Journal of information and communication convergence engineering
http://jicce.org

J. Inf. Commun. Converg. Eng. 19(2): 102-107, Jun. 2021 Regular paper

3D Visualization for Extremely Dark Scenes Using Merging Reconstruction and Maximum Likelihood Estimation

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Abstract

In this paper, we propose a new three-dimensional (3D) photon-counting integral imaging reconstruction method using a merging reconstruction process and maximum likelihood estimation (MLE). The conventional 3D photon-counting reconstruction method extracts photons from elemental images using a Poisson random process and estimates the scene using statistical methods such as MLE. However, it can reduce the photon levels because of an average overlapping calculation. Thus, it may not visualize 3D objects in severely low light environments. In addition, it may not generate high-quality reconstructed 3D images when the number of elemental images is insufficient. To solve these problems, we propose a new 3D photon-counting merging reconstruction method using MLE. It can visualize 3D objects without photon-level loss through a proposed overlapping calculation during the reconstruction process. We confirmed the image quality of our proposed method by performing optical experiments.

Index Terms: Integral imaging, Photon counting, Statistical optics, Three-dimensional (3D) visualization.

I. INTRODUCTION

Recently, three-dimensional (3D) imaging under low-luminance conditions has emerged as the most important technique in several industries. LiDAR is being used to recognize object shapes in dark conditions [1]; however, it cannot visualize the object colors or provide detailed information. Therefore, it is unfeasible for object recognition under dark conditions. On the other hand, photon-counting imaging and statistical models can be used to detect photons that occur rarely in unit time and space [2-5]. Such models use the Poisson random process and maximum likelihood estimation (MLE) to visualize an object in a dark scene. To generate the 3D information of the object, the integral imaging technique is typically used with the photon-counting method. Integral imaging is one of the most valuable passive 3D imaging techniques that can provide full parallax without using expensive equipment and constant light sources. The technique uses a camera or lens array to record two-dimensional (2D) images with different perspectives for creating 3D scenes [6]. The recorded images are referred to as elemental images. When each elemental image passes through the lenslet array, a 3D scene can be generated. To generate the 3D scene using a computational process, volumetric computational reconstruction (VCR) has been used [7-10]. In addition, VCR has also been used with the photon-counting method, which is called the 3D photon-counting integral imaging technique [11-18], to generate 3D scenes under dark conditions. Moreover, visualizing 3D objects in a low-light environment may require photon-limited elemental images, which can be generated using a computational statistical photon-counting model. These elemental images can con-

Received 25 January 2021, **Revised** 14 April 2021, **Accepted** 15 April 2021
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Open Access https://doi.org/10.6109/jicce.2021.19.2.102 print ISSN: 2234-8255 online ISSN: 2234-8883

struct a likelihood function for MLE [11-12] and the MLE can then visualize the 3D object in the dark scene. However, the conventional method has certain critical problems in visualizing 3D scenes. If the number of elemental images required for reconstruction is insufficient, estimating the object in the scene becomes difficult. Furthermore, insufficiency in the number of photons for visualizing the 3D scene can lead to an inaccurate visualization of the object. To solve these problems, we propose a new reconstruction method to visualize 3D scenes under extremely dark conditions. We believe it to be an effective method for visualizing an object with a few elemental images and expected photons.

The paper is organized as follows. In Section 2, we explain the principle of conventional 3D photon-counting imaging using MLE and present the proposed method. In Section 3, we introduce the optical experimental setup and results to demonstrate the performance of our proposed method. Finally, we present our conclusions in Section 4.

II. PHOTON-COUNTING INTEGRAL IMAGING METHOD

A. Conventional Photon-counting Integral Imaging

Computational photon counting can be defined by a statistical distribution, such as a Poisson distribution. This is because photons are rarely detected in unit time and space [3,4]. The distribution can be used to extract the photons from a normalized scene, which contains a certain number of photons, as follows:

$$\lambda(x) = \frac{N_p R(x)}{\sum_{x=1}^{P_x} R(x)}, \tag{1}$$

where $R(x)$ is the original elemental image, N_p is the number of photons, and P_x represents the total number of pixels in the elemental image. Finally, we obtain the normalized irradiance $\lambda(x)$ of the detected image. The Poisson random process is used to estimate the photons in the normalized image as follows:

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

where $C(x)$ is a photon-limited image with the expected number of photons. Fig. 1 illustrates these processes.

To generate a color photon-limited image, red, green, and blue channels are considered. Each color has a different optical frequency and photon energy. Therefore, photons can be defined according to each channel as follows:

$$\overline{N}c = \tau_c W = \frac{\eta W}{h\overline{v}_c}, \tag{3}$$

$$\tau_c = \frac{\eta}{h\overline{v}_c}, \tag{4}$$

where $\overline{N}_c$ represents the number of photons in the color dimension, h represents the Planck constant, W represents the energy radiating from the object surface during the photon observation process, $\overline{v}_c$ is the mean optical frequency value of each color dimension, and η represents the quantum efficiency.

To reconstruct 3D images from the photon-limited 2D images, an integral imaging technique is used. The technique can be divided into two processes: pick-up and reconstruction, as described in Fig. 2.

In general, a lens array is used to record the elemental images of the 3D objects [6]. However, the resolution of the elemental images can be low because of being recorded together in a single image sensor. To solve this problem, synthetic aperture integral imaging (SAII) [7,8] can be used. In SAII, because a camera array is used, each elemental image has the resolution of a single image sensor and high-resolution elemental images can be recorded. To obtain high-resolution photon-limited elemental images, Eqs. (1) and (2) are used with SAII. Photon-limited elemental images follow a Poisson distribution in a 3D scene. Therefore, the likelihood function can be defined as follows:

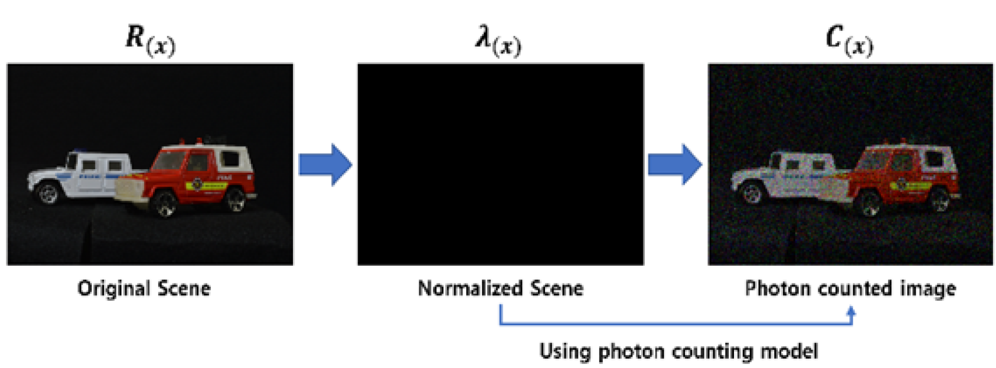

Fig. 1. Computational photon counting model.

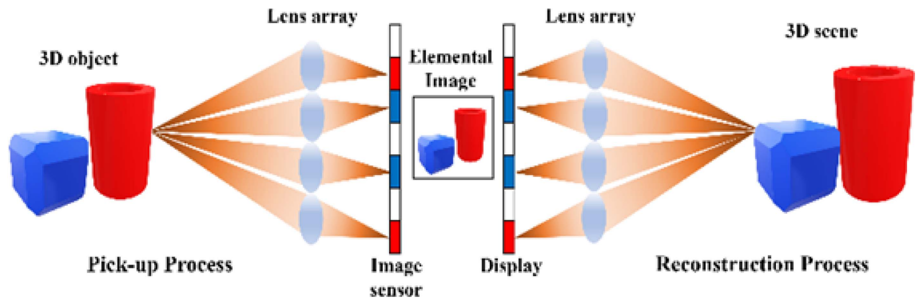

Fig. 2. Principle of integral imaging.

$$L(\lambda) = \prod_{k=1}^{K} \frac{\lambda_k^{C_k} - e^{-Np\lambda_k}}{C_k!}, \quad (5)$$

$$\hat{\lambda}_k = C_k, \quad (6)$$

where $L(\lambda)$ is the likelihood function of the Poisson random process, C_k represents the photon-limited elemental image, and $\hat{\lambda}_k$ is the estimated elemental images. k and K are the index and number of photon-limited elemental images, respectively.

Using Eqs. (5) and (6), the normalized image can be estimated as C_k. Using these estimated elemental images, 3D reconstructed images can be generated [13-18].

Fig. 3 illustrates the conventional photon-counting integral imaging technique, where f represents the distance between the estimated elemental images and the virtual pinhole array, Z_r is the distance between the virtual pinhole array and the reconstruction depth plane, Δx is the shifting pixel value of each photon-limited elemental image on the reconstruction plane, and p represents the interval between the virtual pinholes. The elemental images overlap on the reconstruction plane through the pinholes. Finally, 3D photon-limited images are reconstructed using the following equations:

$$\Delta x = \frac{fpE_x}{S_x Z_r}, \quad (7)$$

$$R(x, Z_r) = \frac{1}{0(x)} \Sigma_{k=1}^{k} C_k(x + \Delta x(k-1)), \quad (8)$$

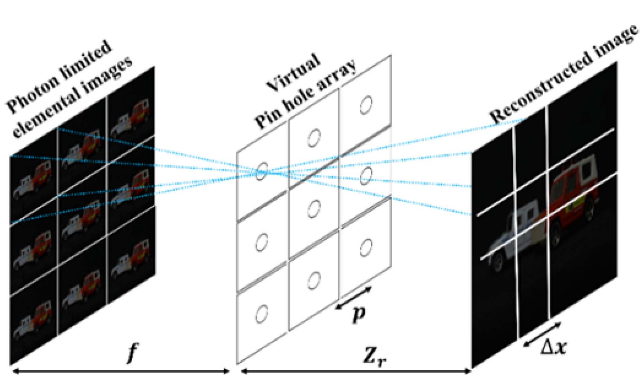

Fig. 3. Photon counting Integral imaging reconstruction process.

where E_x represents the number of elemental image pixels, S_x is the camera sensor size, and $O(x)$ represents the overlap count of the elemental images. Finally, we can generate the 3D photon-counting image under low-luminance situation by using MLE with the estimated elemental images. However, the conventional method cannot visualize the 3D scene accurately under extremely dark conditions. In addition, the generated 3D image may be of low visual quality if the elemental images are insufficient. To solve these problems, we propose a method that can provide high visual quality in photon-limited situations.

B. Merging Reconstruction Method Using MLE

The conventional method cannot effectively utilize the photons of the elemental image [13,15]. For more effective utilization, we propose a new merging reconstruction method that can utilize the photon information effectively even in extremely dark conditions. Fig. 4 illustrates the proposed merging reconstruction method. Unlike the conventional reconstruction process, our proposed method employs merging reconstruction layers to generate the 3D reconstructed image from partial elemental images. In addition, these reconstructed images can be reused as elemental images because each elemental image has a different perspective information of the scene, and the photons can be present at various locations in the estimated image. Partial reconstruction can effectively accumulate this photon intensity. When we cannot obtain the elemental image sufficiently under dark conditions, the conventional method may have a critical problem

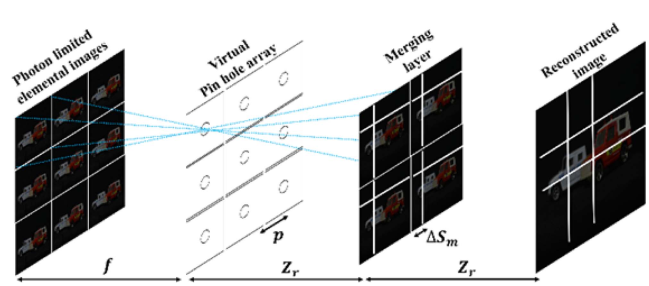

Fig. 4. Proposed reconstruction process.

in visualizing the scene. On the contrary, because our proposed method reuses the reconstructed images as elemental images, it can visualize the scene better than the conventional method. Finally, we can generate a single reconstructed image at the end of the merging reconstruction process.

To gather the photons in a sufficient number during the reconstruction process, an improved overlap matrix is used in our proposed method. In the conventional overlap process, we use the overlapping matrix $O(x)$ without considering the existence of photons on the reconstruction plane. The conventional method calculates the overlapping counts using the complete elemental images. However, this averaging calculation can reduce the photon intensity. In particular, when the photon has a low intensity, the photon level can reduce owing to conventional overlapping calculations, causing a loss of photon information. On the other hand, our proposed method calculates the overlapping matrix by considering the existence of photons. For example, if the photon intensity is zero at a pixel in the estimated image, the incident photon does not exist in the estimated image. To consider this condition, our proposed method only calculates the photon overlapping counts according to the photon presence in the image. The merging reconstruction and shift values can be defined as follows:

$$\Delta S_m = \frac{fpE_x^m}{S_x Z_r}, \tag{9}$$

$$C_k^{m+1} = \frac{1}{O(x)} \sum_{k=1}^{K} C_k^m (x + \Delta S_m (k-1)) \quad (C_k^m > 0), \tag{10}$$

where ΔS_m is a shifting pixel value on each merging layer, E_x^m is the total number of pixels for the elemental image on the mth merging layer, and C_k^m represents the kth reconstructed elemental images on the mth merging layer. This merging reconstruction process regenerates the elemental image from the first reconstructed image layer and is implemented continuously until a single image is generated. Thus, we obtain a high-visual-quality reconstructed image that can visualize the 3D scene effectively without using numerous elemental images and expected photons.

III. EXPERIMENTAL SETUP AND RESULTS

To prove the enhancement in image quality after applying our proposed method, we performed an optical experiment. We used a 5(H) × 5(V) camera array to generate elemental images. The focal length was set as 55 mm, the pitch between the cameras as 2 mm, and the dimensions of the elemental image as 400(H) × 600(V) pixels. Fig. 5 illustrates our experimental setup.

To estimate the photons using the photon-counting model, normalized images were generated using Eq. (1). Fig. 6 shows the original elemental image and its normalized version used in this experiment.

To compare the performances of the conventional and proposed methods, we composed various dark conditions. In this experiment, we assumed the number of photons to be from 100 to 1000. Figs. 7 and 8 show the experimental results obtained using the conventional and proposed method, respectively. The reconstruction depth of the first object was 250 mm.

As shown in Fig. 7, it is very difficult to recognize the toy shape satisfactorily until 1000 expected photons are used. To visualize the object using the conventional method, we had to use more photons, as shown in Fig. 7(c) and (d). We can observe the object shape slightly only after using over 3000

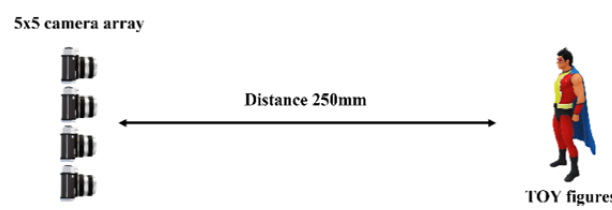

Fig. 5. The optical experimental setup.

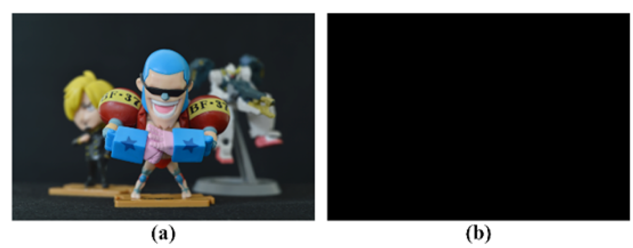

Fig. 6. Photon counting process; (a) original elemental image and (b) its normalized image.

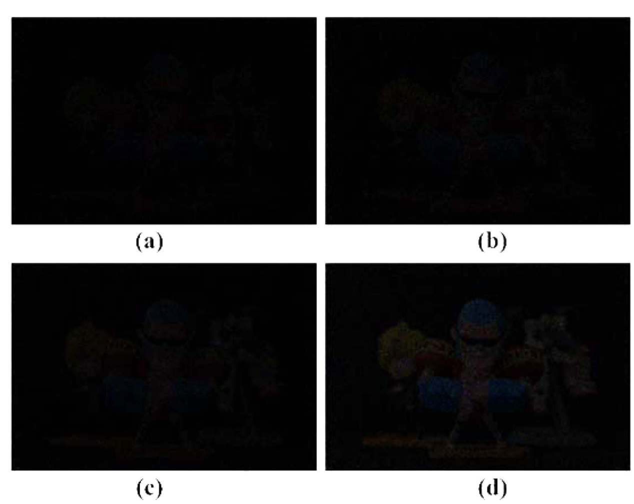

Fig. 7. Conventional reconstructed image; (a) 700 expected photons are used, (b) 1000 expected photons are used, (c) 3000 expected photons are used, (d) 6000 expected photons are used.

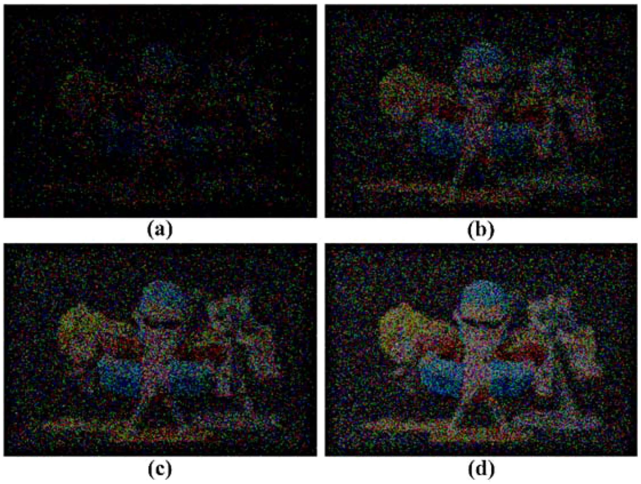

Fig. 8. Proposed reconstructed image; (a) 100 expected photons used, (b) 400 expected photons used, (c) 700 expected photons used, (d) 1000 expected photons used.

Table 1. Photon intensity analysis data of conventional and proposed methods.

Expected photons	Photon intensity mean	
	Conventional	Proposed
Np=100	0.0008/image	0.0092/image
Np=400	0.0016/image	0.0358/image
Np=700	0.0027/image	0.613/image
Np=1000	0.0040/image	0.0852/image

expected photons. Therefore, the conventional method requires more than 3000 expected photons to visualize an object under dark conditions.

In contrast, the proposed method can visualize the 3D object shape slightly even when 100 expected photons are used, as shown in Fig. 8(a). As the number of photons increase, the proposed method can visualize the background scene better in the dark situation because each elemental image contains a uniform probability of photon occurrence. Therefore, our proposed method can enhance the overall visual quality. As a result, our proposed method can even recognize the details of the toy (e.g., the words on the shoulders of the first toy), as shown in Fig. 8(d).

To verify the performance of our proposed method, we calculated the photon intensity average value for the photon-limited image. To obtain this value, we used the mean of the reconstructed image, as shown in Table 1.

According to Table 1, the proposed method can enhance the photon intensity value by approximately 10 to 20 times than that by the conventional method. In other words, our proposed method can preserve the photon information excellently under dark conditions. To evaluate the image quality of the reconstructed image, a correlation analysis was performed, as shown in Fig. 9.

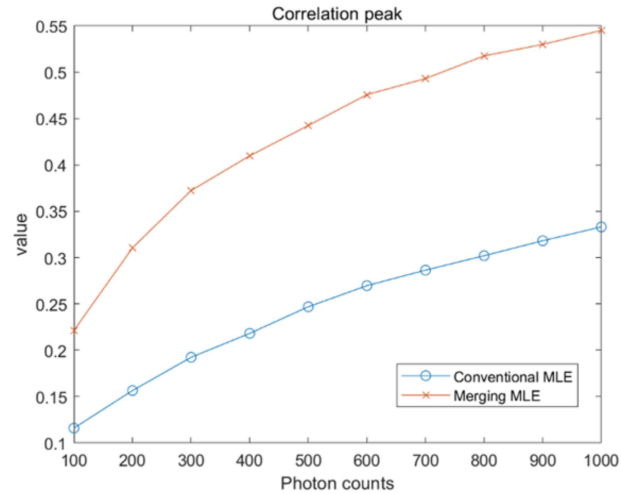

Fig. 9. Correlation analysis data.

For plotting the graph, the correlation peak value was used as the performance metric. As evident from the graph, our proposed method shows the highest correlation peak overall, that is, it can visualize 3D objects effectively under dark conditions. In conclusion, the conventional MLE has a critical problem in visualizing objects under dark conditions, and also requires sufficient elemental images for visualization. However, our proposed method can be utilized even under harsh conditions without sufficient photons and elemental images.

IV. CONCLUSION

Through optical experiments, we proved that our proposed method can visualize 3D scenes effectively even under extremely dark conditions. Especially, while reconstructing a 3D image, the conventional 3D photon-counting technique can diminish the photon levels, because the conventional overlapping matrix causes a photon intensity loss. In contrast, the proposed method can visualize the object even without sufficient elemental images because it regenerates the elemental images on multiple merging layers, which are reused as elemental images on each merging layer. It can also enhance the number of photons on each merging layer. Therefore, our proposed method can effectively accumulate photons from each elemental image, even under extremely dark conditions. However, the method requires several calculations during the reconstruction process, increasing the processing time. We aim to find a solution for this problem in the future. Our proposed method can be used for night vision systems, autonomous vehicle systems, unmanned cameras, and microscopy under low-luminance conditions.

ACKNOWLEDGEMENTS

This work was supported by a National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT) (NRF-2020R1F1A1068637).

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