Supplementary: Reconstructing Translucent Objects using Differentiable Rendering

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1 OBJECTIVE

We compare our unbias loss function with bias loss function (L2 Loss) at different sample per pixel per iteration.

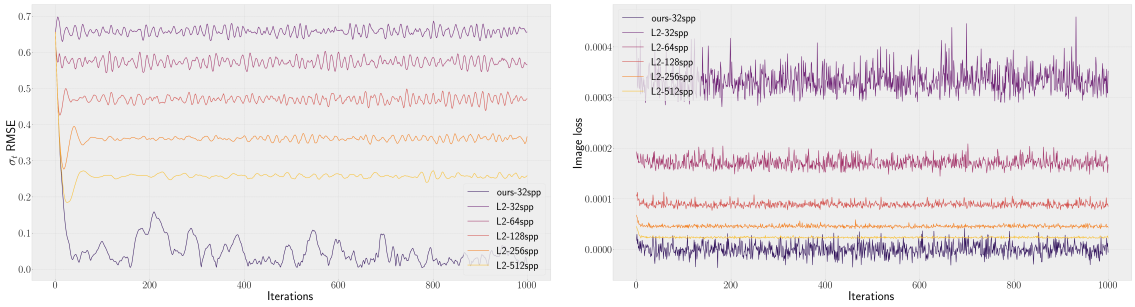

Fig. 1. Equal-sample comparison on inverse rendering of a translucent bunny by utilizing automatic differentiation directly on the L2 loss vs. our proposed dual-buffer loss. At every iteration, we render two 32spp buffers for computing our loss. For all iterations, we use a fix distribution to important sample the distance from, this makes it easier to analysis the variance of L2 loss. We render 32spp, 64spp, 128spp, 256spp and 512spp for L2 loss. As shown in the plot, optimizing with our loss (purple) converges to match the reference better in parameter error, compared to using L2 loss (yellow) which converges to a biased value. The bias of L2 loss optimization can be reduced by taking more sample to render per iteration.

2 RESULTS

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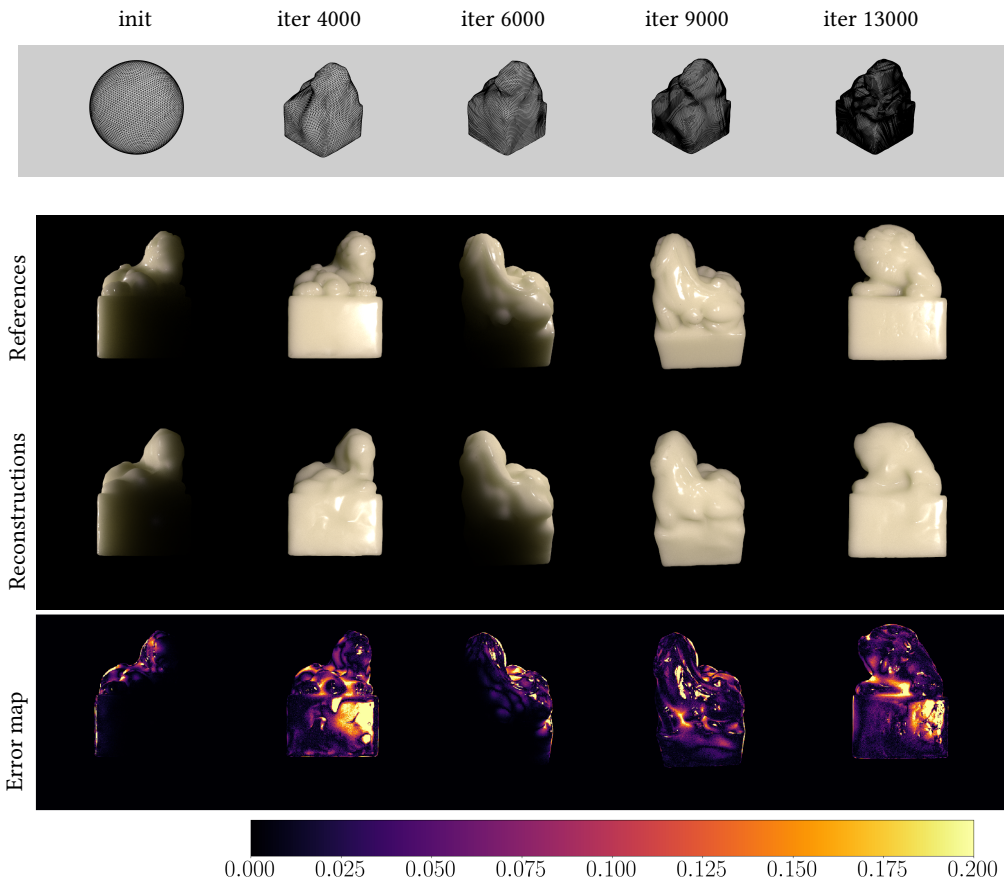

Fig. 2. Here we show a reconstruction of combined shape and homogeneous volume, of a jade seal. The reference are 48 synthetic renderings. We remeshed the shape 3 times along the optimization. We also used a silhouette loss for the shape optimization.