SSN: Soft Shadow Network for Image Compositing
Supplementary Materials

Yichen Sheng
Purdue University

Jianming Zhang
Adobe Research

Bedrich Benes
Purdue University

1. SSN architecture details

Fig. 1 shows the details of the AOP and the SR module. The AOP module is almost the same as the SR module. The AOP module takes masks as input and outputs AO maps.SR module takes masks, AO maps and ELMs as input, and outputs soft shadows. The encoder part follows convolution-group norm-ReLU fashion. At the bottleneck of the SR module, we inject ELMs by flattening the original 16×32 map to a $1 \times 1 \times 512$ feature block, tiling to a $16 \times 16 \times 512$ feature block, going through a convolutional layer and being concatenated with the bottleneck code. The decoder part follows bilinear upsampling-convolution-group norm-ReLU fashion. The detailed kernel sizes for each layer are shown in Fig. 1. In our training setting, we separatly trained the AOP module and the SR module to ensure using a maximum batch size.

2. Qualitative Evaluation

Perceived Realism (user study 1): Fig. 2 shows some examples of the pairs of images used in our first user study.

Ease-of-Use (user study 2): Fig. 3 shows the GUI used in the second user study. The application contains three windows, left is the input, the middle is a 2D mask with no shadows, and right is an interactive window that allows adding, modify, and delete lights. The user interactively modified the ELM and observed the generated soft shadows while attempting to recreate the input image.

We asked 8 subjects (4 males and 4 females) with the following age distribution: 50-59 (1), 40-49 (1), 20-29 (4), 10-19 (2). Three subjects reported experience in computer graphics. We asked the users ”how easy was it to use the tool to recreate the soft shadows” and they responded on scale 1(difficult) - 5(extremely easy). The average of responses was 4.125 with a standard deviation of 0.95 indicating that our tool can be used for soft shadow image compositing by inexperienced users. An example in Fig. 4 shows the input example on the left, and some of the user-generated results on the right. We also collected responses and some of them were: ”it would be good to know how many lights are needed”, ”it is intuitive, but it takes some time to tweak the sliders”, ”fast feedback, but changing one shadow affects the others”, ”axis labels would help”. The supplementary material includes all user-generated results. Our second user study results seem to indicate that our approach is suitable for fast and intuitive creation of soft shadows from 2D masks.

3. Failure cases

Although AO map provides some ”hints” for SR module, some ambiguous cases still cannot be solved. It is very common in those non-iconic views for some objects having ambiguous cutout shapes. One example(see Fig. 5) is a U shape object in a direction that U shape is not observable in the mask.

References

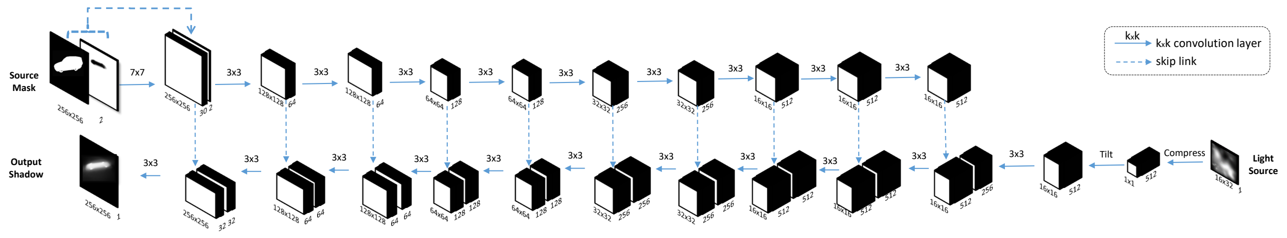

Figure 1: SSN Details: The AOP module is almost the same as the SR module. the AOP module takes masks as input and outputs the AO maps. The SR module takes masks, AO maps and ELMs as input, and outputs soft shadows.

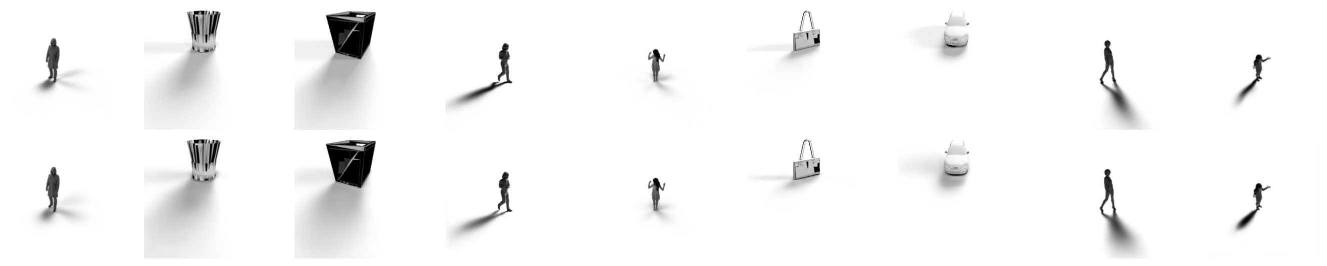

Figure 2: Perceptual evaluation: samples of images from our perceptual evaluation. Output generated from 3D objects rendered by Mitsuba (upper) and output generated by SSN from binary masks (bottom). We attempted to cover a wide variety of shadows.

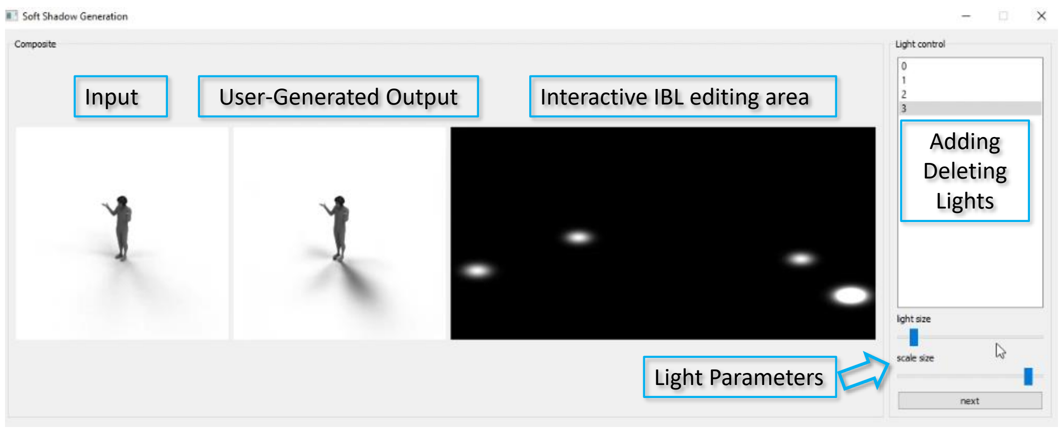

Figure 3: GUI for the user study 2: Users were asked to recreate the shadow from the input image by adding and deleting Gaussian lights and varying their parameters.

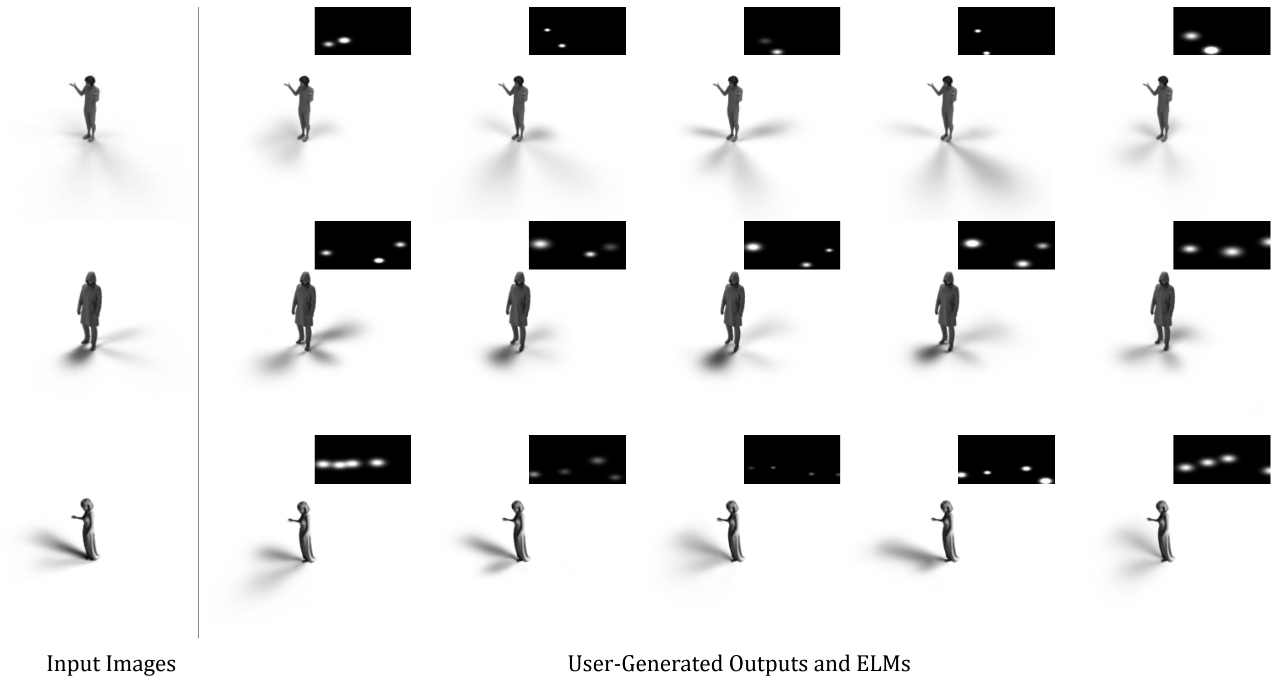

Figure 4: Results of the second user study: The input image (left, rendered by Mitsuba) and the user-generated outputs (right, rendered by SSN) with the corresponding ELMs.

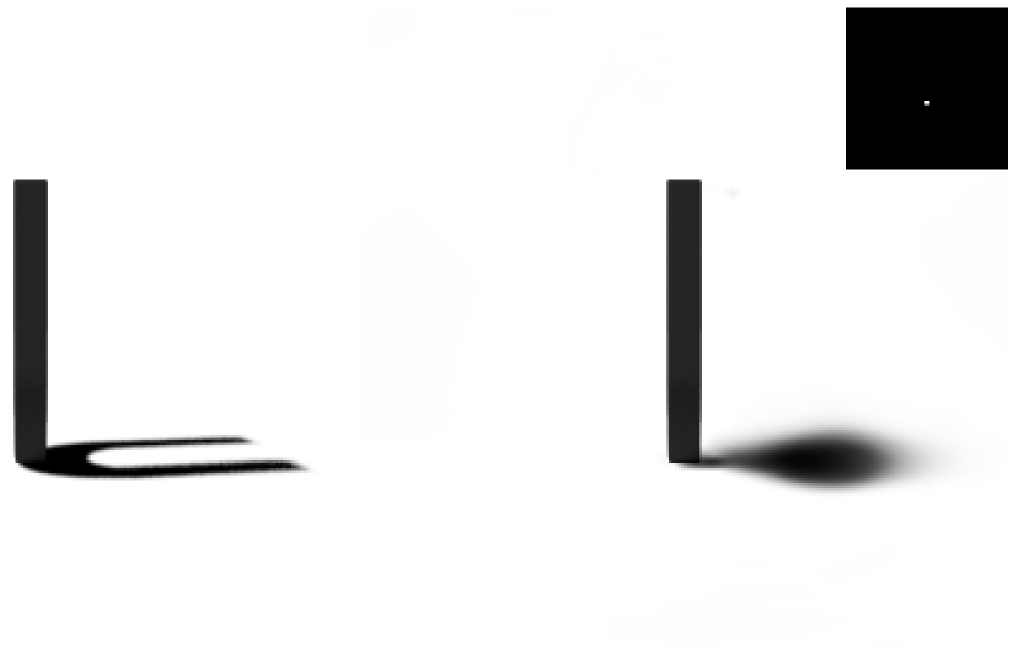

Figure 5: Ambiguous case: For the side view of the magnet, it is still ambiguous when we have correct AO input. Left image is rendered by Mitsuba, right image is rendered by the SSN with a ground truth AO map(corner of the right image) as input.