \prod_{i=1}^{I} \frac{(N_p\lambda_i)^{C_i} e^{-N_p\lambda_i}}{C_i!} \tag{5}$$

$$\lambda_m = \frac{C_i}{N_p} \tag{6}$$

Where L(λ) is the likelihood function of Poisson random process, C_i is a photon-limited elemental image, and λ_m is the estimated original elemental images. To generate the 3D image with the estimated original elemental images, VCR technique is used. Fig. 3 shows the VCR process in photon counting integral imaging.

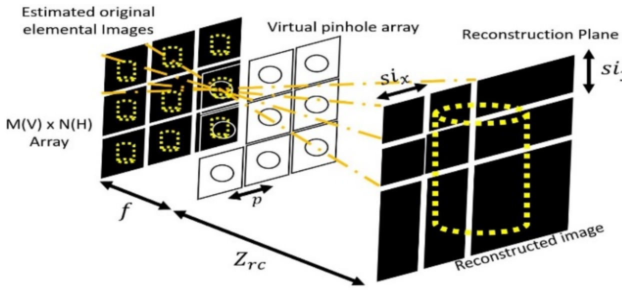

Fig. 3. Photon counting Integral imaging reconstruction process.

f is a distance between the estimated original elemental images and virtual pinhole array, and Z_{rc} is a distance between virtual pinhole array and reconstruction depth plane. si_x and si_y are the shifting pixel value of the elemental image in each axis. p is the pitch between the virtual pinholes. Each estimated original elemental image passes through the pinhole and is overlapped with each other on the reconstruction plane. Finally,3D images are reconstructed. The shifting pixel value of elemental images and reconstruction process are defined as the following equations:

$$si_x = \frac{fpE_x}{S_{cx}Z_{rc}},\ si_y = \frac{fpE_y}{S_{cy}Z_{rc}} \tag{7}$$

$$\mathrm{R}(\mathrm{x}, Z_{rc}) = \frac{1}{N_p OV(x, Z_{rc})} \sum_{m=1}^{M} \lambda_m\big(x + si_x(m-1)\big) \tag{8}$$

S_{cx} is a camera sensor size and $OV(x, Z_{rc})$ is overlap matrix for elemental image. M represents the number of elemental images. Finally, we can generate the 3D photon counting image with photon estimated elemental images. However, it is not enough to visualize the object in low-light level environment. Also, we cannot generate high visual quality 3D images without many elemental images. To overcome these problems, our proposed method is required.

B. Proposed Merging Reconstruction system for Photon Counting Integral Imaging System

The conventional method cannot use the estimated elemental image photons effectively. To visualize the object, we propose the new reconstruction process for photon counting Integral imaging. It can visualize the object without plenty of the elemental images, and it can use photons more efficiently than the conventional method. Fig. 4 illustrates our proposed merging reconstruction method.

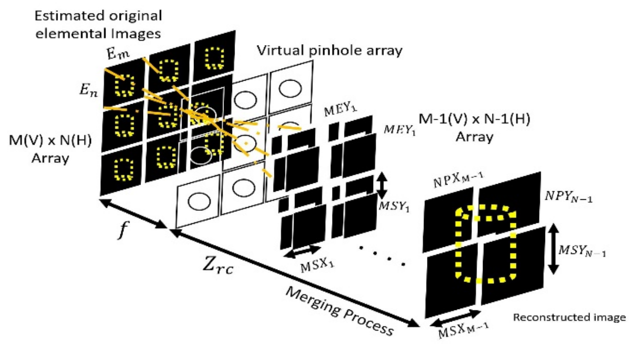

Fig. 4. Proposed method reconstruction process.

We estimate the estimated original elemental images by the conventional method. In the reconstruction process, we first implement the partial merge reconstruction, because we cannot generate high visual quality reconstructed images when we do not have enough elemental images in integral imaging technique. Therefore, we need to make a new elemental image in the merging process. First of all, we reconstruct the 2(H) x 2(V) elemental images respectively using the same reconstruction process of the conventional method (See Eq. (7) and (8)). This is because we can make new elemental images layers to enhance the visual quality of 3D images, and also each image has a different perspective so we can gather various photons in the photon estimated images. However, some of the noise from the background may exist in the image. Thus we use the threshold value to reduce the noise. We represent the noise reduction process as follows:

$$\overline{A} = \frac{1}{n}\sum_{i=1}^{n} ME_i \tag{9}$$

ME_i is a reconstructed image in the first merging layer, and $\overline{A}$ is the average pixel value of ME_i and n is a number of pixels in the image. If the pixel value is lower than the average pixel value, we treat it as a noise in the image. We set it to 0. If the pixel value is the same or higher than the average pixel value, we maintain the pixel value of the reconstructed image.

After reducing the noise, we use the modified reconstruction overlapping matrix for the merging process. In the conventional overlap process, we divide into $\mathrm{OV}(x)$ without considering the presence of photons in the image. The conventional method divides into the overlap count of whole elemental images. Therefore, this reconstruction method can reduce the pixel value of the photon counting part. However, we just calculate the overlap part with considering the existence of photons. Fig.5 shows the difference between conventional overlap process matrix $\mathrm{OV}(x)$ and the proposed image overlap matrix $\mathrm{OVN}(x)$.

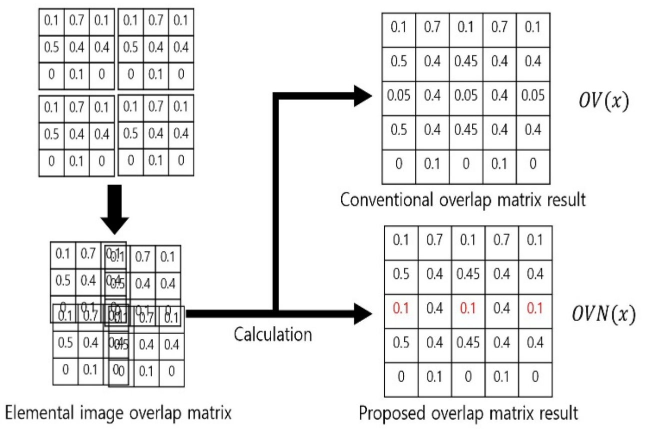

Fig. 5. Difference between conventional and proposed overlap method.

As shown in Fig.5, our proposed overlap calculation can distinguish the pixel existence. For example, if we have no value in the pixel we do not count up the overlap index. Equation (10) and (11) are the reconstruction process and the shifting value of the proposed method.

$$\mathrm{R}(x, Z_{rc}) = \frac{1}{N_p OVN(x)} \sum_{m=1}^{M-1} ME_m(x + MSX_m) \quad (m=1,\ldots,M-1) \tag{10}$$

$$MSX_m = \frac{f p ME_m}{S_{cx} Z_{rc}} \quad (m = 1, \ldots, \mathrm{M}-1) \tag{11}$$

$\mathrm{MSX_m}$ is a new image shift value in each merging layer, and ME_m is a number of the pixels in each merging layer elemental image. $\mathrm{OVN}(x)$ is a new overlap reconstruction matrix for photon counting integral imaging. We use this new reconstruction process from the first reconstructed image layer, and we continue to merge the partially reconstructed image until the last one reconstructed image is made. Finally, we can get a high visual quality reconstructed image without plenty of elemental images, and we can visualize the object in the low luminance situation with a small number of the expected photons.

III. Experimental Setup and Results

To prove the performance of our proposed method, we carry out the simulation experiment. We used 5(H)×5(V) camera array to record elemental images. The focal length of the camera is 50mm. The pitch between the camera is 2 mm. Each elemental image has 3000(H) × 2000(V) pixels. We located two cars in front of the camera with different distances. Fig. 6 shows our experiment setup.

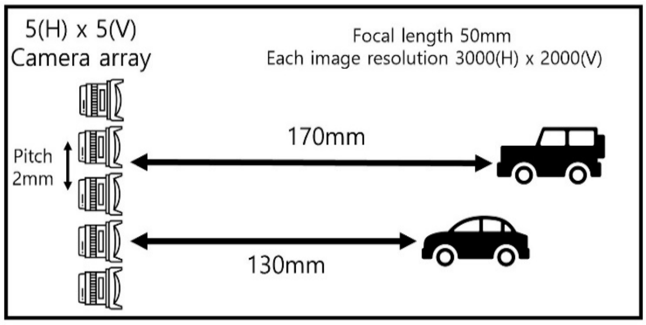

Fig. 6. The simulation experiment setup.

To detect the photons from the elemental images, we need to normalize the elemental images. Fig. 7 shows the original elemental image and normalized elemental image in this experiment.

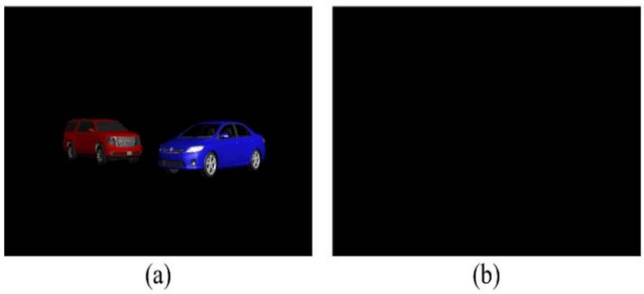

Fig. 7. Images; (a) Original elemental image; (b) Normalized image.

We used 5(H) x 5(V) elemental images, and we extracted the expected number of photons with 4 different conditions. To prove the performance of our proposed method, we just set the low number of expected photons in the elemental image. We generate the photon-limited elemental image with $N_p = 1500$, $N_p = 3000$, $N_p = 4500$, and $N_p = 6000$.

To compare the visual quality of the reconstructed images with the conventional method, we represent the conventional method result image in fig. 8 and the proposed method result image in fig. 9.

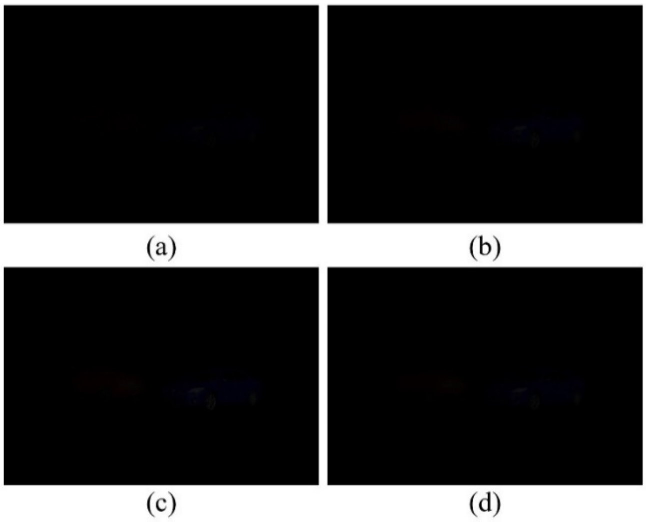

Fig. 8. The conventional method reconstructed image; (a) $\boldsymbol{N_p}$=1500 result; (b) $\boldsymbol{N_p}$=3000 result; (c) $\boldsymbol{N_p}$=4500 result; (d) $\boldsymbol{N_p}$=6000 result.

The reconstruction depth in the conventional method is 133mm. As shown in Fig. 8, we cannot visualize any object from the elemental images. In Fig. 8 (d), we can recognize the blue car front part slightly, but it is hard to see the object in the result image. However, our proposed method can visualize the object with the same number of expected photons N_p. Fig. 9 shows the result of the proposed method.

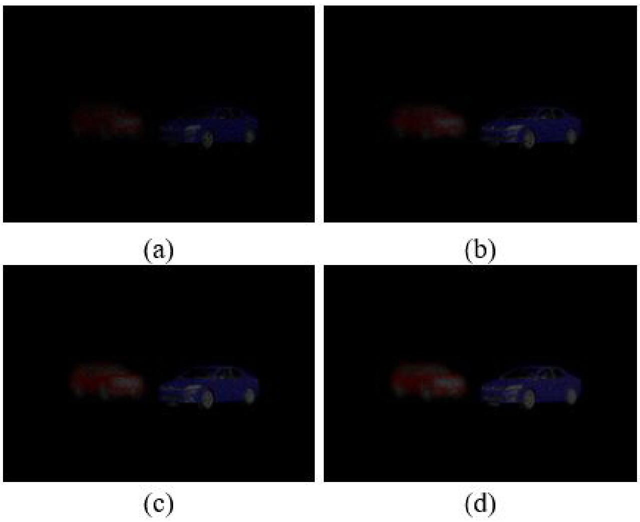

Fig. 9. The proposed method reconstructed image; (a) $\boldsymbol{N_p}$=1500 result; (b) $\boldsymbol{N_p}$=3000 result; (c) $\boldsymbol{N_p}$=4500 result; (d) $\boldsymbol{N_p}$=6000 result.

In our proposed method result, we can recognize the blue car and the red car. From Fig. 9, our proposed method's image quality is gradually increasing when we increase the number of expected photons. In addition, it can visualize the object and can generate a 3D image without a lot of expected photons. We also counted the photons in the image. We divided the number of photon pixels into the whole image pixels and we represented with percentage in table 1.

TABLE I. PHOTON COUNTS IN THE 3D IMAGE

	Conventional	Proposed
N_p 1500	0.16%	1.39%
N_p 3000	0.32%	2.32%
N_p 4500	0.47%	3.01%
N_p 6000	0.62%	3.53%

We can detect more photons than the conventional method with the same number of expected photons. Fig. 10 shows the pixel intensity difference of the two methods.

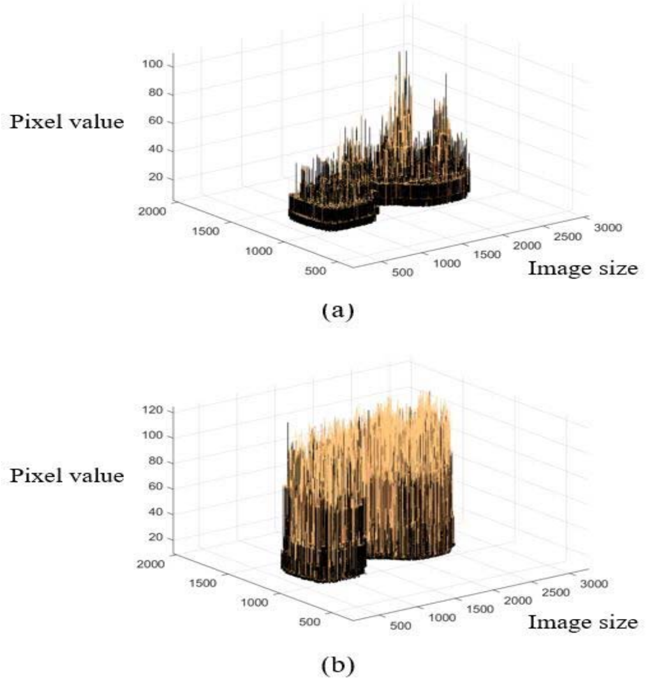

Fig. 10. The pixel intensity of reconstructed image; (a) conventional result image; (b) proposed result image.

Fig. 10 (a) has a very low pixel value of the result image. It cannot visualize the object well. In addition, since the - conventional method used the normal overlap matrix, it decreased the pixel value of the 3D image. On the other hand, in Fig. 10 (b), higher pixel values are shown than the conventional result. It can generate a high- intensity pixel 3D image, and it has a high pixel average value than the previous method.

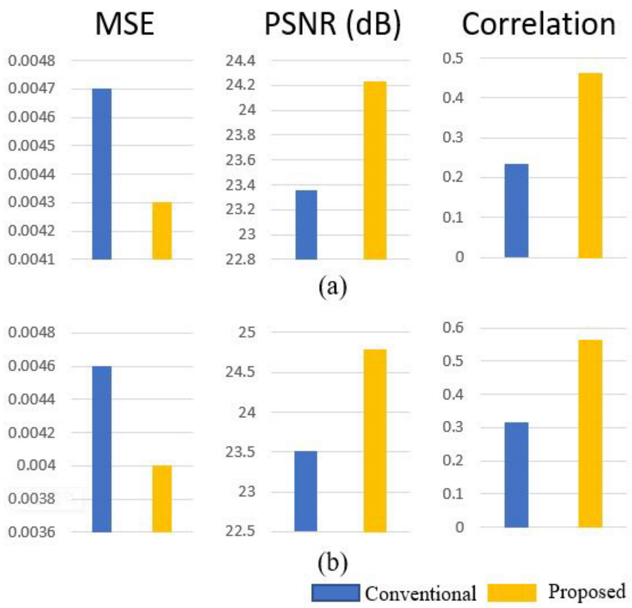

Fig. 11. Image test result; (a) $\boldsymbol{N_p}$=1500 case; (b) $\boldsymbol{N_p}$=3000 case.

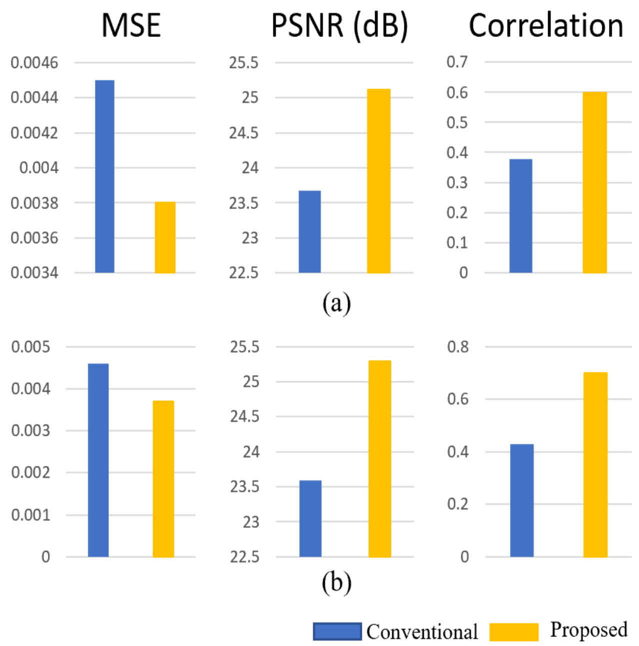

Fig. 12. Image test result; (a) $\boldsymbol{N_p}$=4500 case; (b) $\boldsymbol{N_p}$=6000 case.

Fig. 11 and 12 show the result of the image quality test with various N_p. We tested the image with MSE, PSNR, and correlation. As we can see in Fig. 11, our proposed method can visualize the object in the severely photon-starved conditions better than the conventional method.

IV. Conclusion

Our proposed method can generate high-quality 3D images in the severely photon-starved conditions. In the reconstruction process, the conventional method can reduce the photons intensity because of the overlapping process. However, our proposed method can detect the more photons than the conventional method. In addition, it can visualize the object without many elemental images. This is because we produce the merging layer after the estimation of the original elemental images, and we can generate other elemental images that have more photons than the previous merging layer. Therefore, we can visualize the object with elemental images which has the low number of expected photons. Finally, our proposed method can be used for autonomous vehicle systems, unmanned cameras, and microscopy in low luminance situations.

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