Indoor Lighting Estimation using an Event Camera (Supplementary Material)

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This file provides: (i) details of our optimization-based method (Section 7), (ii) analysis of the range of effective distance (Section 8), (iii) introduction of our methods applying to real scenes (Section 9 with a video demonstration [a]).

7. Details of Optimization-based Method

Equation (8) in the main paper can be divided into two parts to optimize ($\mathbf{n}_l$ and $\{d, a, b, c\}$). To avoid the influence of noises, we selected the points $\mathbf{x}$ that generate two or more events to optimize $\mathbf{n}_l$ based on Equation (9) the main paper.
Data preprocessing. We use the estimated $\mathbf{n}_l$ to optimize the remaining parameters (*i.e.*, $\{d, a, b, c\}$). To mitigate the impact of noise in the event stream, we first preprocessed the event streams by clustering the points according to their cosine values $\max(\langle \mathbf{n}_l, \mathbf{n}_\mathbf{x} \rangle, 0)$ and obtain 10 subsets of points. We then generate a sequence for each subset by averaging the timestamp for points with the same number of events. Finally, these ten sequences are used to estimate $\{d, a, b, c\}$.
Initial values of $\{a, b\}$. We observe that the optimization results are sensitive to the initial values of $\{a, b\}$. To achieve satisfying results, we obtain a good initialization based on a small amount of real data. Specifically, we select 40 real data (10 for each type of lamp) and calculate the mean and standard deviation of parameters $\{a, b\}$ using the same method as that in Section 5.3. Table 4 displays the mean and standard deviation of parameters $\{a, b\}$. We find that good optimization results can be achieved when the initial values of $\{a, b\}$ are set as $\{5, 0.01\}$. Note that we use this initialization for all data with different lamps.

8. Effective Distance

In this section, we discuss the effective distance of our methods. We find our the light source is too close (< 70 *cm*), the event camera fails to capture the intensity changes due to the strong light, as shown in Figure 14. When the distance of the light source is too far away, the unexpected noise of event streams becomes dominant while the events caused by intensity changing are less obvious (Figure 15). Therefore, the effective distance of our methods is relevant to the power of lamps, *i.e.*, a larger effective distance for lamps with bigger power. We empirically set the effective distance as those in Table 4 for our experimental lamps and we sample evenly within the effective distance of each light source for our experimental data (Section 4.3).

Table 4. The mean and standard deviation of parameters $\{a, b\}$ (mean $\pm$ std) and the effective distance (*cm*) for different lamps.

Lighting type	a	b	Effective Distance
LED(0.5w)	1.78±1.88	-2.41±5.64	[70, 165]
LED(3w)	2.40±2.45	-4.34±5.66	[70, 300]
LED(5w)	2.11±2.11	0.59±1.13	[165, 300]
ILB (15w)	4.73±4.78	-19.84±20.58	[70, 300]

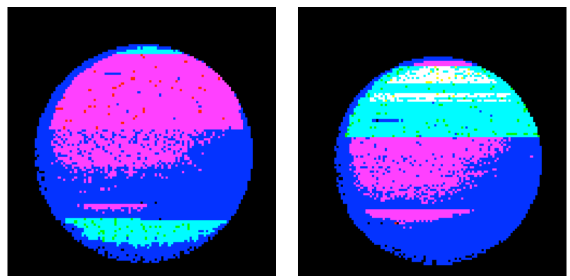

Figure 14. Examples of failing to capture the intensity changes due to the strong light.

9. Applying to Real Scenarios

In this section, we show real scenarios of using our methods to estimate lighting in three different real scenarios. A video demonstration can be found in the attached video. In our rendering scene, the intensity of the light source is determined by I_0 multiplied by a fixed scale (set as 10 in all our experiments).
Light up a lamp. In the first scenario, we show the results of lighting up a lamp. This is a scenario that pretty much matches our analysis in the main paper. We use the same

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[a] https://www.bilibili.com/video/BV1c5411N7Do/

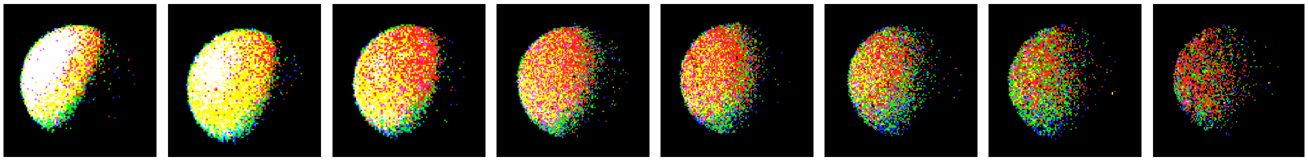

Figure 15. Examples of the relationship between distance of light source LED 0.5w and event streams(visualized based on the method in [2])

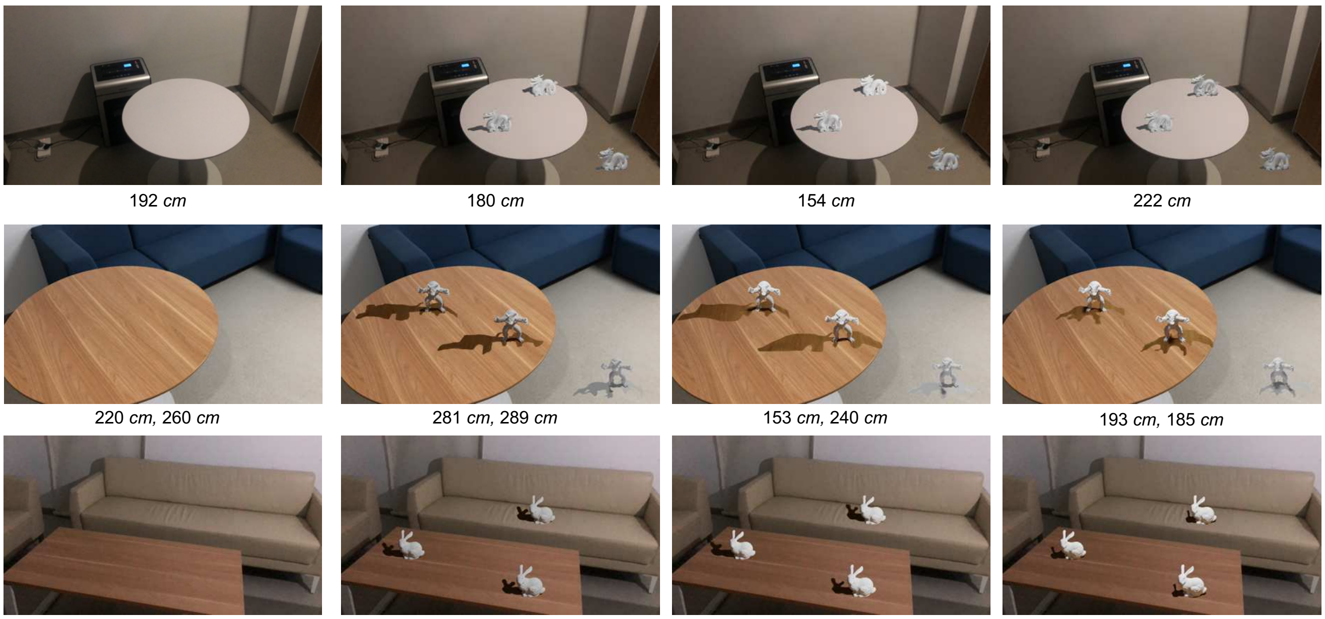

Figure 16. Object insertion results of real indoor scenes. From left to right: the scene image, results from our optimization-based method, our learning-based method, and GH19 [1]. From upper to bottom: scenarios of light up a lamp, light up two lamps in sequence, remove the lampshade. Numbers below each image indicates the ground truth or predicted results of light source distance.

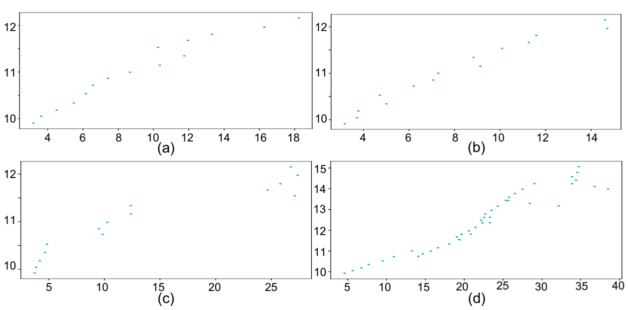

Figure 17. The x-axis represents logarithm of intensity, and the y-axis represents the time. (a) The intensity changing curve of the lamp in the scenario of lighting one lamp. (b) The intensity changing curve of the lamp in the scenario of lighting two lamps. (c) The intensity changing curve of the lamp in the scenario of lighting two lamps. (d) The intensity changing curve of the lamp in the scenario of removing the lampshade.

methods in the main paper to estimate the light source. The $\Phi(t)$ is shown in Figure 17 (a). Figure 16 shows that the distance estimated by our optimization-based method is the closest to the ground truth.

Light up two lamps in sequence. In the second scenario, we explore a scene with multiple light sources. We light up two lamps in sequence. When we estimate the second lighting, I_0 is determined by the radiant intensity value captured with the first lighting. The lighting intensity of our second lamp for our rendering is calculated based on the estimated intensity of the first lamp. Figure 17(b), (c) show the $\Phi(t)$ of the first lamp and the second lamp. Note that the inaccurate shape of curve $\Phi(t)$ in Figure 17 (c) is caused by the strong lighting (can be observed in our video demo, the event streams also appears in a noisy pattern). We find that such a pattern has little impact on the accuracy of lighting estimation in our methods. The cast shadow of the object inserted by our methods can be clearly observed. These results indicate that our methods can also be used for multiple light sources estimation.

Remove the lampshade. In the third scenario, we investigate a more general scenario of quickly removing the lampshade (more details can be found in the video). We observe that $\Phi(t)$ becomes a function that describes the action of removing the lampshade and appears a different shape as that for lighting up, as shown in Figure 17(d). Considering this split time is shorter than turning the light on, we set the t_n as 48 *ms*. Figure 16 shows that the intensity of the rabbits rendered by our optimization-based method is the closest to the environment.

References

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