

OLATverse: A Large-scale Real-world Object Dataset with Precise Lighting Control

Supplementary Material

In this supplementary document, we first provide additional visualizations of **OLATverse**, including both validation and training sets. We then describe the detailed capture configurations of the cameras and stand supports. Finally, we present additional results on relighting, benchmark for inverse-rendering and normal estimation.

7. Dataset Visualization

7.1. Dataset Statistics

OLATverse contains 765 objects covering approximately 18.5% of the LVIS categories [19], substantially exceeding the category coverage of existing real-world datasets, including OmniObject3D (10.8%) [56], OpenIllumination (4 ~ 5%) [32], and DTC (3%) [11]. The distribution across LVIS categories is shown in Fig. 8. Since many objects in our collection do not fall within the original LVIS taxonomy, we introduce an additional category *others* to include these items.

7.2. An Example in Dataset

We demonstrate all the annotations provided in an example, as shown in Fig. 9. For each captured view, we provide images under uniform white illumination (FB), OLATs, images under environmental illumination (ENV), object masks, and surface normals acquired through color gradient illumination. Additionally, for five polarized views, we offer polarized surface normals, which are more accurate than color gradient normals, and diffuse albedo.

7.3. Selected Validation Data

We construct a validation set consisting of 42 objects spanning a broad range of material categories. We carefully selected 42 validation objects covering 14 material categories, including both Lambertian and glossy objects. Specifically, our validation dataset consists of: 4 plaster, 4 metal, 3 plastic, 3 paper, 4 wood, 5 fabric, 4 leather, 2 ceramics, 1 plant, 3 rubber, 5 food, 2 stone, and 2 wax. A subset is shown in Fig. 12, where we visualize the uniform-illumination images and three OLATs for each object. In Fig. 13, we further visualize surface normals and diffuse albedo from two views, obtained via polarized gradient illumination. For selected objects, we also include meshes reconstructed with MetaShape [1]. These figures demonstrate that our validation set is highly diverse and serves as a strong benchmark for tasks such as relighting and inverse rendering.

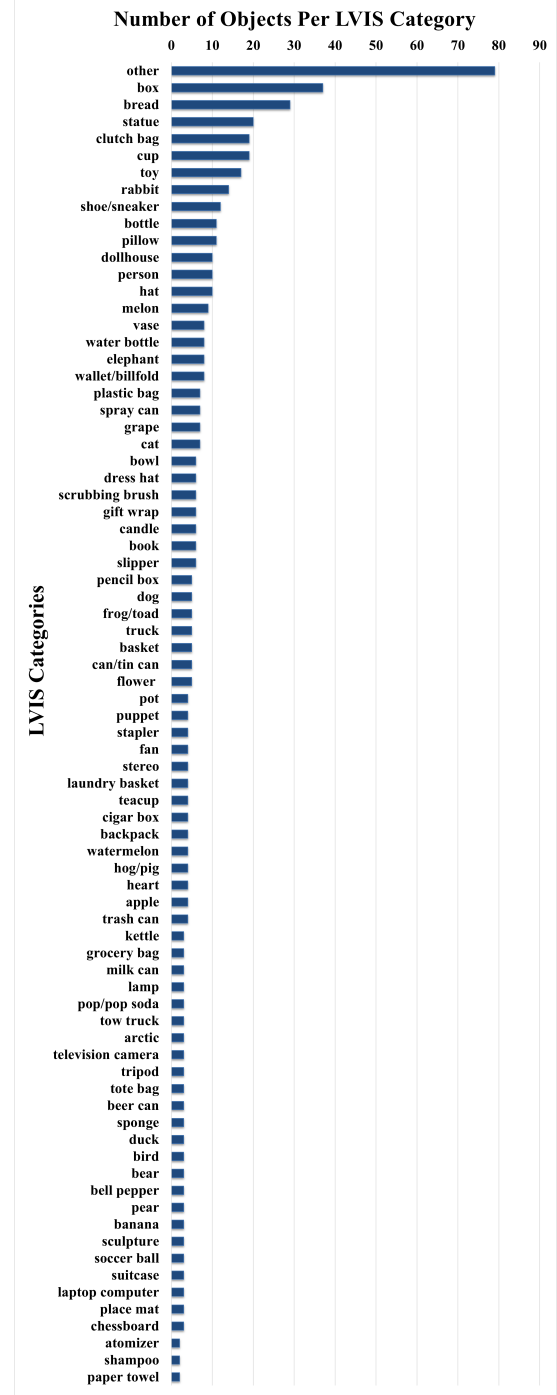


Figure 8. Distribution of LVIS category in **OLATverse**. Note that we add *Others* category to include those objects not covered in LVIS categories.

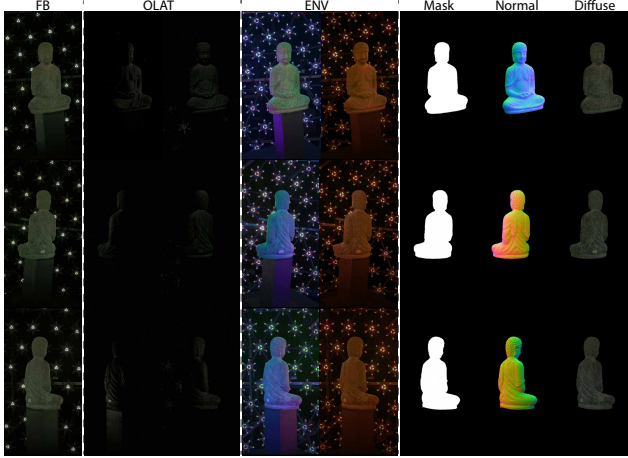


Figure 9. We visualize one sample of **OLATverse**, which includes full bright (FB), OLATs, relit images under varying pre-defined environmental illuminations (ENV), object mask, surface normals, and diffuse albedo.



Figure 10. A set of wooden stand supports utilized for object capture. All stand supports are covered by black matte paper to eliminate color bleeding and specular reflection effects during capture.

7.4. Selected Full Data

We visualize a subset of the full dataset in Figs. 14–16. Since the scale of **OLATverse** is very large, we only demonstrate a small portion in the supplementary material. All statistics will be released in the final version upon acceptance. We list some example object IDs in the following format: "ObjectID; High-level Category; LVIS Category; Material".

- **data-040325-C091**; Animals; rabbit; plaster.
- **data-040325-C101**; Clothing&Accessories; hat; fabric.
- **data-040325-C109**; Sports&Fitness; trophy cup; plastic.
- **data-040325-C111**; Art&Decorations; vase; other.
- **data-040425-C238**; Tools&Hardware; handsaw/carpenter's

saw; metal.

- **data-040425-C240**; Electronics&Appliances; stereo/stereo sound system; plastic.
- **data-040425-C245**; Electronics&Appliances; other; plastic.
- **data-040625-C416**; Tools&Hardware; other; plastic.
- **data-040625-C418**; Food&Drinks; cup; rubber.
- **data-040625-C430**; Tools&Hardware; other; fabric.
- **data-040625-C454**; Food&Drinks; pizza; food.
- **data-040625-C458**; Food&Drinks; other; food.
- **data-040625-C461**; Food&Drinks; watermelon; food.
- **data-040625-C465**; Food&Drinks; other; food.
- **data-040725-C562**; Animals; other; stone.
- **data-040725-C564**; Animals; frog/toad/toad frog; plaster.
- **data-040725-C566**; Animals; hog/pig; plaster.
- **data-040725-C572**; Animals; koala/koala bear; ceramics.
- **data-040725-C576**; Furniture, Household&Containers; cigar box; wood.
- **data-040725-C581**; Electronics&Appliances; fan; plastic.
- **data-040725-C585**; Art&Decorations; toy; plaster.
- **data-040725-C587**; Animals; dog; plastic.
- **data-040725-C589**; Food&Drinks; cup; ceramics.
- **data-040725-C591**; Furniture, Household&Containers; can/tin can; metal.
- **data-040725-C593**; Food&Drinks; cup; ceramics.
- **data-040725-C595**; Animals; squirrel; plaster.
- **data-040725-C597**; Food&Drinks; mug; ceramics.
- **data-040725-C599**; Art&Decorations; Christmas tree; wood.
- **data-040725-C602**; Food&Drinks; teacup; ceramics.
- **data-040725-C606**; Animals; rabbit; plaster.
- **data-040725-C610**; Food&Drinks; cup; ceramics.
- **data-040725-C677**; Animals; hog/pig; plastic.
- **data-040725-C679**; Animals; duck; plastic.
- **data-040725-C681**; Animals; rabbit; other.
- **data-040725-C683**; Art&Decorations; toy; fabric.
- **data-040725-C775**; Food&Drinks; cup; metal.
- **data-040725-C777**; Electronics&Appliances; other; plastic.
- **data-040725-C817**; Food&Drinks; beer can; metal.
- **data-040725-C855**; Food&Drinks; bell pepper/capsicum; food.
- **data-040725-C857**; Food&Drinks; other; food.
- **data-041925-C034**; Food&Drinks; cup; ceramics.
- **data-042125-C166**; Animals; cat; plaster.
- **data-042125-C170**; Animals; butterfly; ceramics.
- **data-042125-C172**; Animals; cat; plaster.
- **data-042125-C174**; Office&Stationery; book; plaster.
- **data-042125-C181**; Animals; bird; plaster.
- **data-042325-C273**; Art&Decorations; vase; ceramics.
- **data-042325-C276**; Clothing&Accessories; tote bag; leather.
- **data-042325-C278**; Nature&Plants; other; ceramics.
- **data-042325-C280**; Food&Drinks; cup; plaster.
- **data-042325-C282**; Art&Decorations; vase; plaster.
- **data-042525-C322**; Clothing&Accessories; hat; fabric.
- **data-042525-C326**; Clothing&Accessories; hat; fabric.
- **data-042725-C446**; Art&Decorations; heart; wood.
- **data-042725-C448**; Nature&Plants; other; plastic.
- **data-042725-C450**; Animals; frog/toad/toad frog; fabric.
- **data-042725-C503**; Nature&Plants; other; plant.
- **data-042925-C009**; Food&Drinks; chocolate cake; food.
- **data-042925-C016**; Art&Decorations; vase; stone.



Figure 11. Visualization of textured meshes of some validation data. We extract meshes using MetaShape [1], which are then utilized for initialization in benchmark methods.

- **data-070425-C004**; Food&Drinks; bread; food.
- **data-072125-C015**; Furniture, Household&Containers; trash can/garbage can/wastebin/dustbin/trash barrel/trash bin; metal.
- **data-072125-C021**; Art&Decorations; other; other.
- **data-072125-C025**; Office&Stationery; lantern; plaster.
- **data-072125-C027**; Food&Drinks; pumpkin; plaster.
- **data-072125-C102**; Furniture, Household&Containers; trash can/garbage can/wastebin/dustbin/trash barrel/trash bin; plastic.
- **data-072125-C104**; Furniture, Household&Containers; bottle cap/cap/cap container lid; plastic.
- **data-072125-C107**; Sports&Fitness; baseball glove/baseball mitt; leather.
- **data-072125-C109**; Clothing&Accessories; clutch bag; leather.
- **data-072125-C111**; Clothing&Accessories; clutch bag; leather.
- **data-072125-C113**; Clothing&Accessories; clutch bag; leather.
- **data-072225-C118**; Tools&Hardware; other; plastic.
- **data-072225-C120**; Tools&Hardware; scrubbing brush; plastic.
- **data-072225-C122**; Animals; squirrel; plaster.
- **data-072525-C206**; Sports&Fitness; volleyball; rubber.
- **data-072825-C311**; Sports&Fitness; dartboard; plastic.
- **data-072825-C313**; Furniture, Household&Containers; folding chair; metal.
- **data-072825-C319**; Furniture, Household&Containers; suitcase/baggage/luggage; leather.
- **data-072825-C321**; Clothing&Accessories; helmet; plastic.
- **data-072825-C325**; Sports&Fitness; chessboard; wood.

8. Capture Configuration

8.1. Cameras

All data is captured using 35 DSLR cameras positioned on a spherical dome within the light stage. We experimented with different hyperparameter configurations and selected those that best balance brightness, sharpness, and appropriate object scale. Across all captures, we set ISO to 800, exposure time to 288, and aperture to f/8. We use two types of camera lenses, with focal lengths ranging from 24mm to 105mm and 14mm to 28mm, respectively, and manually adjust the focus for each capture session to ensure consistent image quality and proper scaling for objects of varying sizes.

8.2. Stand Support

We designed stand supports of multiple sizes to accommodate different objects, as shown in Fig. 10. All stands are made of wood and covered with matte black paper to minimize reflections and color bleeding artifacts during capture. We select a stand whose top surface is slightly smaller than the object footprint, ensuring stability while avoiding occlusions from cameras and light sources located in the lower hemisphere.

Table 4. Comparison of methods across environments (Env0–Env3) with metrics (Mean, Median, $< 12.5^\circ$, $< 22.5^\circ$, $< 30^\circ$).

Env	Method	Mean↓	Med↓	$11.25^\circ \uparrow$	$22.5^\circ \uparrow$	$30^\circ \uparrow$
4*Env0	SN [57]	32.9	31.1	9.0	32.6	52.7
	RGBX [60]	47.3	44.4	6.8	24.1	38.3
	DR [29]	37	35	6.7	27.8	45.8
	GW [14]	36.4	33.7	10	32	46.7
4*Env1	SN [57]	31.0	29.4	9.2	35.2	57.9
	RGBX [60]	54.7	52.4	6.4	22.3	34.5
	DR [29]	34.4	32.9	7.9	30.3	50.6
	GW [14]	33.4	31.1	11.5	35.2	51.9
4*Env2	SN [57]	33.0	31.6	7.6	31.1	52.0
	RGBX [60]	43.5	41.4	7.3	26.8	41.8
	DR [29]	34.0	32.6	7.8	31.5	52.0
	GW [14]	34.7	32.1	11.6	34.3	49.7
4*Env3	SN [57]	30.5	28.9	9.9	37.0	59.0
	RGBX [60]	62.3	60.6	5.1	18	28.5
	DR [29]	34.1	32.6	8.1	31.3	52.2
	GW [14]	33.2	31.2	10.8	34.9	51.9

9. Applications

9.1. Relighting

Leveraging the linearity of light transport, the provided OLATs can be linearly combined to render images under arbitrary illumination. In Fig. 17, we show the RGB OLAT captures alongside their corresponding projected equirect-angular masks. Using these OLATs and the mask-based weighting described in Eq. 5, we synthesize relit images under various environment maps, as visualized in Fig. 18.

9.2. Additional Validation

We additionally demonstrate qualitative results for inverse rendering and normal estimation tasks in Fig. 19 and Fig. 20. Quantitative normal estimation results under different environment illuminations are reported in Tab. 4.

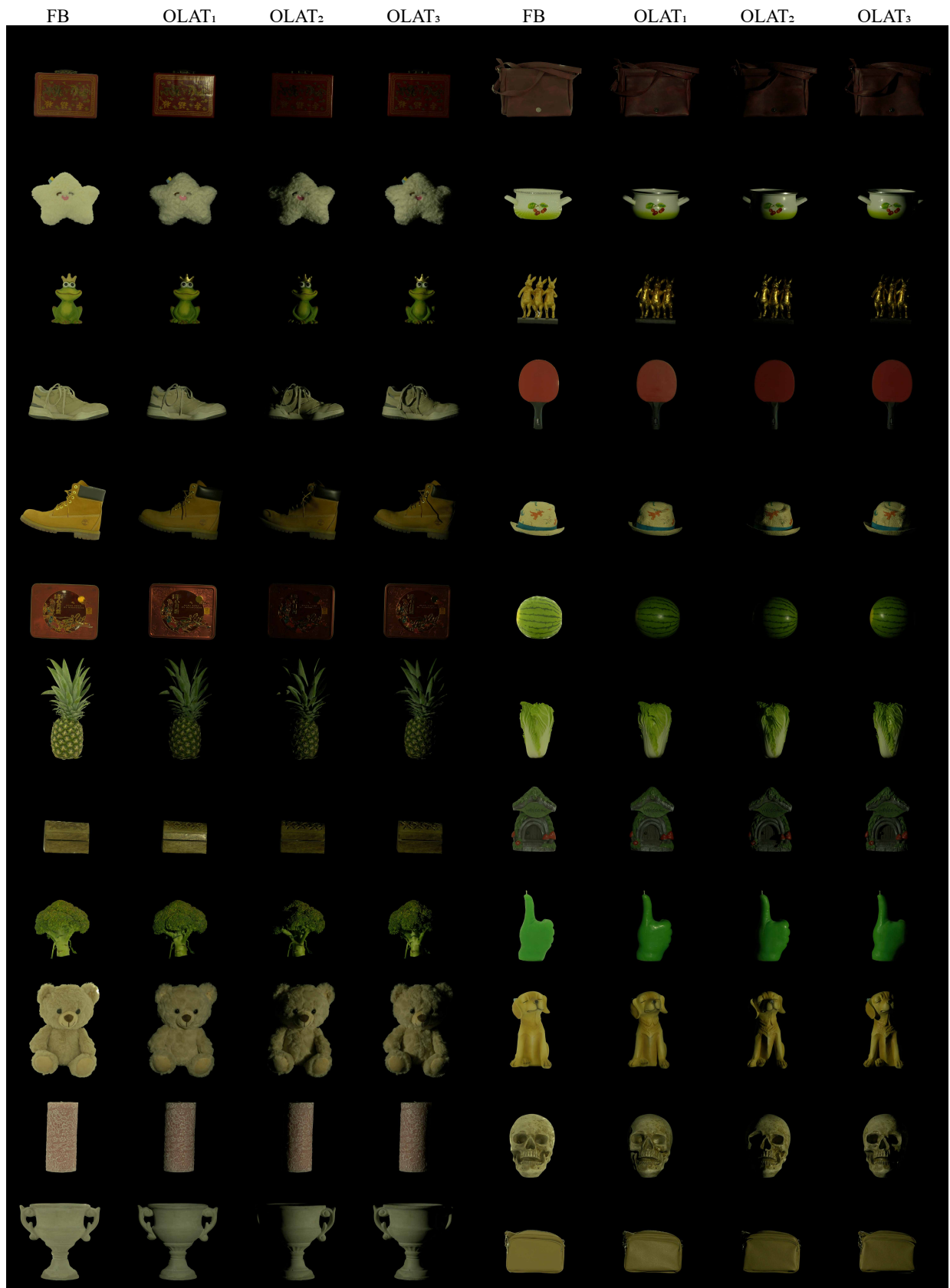


Figure 12. Visualization of a subset of validation data. We show full bright images, captured under uniform illumination, and three OLATs, each captured under a single light source.

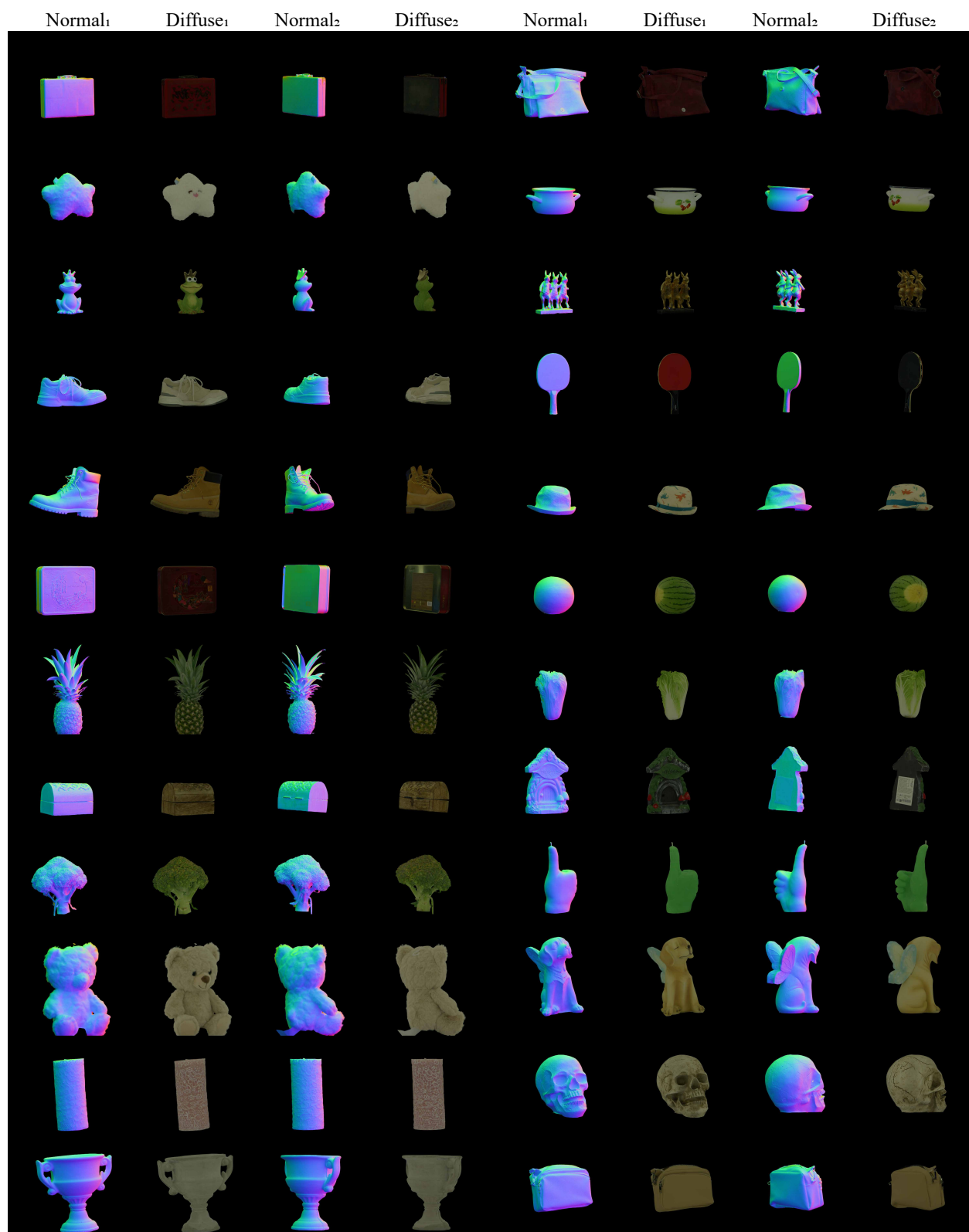


Figure 13. Visualization of surface normals and diffuse albedo extracted from two polarized views. To mitigate the effects of view-dependent specular reflections on non-Lambertian surfaces, we use linear polarizing filters and polarized gradient illumination to extract surface normals and diffuse albedo.



Figure 14. Visualization of more examples in **OLATverse**. OLATverse offers a large and diverse set of objects with a broad range of material categories.



Figure 15. Visualization of more examples in **OLATverse**. OLATverse offers a large and diverse set of objects with a broad range of material categories.



Figure 16. Visualization of more examples in **OLATverse**. OLATverse offers a large and diverse set of objects with a broad range of material categories.

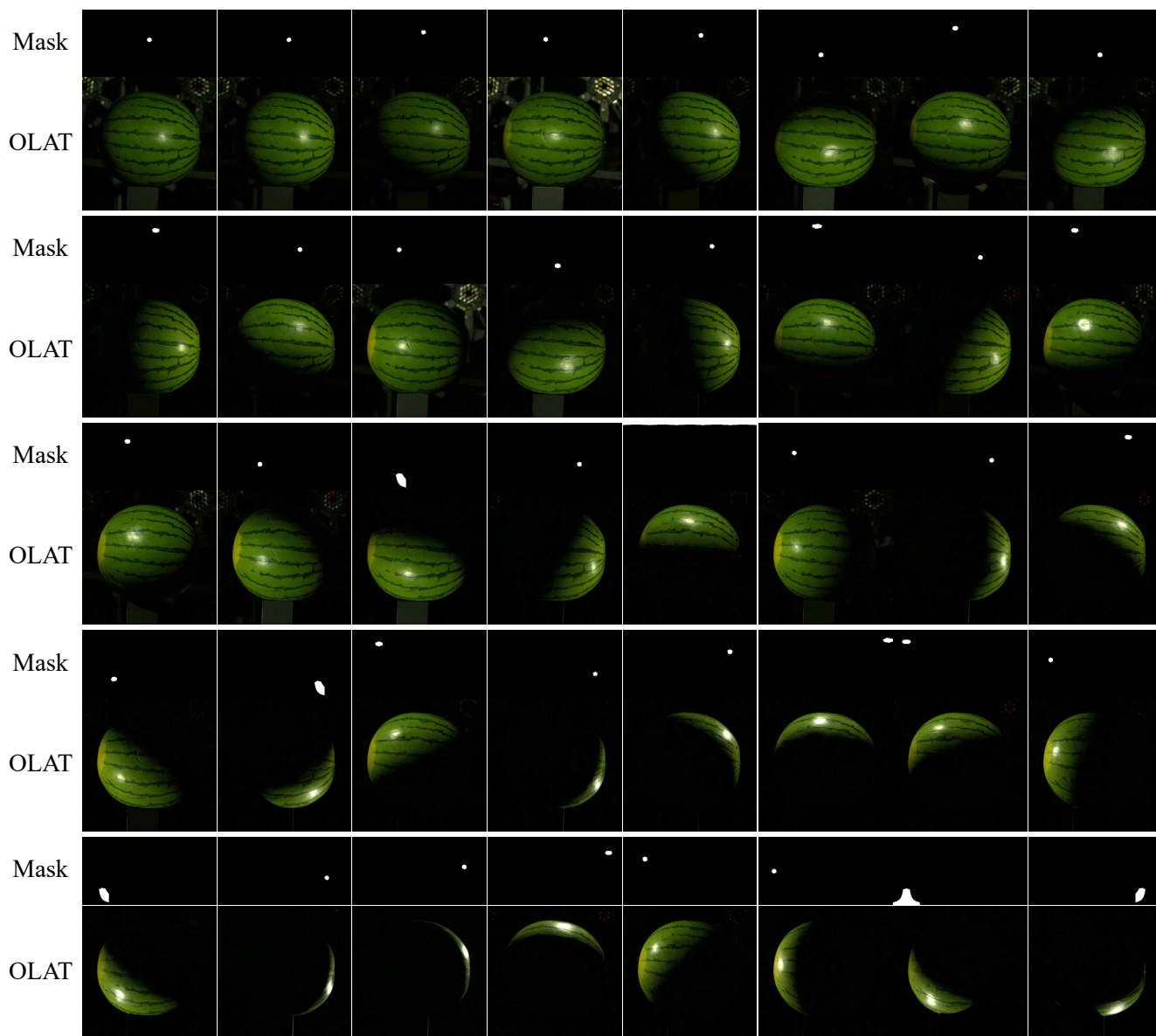


Figure 17. Visualization of a subset of OLATs for one example. We show both relit RGB images and the equirectangular masks for the corresponding light source. These masks are used to synthesize images under arbitrary environmental illuminations.

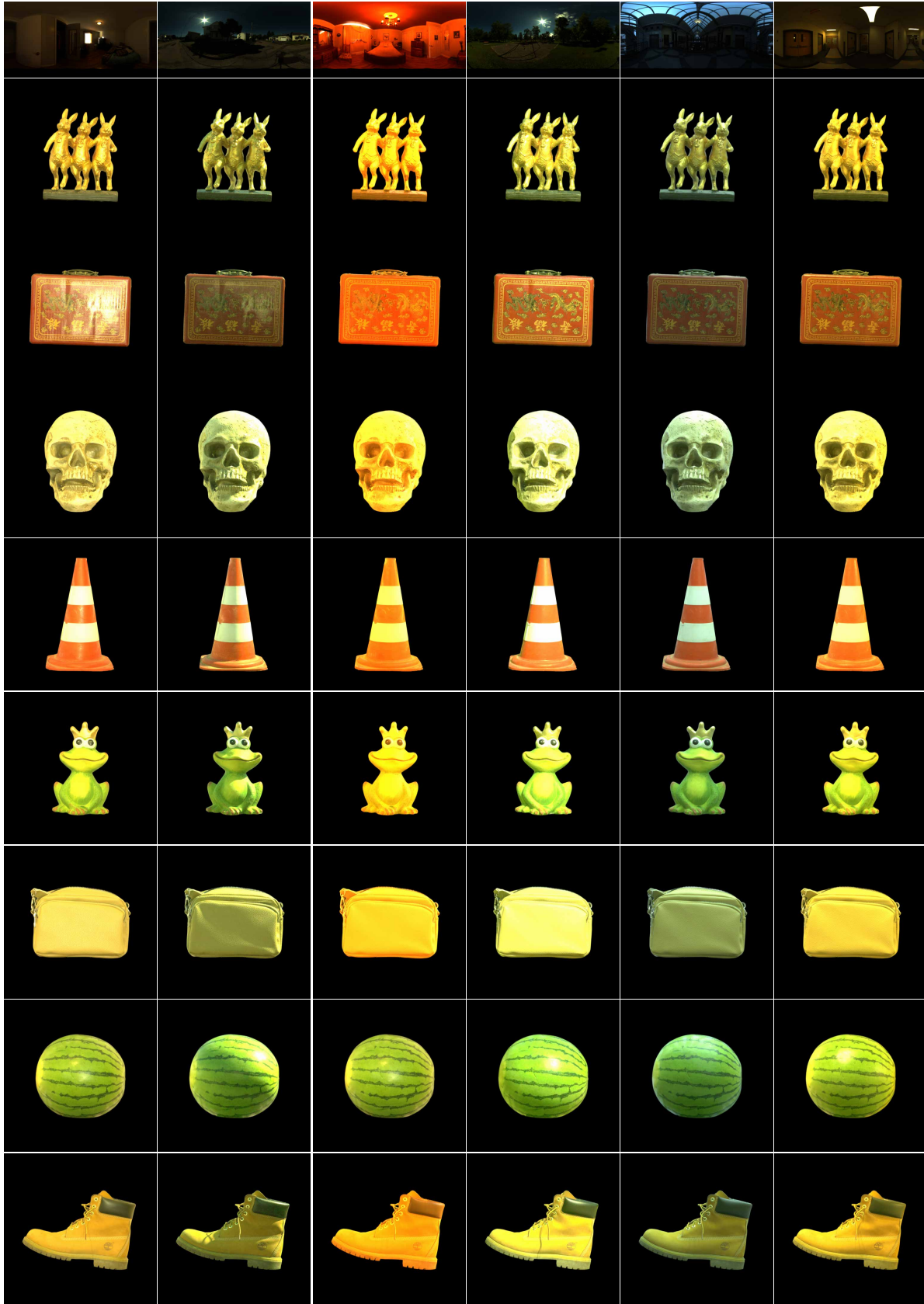


Figure 18. Illustration of objects under arbitrary environmental illuminations. Leveraging the linearity of light transport, the captured OLATs can be utilized to synthesize relit images under any arbitrary environmental illuminations.

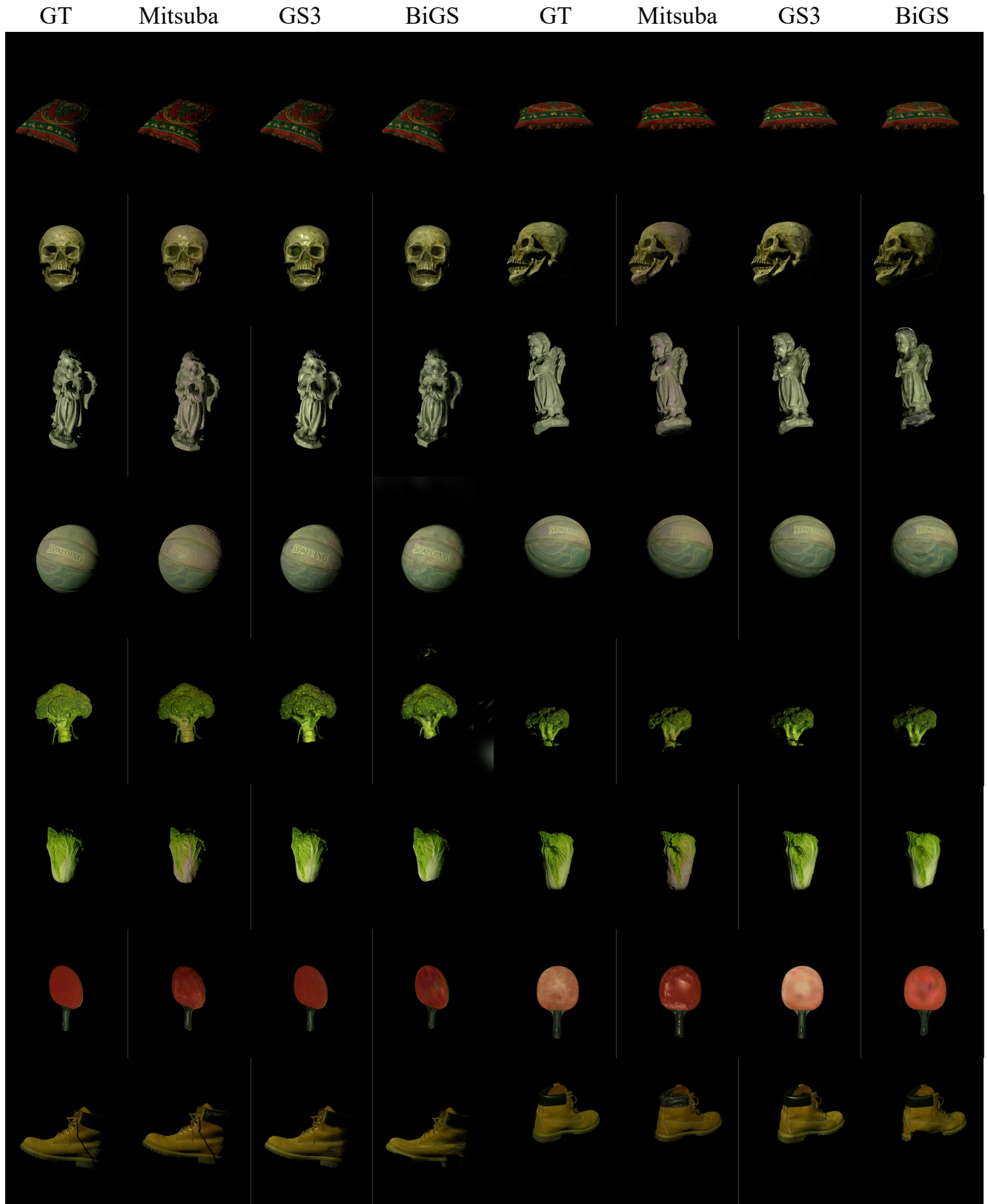


Figure 19. Additional visualization of the inverse rendering and novel view synthesis results of several baseline methods (Mitsuba [37], GS³ [2], BiGS [68], and RNG [13]) evaluated on our validation dataset. We show relit objects from inference views and light directions.

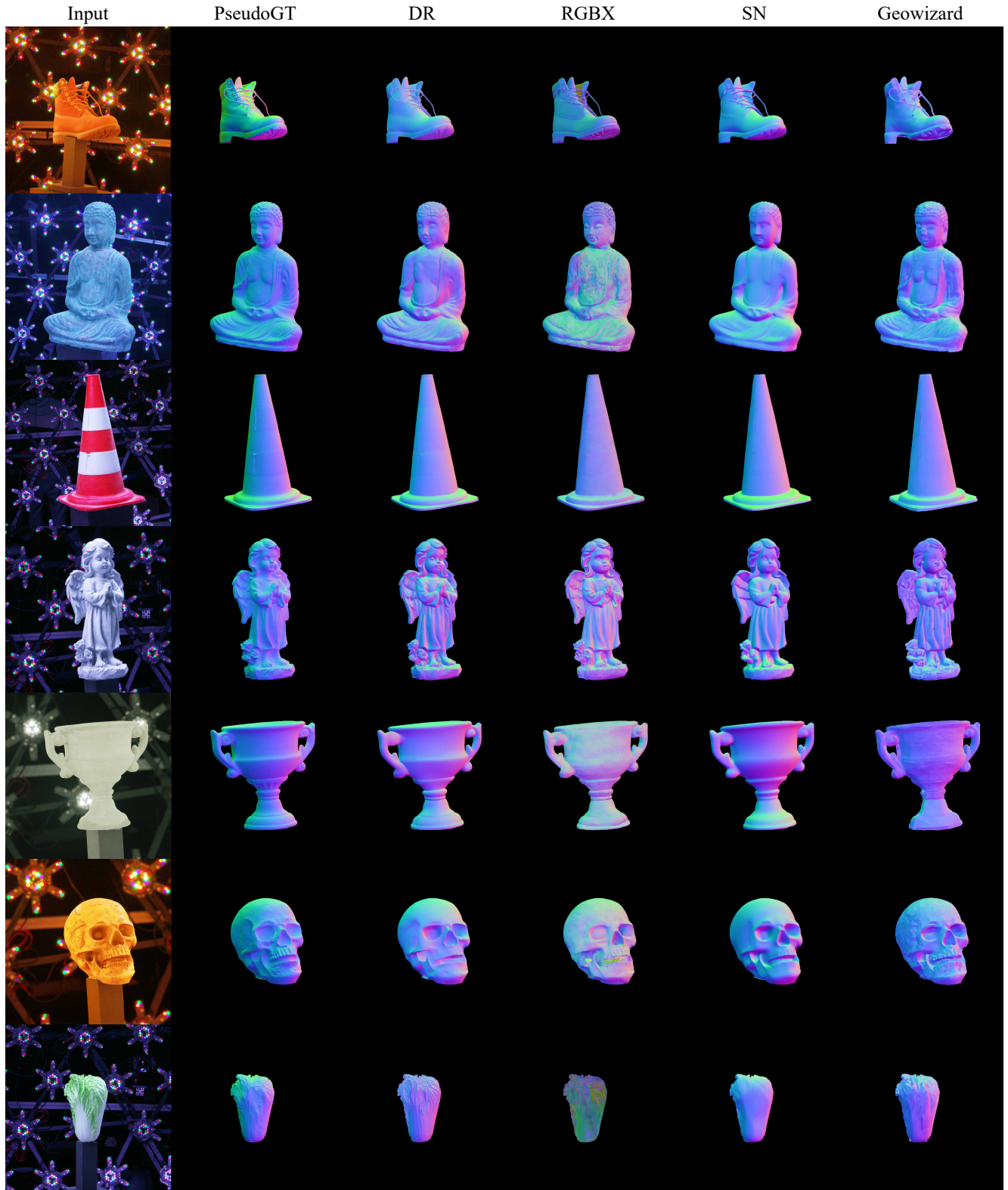


Figure 20. Additional qualitative comparison of pseudo ground truth normals with normals estimated by DR [29], RGBX [60], SN [57] and GW [14]. To facilitate a robust comparison, we provide input images of each validation object under four different illumination conditions.