

Supplementary Material: In-the-wild Material Appearance Editing using Perceptual Attributes

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1. Additional Results

We provide additional results of image editing by our framework for both attributes *glossy* and *metallic* (Section 1.1). Also, we give extra comparisons with the previous method proposed by Delanoy et al. [DLC*22] (Section 1.2).

1.1. Image Editing

In this section, we provide additional editing outcomes for the *glossy* and *metallic* attributes. In Figure 1 we show additional edits that prove the robustness of our framework for the *glossy* attribute while varying scene parameters for synthetic and real images. Figures 2 and 3 show edited images from the real and synthetic datasets respectively. In Figures 4 and 5 we show editing examples for the *metallic* attribute. As we can see in the last row of Figure 2, changes in appearance are non-uniform since perceptual ratings in the training dataset are also non-uniform.

1.2. Comparison with state-of-the-art

To validate the superior ability of our framework in comparison with the previous method [DLC*22] in editing tasks, we provide in this section an additional comparison between both methods. Figures 6 and 7 show comparisons between both methods by editing the *glossy* attribute for images from the real and synthetic dataset respectively. In Figures 8 and 9 we show comparisons between both methods but editing the *metallic* attribute in real and synthetic images respectively.

References

- [DLC*22] DELANOY J., LAGUNAS M., CONDOR J., GUTIERREZ D., MASIA B.: A generative framework for image-based editing of material appearance using perceptual attributes. *Computer Graphics Forum* 41, 1 (2022), 453–464. [1](#), [4](#), [5](#), [6](#), [7](#)

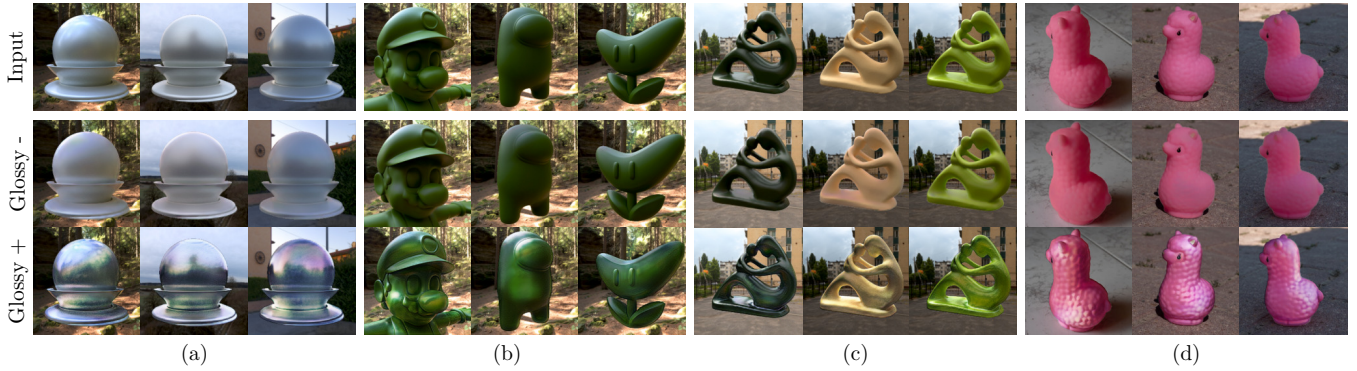


Figure 1: Examples of edited images by our framework. (a) Renders of the Mitsuba Knob geometry under three different illuminations, and a constant material. (b) Renders of Mario, Among Us, and Boomerang Flower geometries with the same material and light conditions. (c) Renders of the Fertility geometry with the same illumination but different materials. (d) Photographs of a rubber alpaca taken in different places under three light conditions. Our framework is capable of producing compelling and consistent edits in all cases. The “+” corresponds to an increase in the target glossy attribute value att_t , while the “-” corresponds to a decrease.

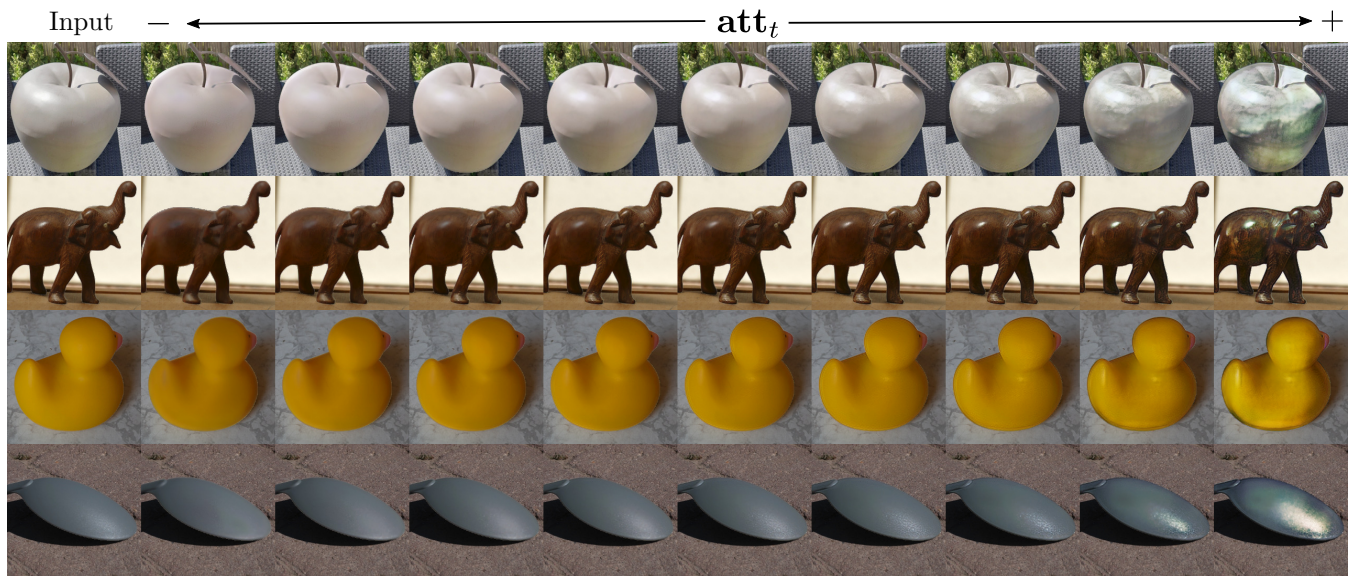


Figure 2: Edited real images varying the target perceptual attribute glossy att_t sampled as $\{0.0, 0.125, 0.25, 0.375, 0.5, 0.625, 0.75, 0.875, 1.0\}$ for each input image.

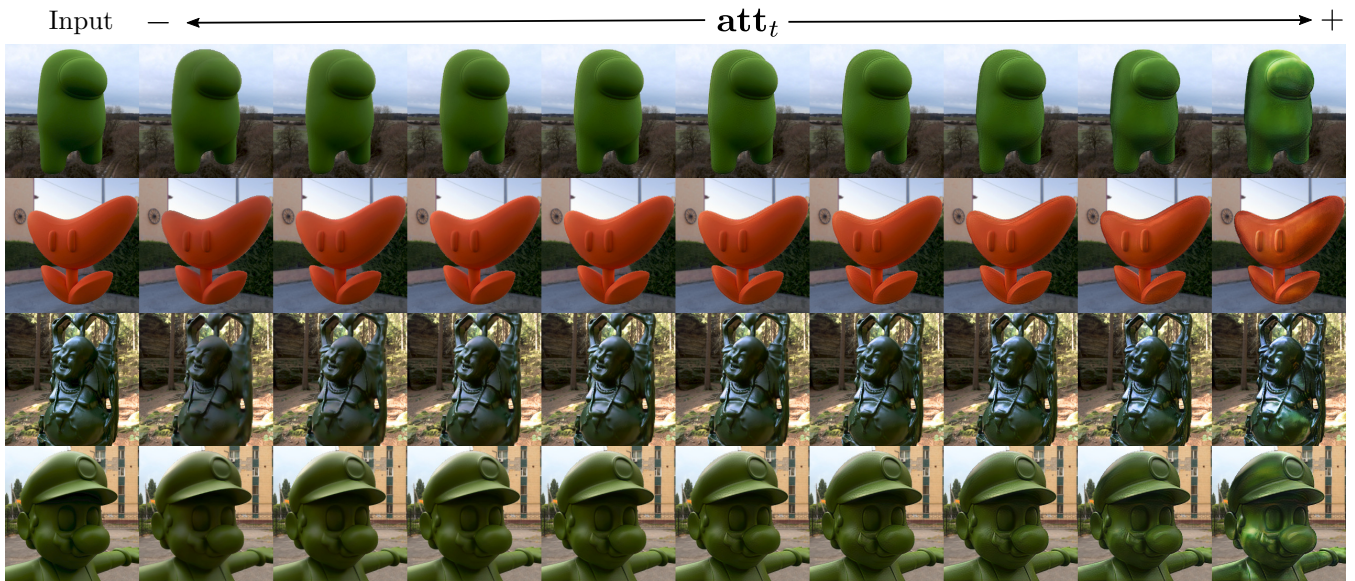


Figure 3: Edited synthetic images varying the target perceptual attribute glossy att_t sampled as $\{0.0, 0.125, 0.25, 0.375, 0.5, 0.625, 0.75, 0.875, 1.0\}$ for each input image.

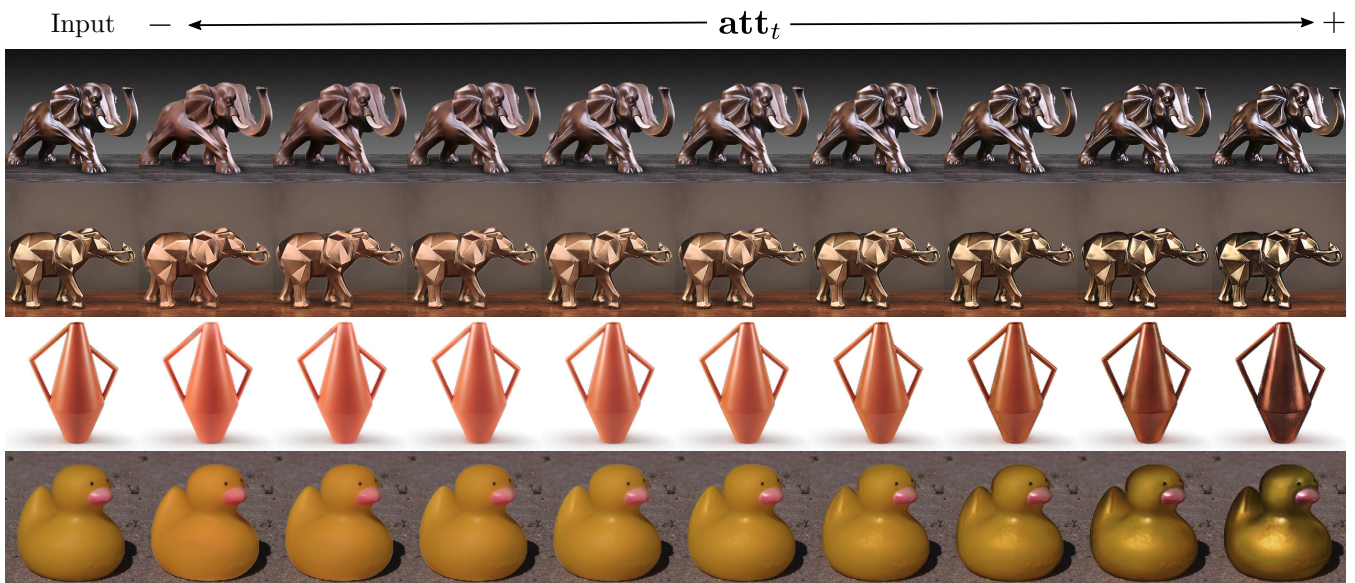


Figure 4: Edited real images varying the target perceptual attribute metallic att_t sampled as $\{0.0, 0.125, 0.25, 0.375, 0.5, 0.625, 0.75, 0.875, 1.0\}$ for each input image.

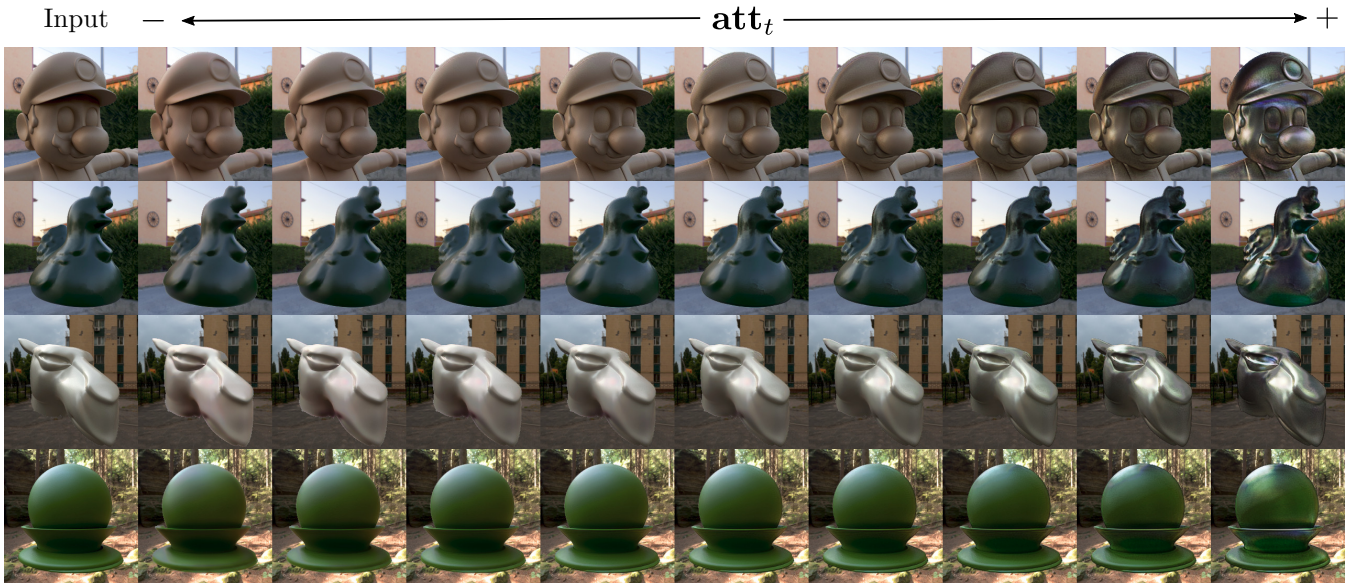


Figure 5: Edited synthetic images varying the target perceptual attribute metallic \mathbf{att}_t , sampled as $\{0.0, 0.125, 0.25, 0.375, 0.5, 0.625, 0.75, 0.875, 1.0\}$ for each input image.

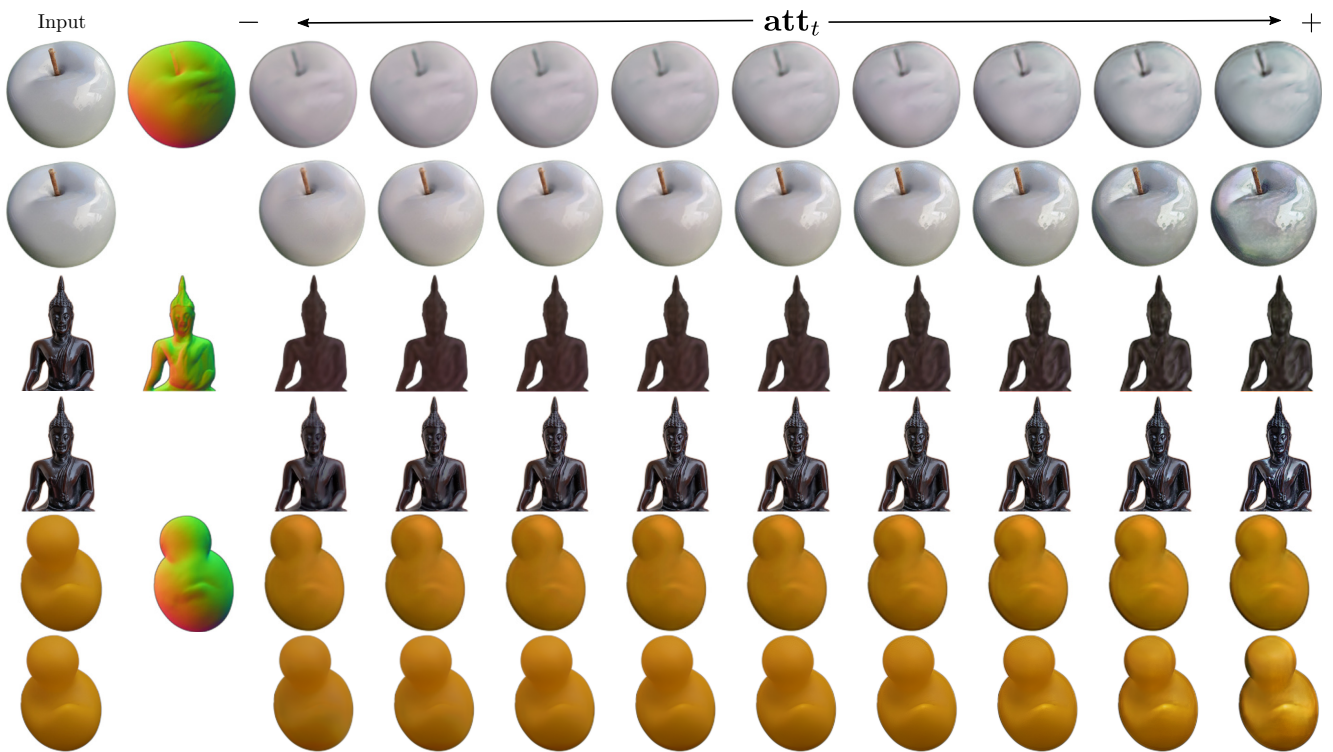


Figure 6: Each pair of rows are the results generated with our framework and the method proposed by Delanoy et al. [DLC*22]. First column represents the input real images, second the estimated normal maps, and following ones are the edited images sampling the value \mathbf{att}_t of target perceptual attribute glossy as $\{0.0, 0.125, 0.25, 0.375, 0.5, 0.625, 0.75, 0.875, 1.0\}$ for our framework, while for the other method \mathbf{att}_t is sampled as $\{-1, -0.75, -0.5, -0.25, 0, 0.25, 0.5, 0.75, 1\}$.

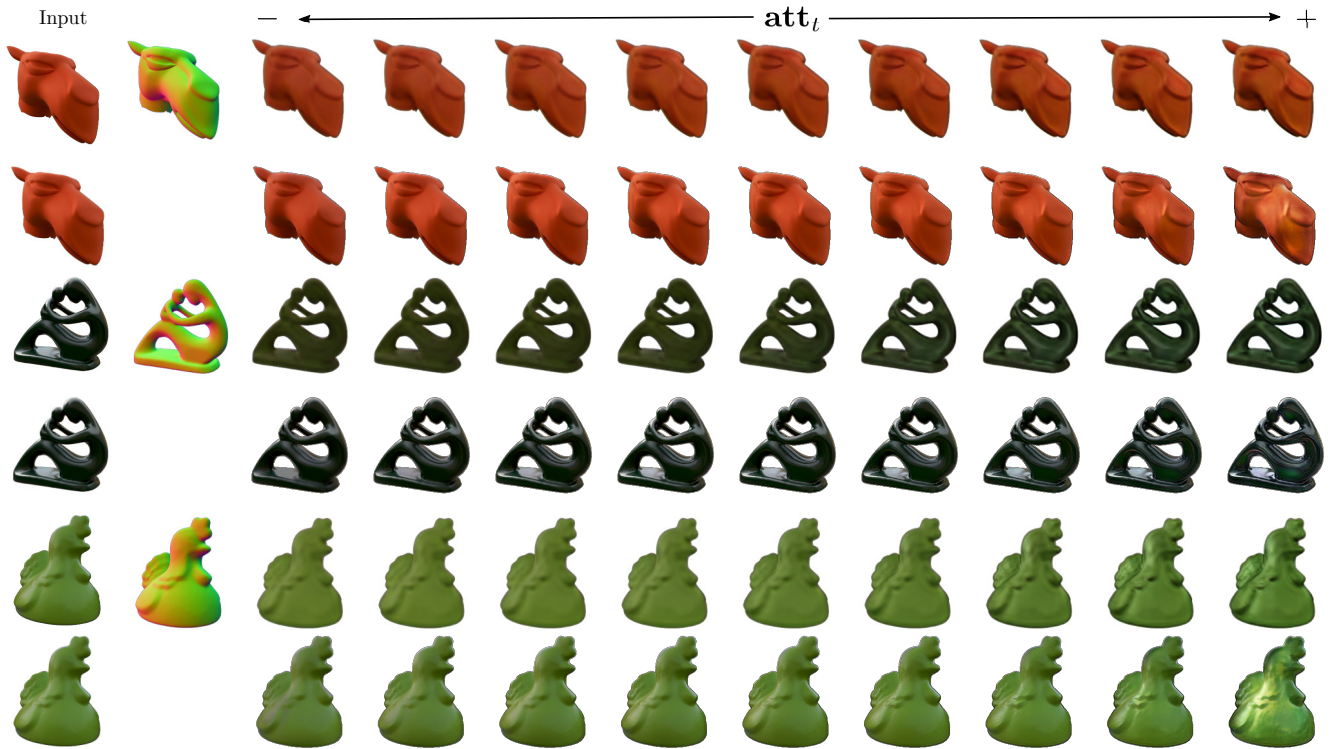


Figure 7: Each pair of rows are the results generated with our framework and the method proposed by Delanoy et al. [DLC*22]. First column represents the input synthetic images, second the estimated normal maps, and following ones are the edited images sampling the value \mathbf{att}_l of target perceptual attribute glossy as $\{0.0, 0.125, 0.25, 0.375, 0.5, 0.625, 0.75, 0.875, 1.0\}$ for our framework, while for the other method \mathbf{att}_l is sampled as $\{-1, -0.75, -0.5, -0.25, 0, 0.25, 0.5, 0.75, 1\}$.

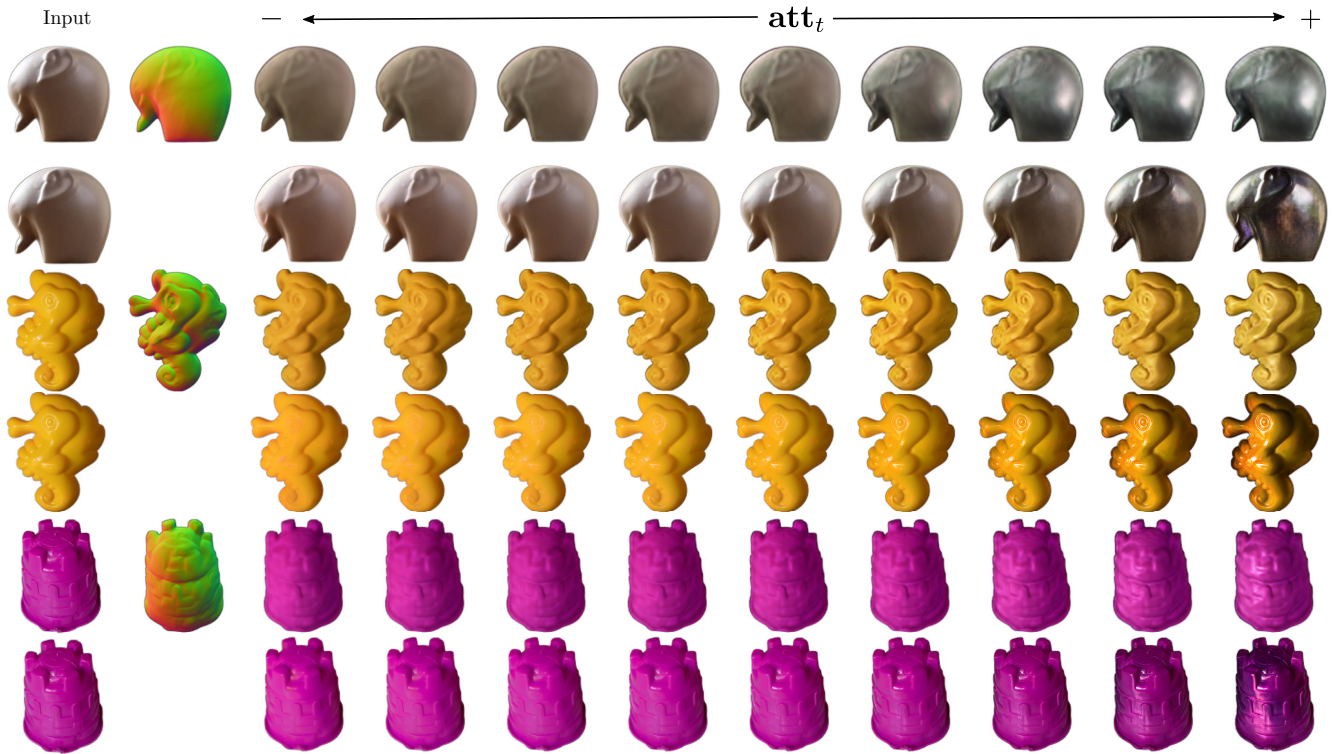


Figure 8: Each pair of rows are the results generated with our framework and the method proposed by Delanoy et al. [DLC*22]. First column represents the input real images, second the estimated normal maps, and following ones are the edited images sampling the value \mathbf{att}_t of target perceptual attribute metallic as $\{0.0, 0.125, 0.25, 0.375, 0.5, 0.625, 0.75, 0.875, 1.0\}$ for our framework, while for the other method \mathbf{att}_t is sampled as $\{-1, -0.75, -0.5, -0.25, 0, 0.25, 0.5, 0.75, 1\}$.

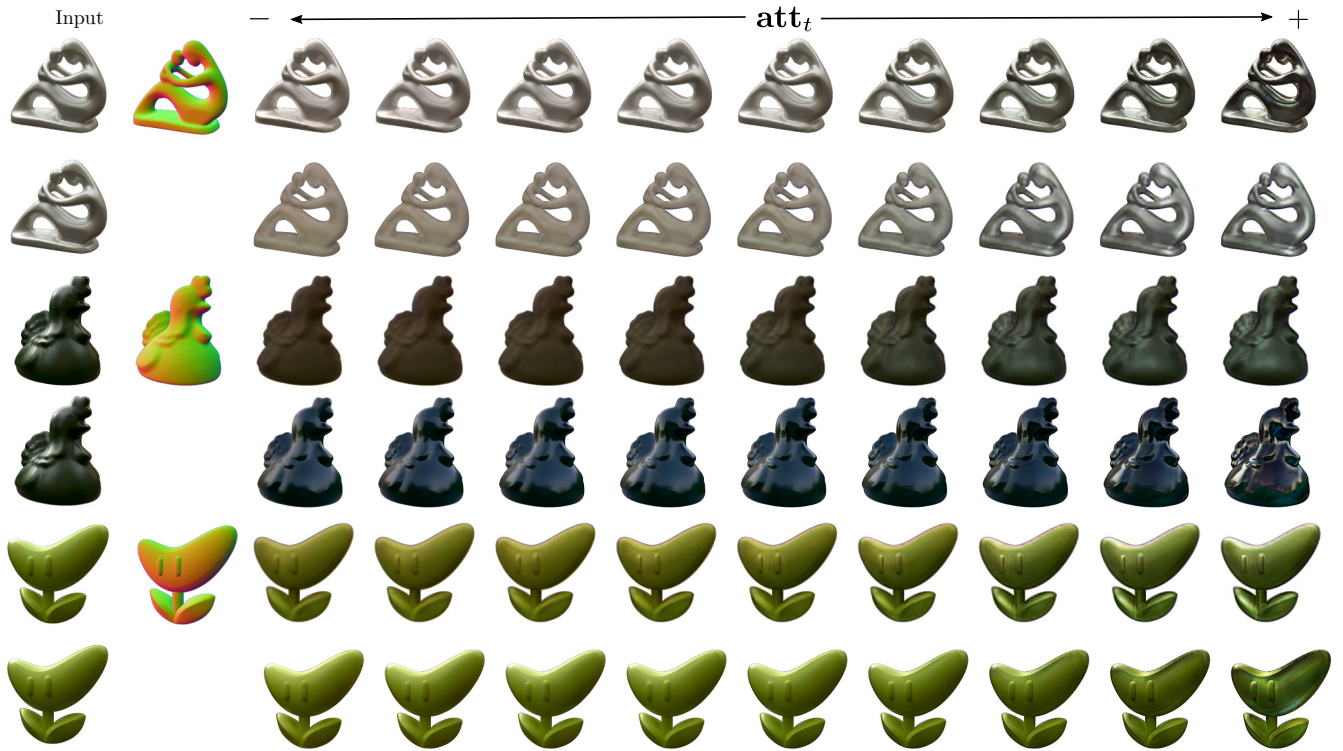


Figure 9: Each pair of rows are the results generated with our framework and the method proposed by Delanoy et al. [DLC*22]. First column represents the input synthetic images, second the estimated normal maps, and following ones are the edited images sampling the value \mathbf{att}_t of target perceptual attribute metallic as $\{0.0, 0.125, 0.25, 0.375, 0.5, 0.625, 0.75, 0.875, 1.0\}$ for our framework, while for the other method \mathbf{att}_t is sampled as $\{-1, -0.75, -0.5, -0.25, 0, 0.25, 0.5, 0.75, 1\}$.