

Specular Lobe Aware Upsampling Based on Spherical Gaussians (Supplemental Material)

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A Derivation

We introduce a weighting function $w_{i,j}$ based on the inner product of two specular lobes. To calculate the inner product analytically, this poster approximates a specular lobe $f(\omega)$ with a spherical Gaussian (SG) $G(\omega)$ as:

$$f(\omega) \approx G(\omega) = \mu \exp(\lambda(\xi \cdot \omega - 1)), \quad (1)$$

where ξ is the lobe axis, λ is the lobe sharpness, and μ is the lobe amplitude. These parameters can be analytically obtained for some BRDFs such as the Blinn-Phong model, the Ward model or the Cook-Torrance model [Wang et al. 2009].

The inner product, or integral of two spherical functions yielding a scalar, is derived in [Tsai and Shih 2006] for SGs and given by

$$\begin{aligned} G_i(\omega) \cdot G_j(\omega) &= \int_{\Omega} G_i(\omega) G_j(\omega) d\omega \\ &= \frac{4\pi\mu_i\mu_j \sinh(d)}{\exp(\lambda_i + \lambda_j)d}, \end{aligned} \quad (2)$$

where $d = \|\lambda_i \xi_i + \lambda_j \xi_j\|$. Thus, from Equation (2), the norm for an SG is given as:

$$\begin{aligned} \|G_i(\omega)\| &= \sqrt{G_i(\omega) \cdot G_i(\omega)} \\ &= \mu_i \sqrt{\frac{\pi(1 - \exp(-4\lambda_i))}{\lambda_i}}. \end{aligned} \quad (3)$$

Since our weighting function is defined as the inner product of two normalized SGs, it is obtained by the following equation:

$$\begin{aligned} w_{i,j} &= \frac{G_i(\omega)}{\|G_i(\omega)\|} \cdot \frac{G_j(\omega)}{\|G_j(\omega)\|} \\ &= \frac{4\sqrt{\alpha_i\alpha_j} \sinh(d)}{\exp(\lambda_i + \lambda_j)d}, \end{aligned} \quad (4)$$

where $\alpha_i = \frac{\lambda_i}{1 - \exp(-4\lambda_i)}$.

B Experimental Results

Figure 1 shows the comparison of a general normal based weighting function and the proposed weighting function. They are rendered with voxel cone tracing [Crassin et al. 2011] and spatio-temporal upsampling [Herzog et al. 2010]. The scene has a dynamic object (a galloping horse). In this experiment, the normal based weighting function has a Gaussian distribution [Yang et al. 2008] and its variance parameter is 0.005. Other weighting functions described in [Herzog et al. 2010] such as a spatial weighting function, a depth based weighting function, and a dynamic temporal weighting function using temporal gradients are also used for all images. Unlike original spatio-temporal upsampling, we additionally apply our weighting function or the normal based weighting function to the temporal axis. This approach efficiently reduces undesirable temporal blurring artifacts for dynamic objects.

In the left images in Figure 1, there are some blurring and flickering artifacts due to estimation errors. On the other hand, our method enables high-quality upsampling without parameter tuning.

Figure 2 shows the close-ups of rendering results for specular indirect illumination and total weights. The upper and lower images use a general normal based weighting function and our weighting function respectively. They are the same scene as Figure 1, but the left images have more rough surfaces. For rough specular surfaces (Figure 2 left), almost all samples are valid to reconstruct a pixel value because the lobes are low-frequency. On the other hand, for sharp specular surfaces (Figure 2 right), there are many inappropriate samples. Therefore, we have to reduce their weights for accuracy. However, the normal based weighting function is independent from specular sharpness, and it produces inappropriate weights. As a result, it induces aliasing artifacts (Figure 2 upper left) and blurring artifacts (Figure 1) for rough and sharp specular surfaces respectively. Conversely, the proposed weighting function ideally performs. Our approach adaptively reduces blurring and flickering artifacts depending on specular sharpness (Figure 2 lower).

Obviously, our weighting function also often produces aliasing artifacts on highly glossy surfaces due to reducing the weights. These errors can be avoided by recomputing the pixel values adaptively as shown in Figure 3, since the errors are detectable from the total weights unlike blurring artifacts.

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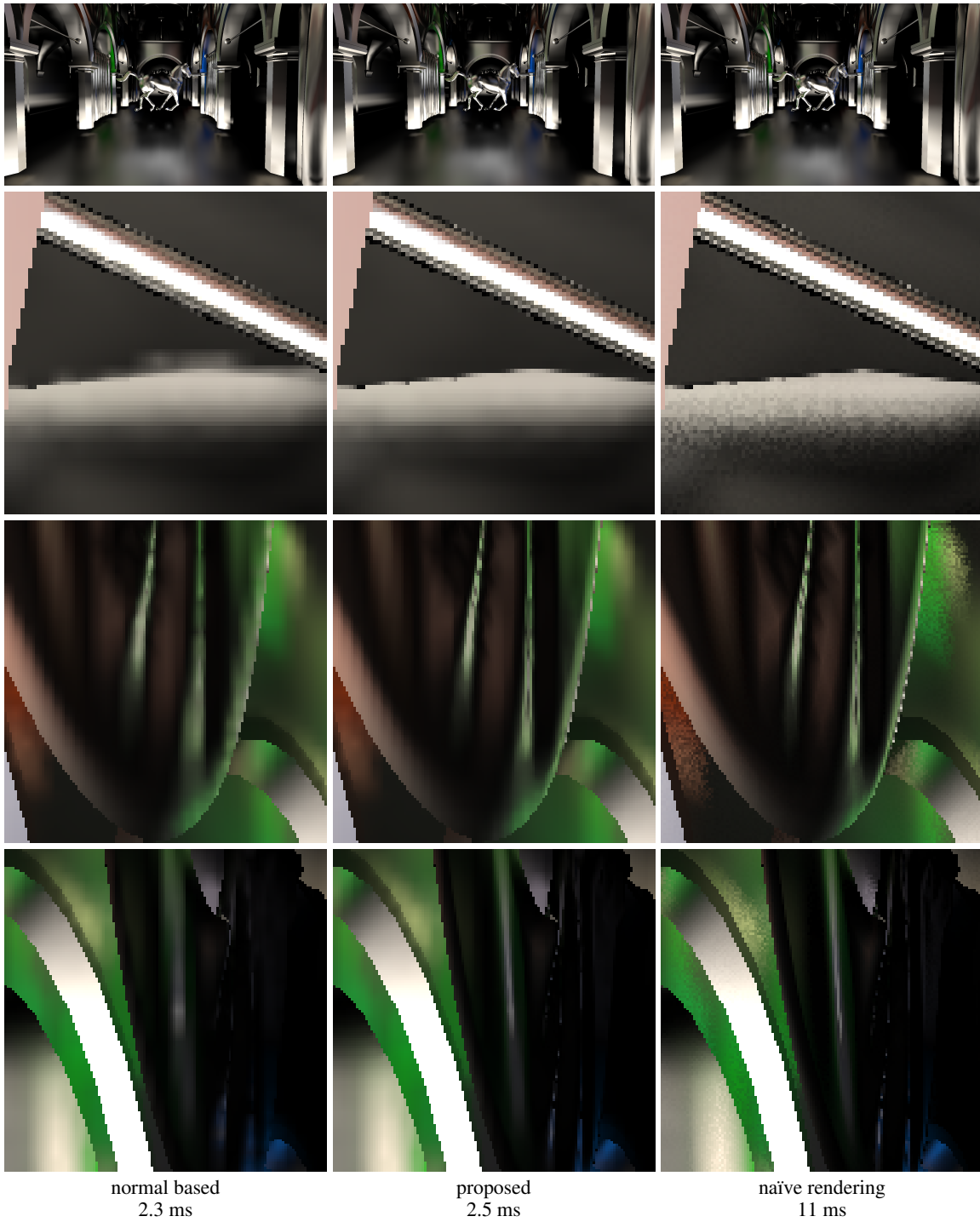


Figure 1: Top: the specular indirect illumination results via voxel cone tracing. Lower: close-ups of the top images (brightness $\times 4$). The left and middle images are upsampled from 480×270 to 1920×1080 pixels. The right images are rendered with naïve per-pixel cone tracing. The high-frequency noise is due to stochastic sampling for ray marching. The BRDF is the Blinn-Phong model (phong exponent: 1023). The normal based weighting function has a Gaussian distribution (the variance parameter: 0.005) for this experiment. The computation time of cone tracing and upsampling is only 2.3 ms (left) and 2.5 ms (middle), while per-pixel cone tracing is 11 ms (right) (GPU: AMD Radeon HD 6990). In addition, our method (middle) produces closer images to the truth.

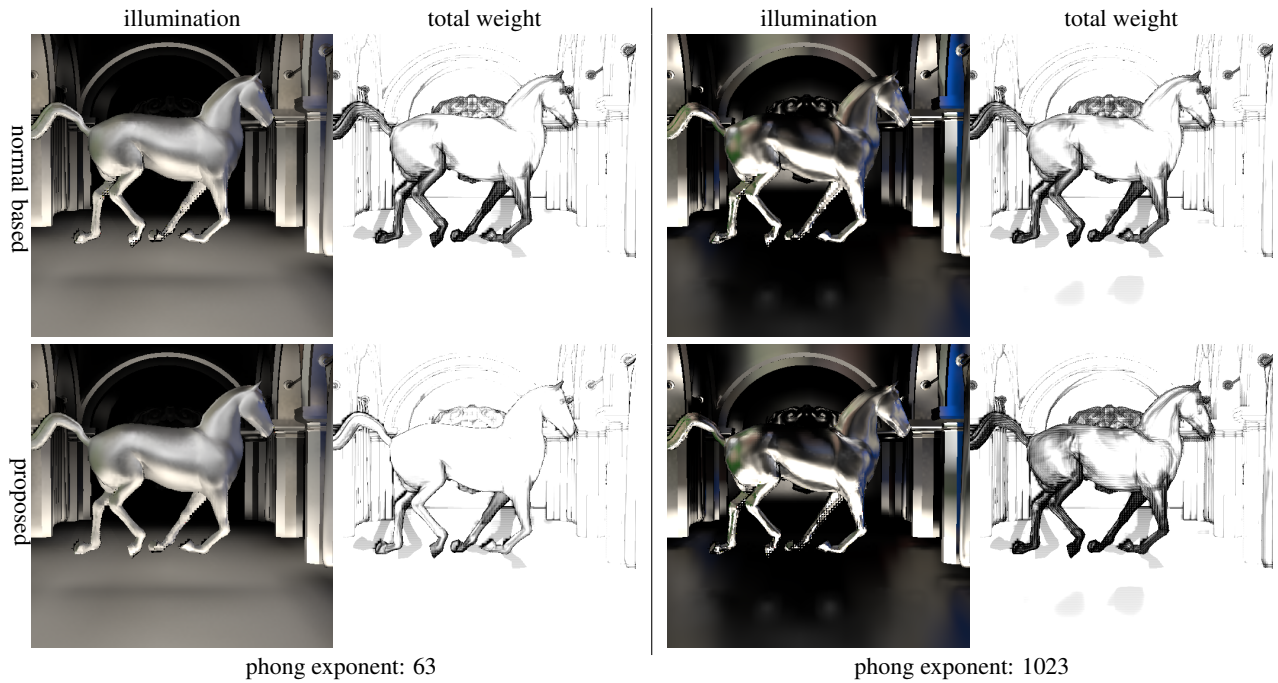


Figure 2: Close-ups of specular indirect illumination and total weights upsampled from 480×270 to 1920×1080 . Since the normal based weighting function [Yang et al. 2008] is independent from specular sharpness, it produces the same weights. Accordingly, the upper total weights are approximately equal, though they are influenced by other weighting functions. In this experiment, the variance parameter (0.005) of the normal based weighting function is too sensitive for rough surfaces. Thus, the upper left image has aliasing artifacts. On the other hand, our weighting function is adaptive for specular sharpness.

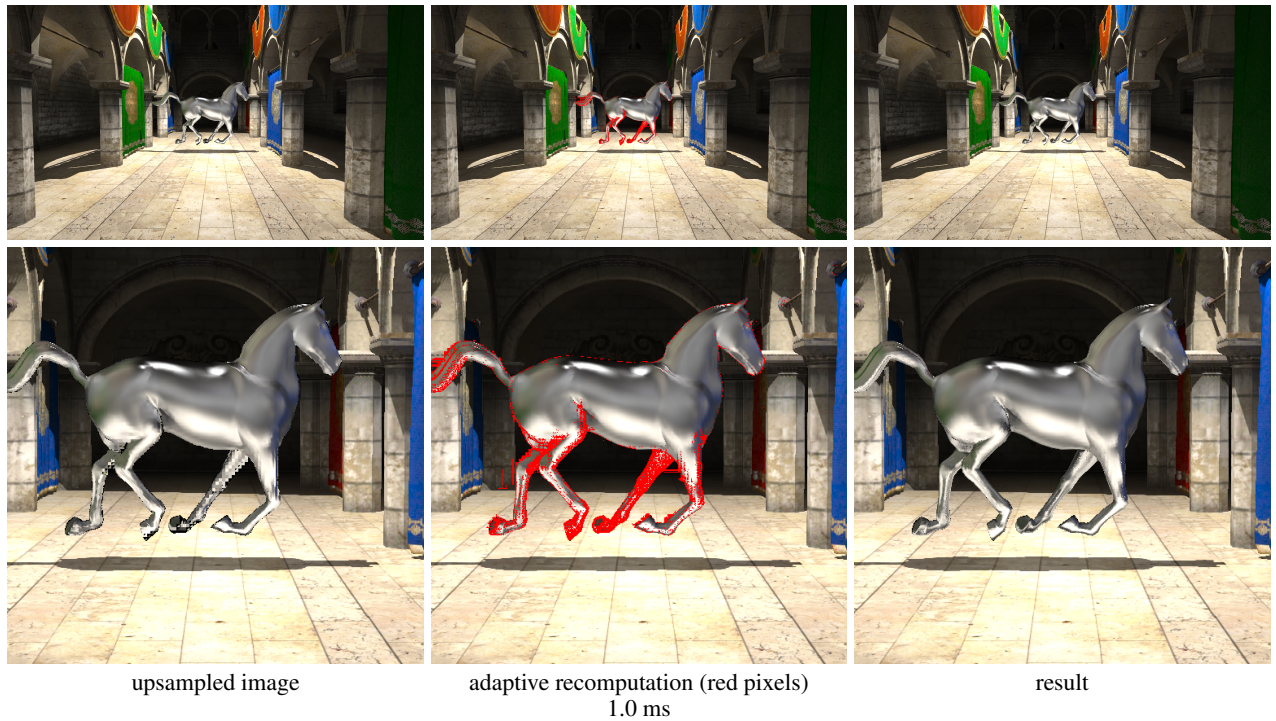


Figure 3: Aliasing artifacts can be avoided by using adaptive re-computation for low-weight pixels, while blurring artifacts are undetectable. Upper: rendered images with upsampling. Lower: close-ups of upper images. Phong exponent: 255, resolution: 480×270 to 1920×1080 , GPU: AMD Radeon HD 6990.