# Supplementary Materials for 3iGS


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## A Training Details

We detail the training methodology for 3iGS as follows:

3iGS is structured around two key components: a Gaussian Splatting backbone and a factorised tensorial illumination field utilising a grid-based representation. To establish a stable training phase, the initial 3,000 iterations focus on optimizing the Gaussian parameters, including standard opacity, anisotropic covariance matrices, and diffused color. Subsequently, specular colors from the neural renderer are incorporated, extending the training up to 30,000 iterations. For the illumination field grid, a consistent grid size of 150 is maintained across each axis (XYZ) to facilitate training on synthetic datasets from NeRF Synthetic Blender and Shiny Blender.

The training process for 3iGS employs two separate Adam optimisers: one dedicated to the 3D Gaussian Splats and the other to the illumination field grid. The initial learning rates are adopted from the benchmarks set by 3DGS and TensoRF, with Gaussian features starting at a learning rate of 0.0025. The illumination grid and neural renderer network have learning rates of 0.02 and 0.001, respectively.

For the 3D Gaussian features, the number of BRDF feature channels is established at 48, aligning with the total channel size used by 3DGS for its radiance field via spherical harmonics. On top of that, we have added an additional parameter for roughness prediction for Integrated Directional Encoding. Separately, the illumination field grid is configured with 48 feature channels on each axis. The neural renderer is designed with a single hidden layer, comprising of 128 feature channels.

## B Colour Decomposition

In Fig. B.1, we illustrate the decomposition of both diffused and specular colour before a linear addition to form a full colour. In the specular component, we observed that intra-scene reflections of the drums and view-dependent illumination is well captured compared to the original Gaussian Splatting work.


**Fig. B.1:** In our methodology, we separate the fully rendered image into its diffuse and specular components prior to performing a linear combination. This approach reveals that the specular component more effectively captures reflections and view-dependent illumination than observed in 3DGS. We ascribe this enhanced performance to the employment of factorised tensors for illumination field modeling.

## C Further Qualitative Comparisons

We direct readers to the supplementary folder for a detailed comparison between our work, 3iGS, and GaussianShader, a closely related work. Owing to the constraints of submission file size limits, our supplementary content primarily features scenes with highly glossy materials. Accompanying the videos, we includes images at full resolution as presented in the main paper.

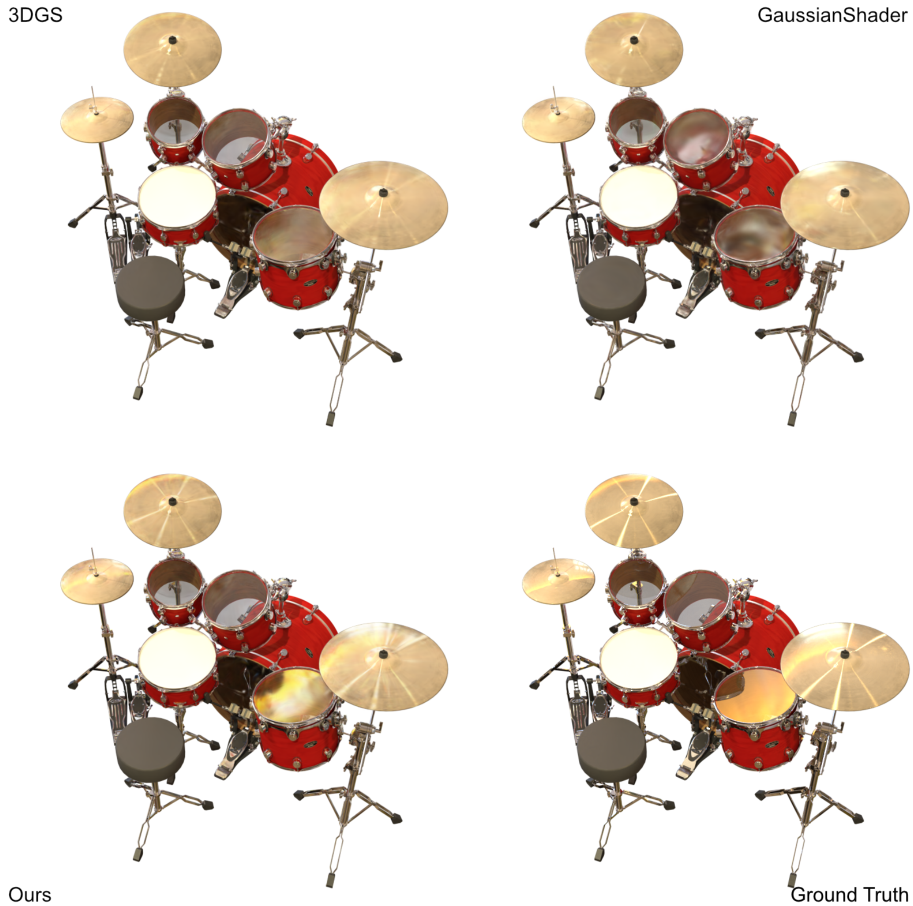


**Fig. C.1:** Comparison of Drums scene rendering

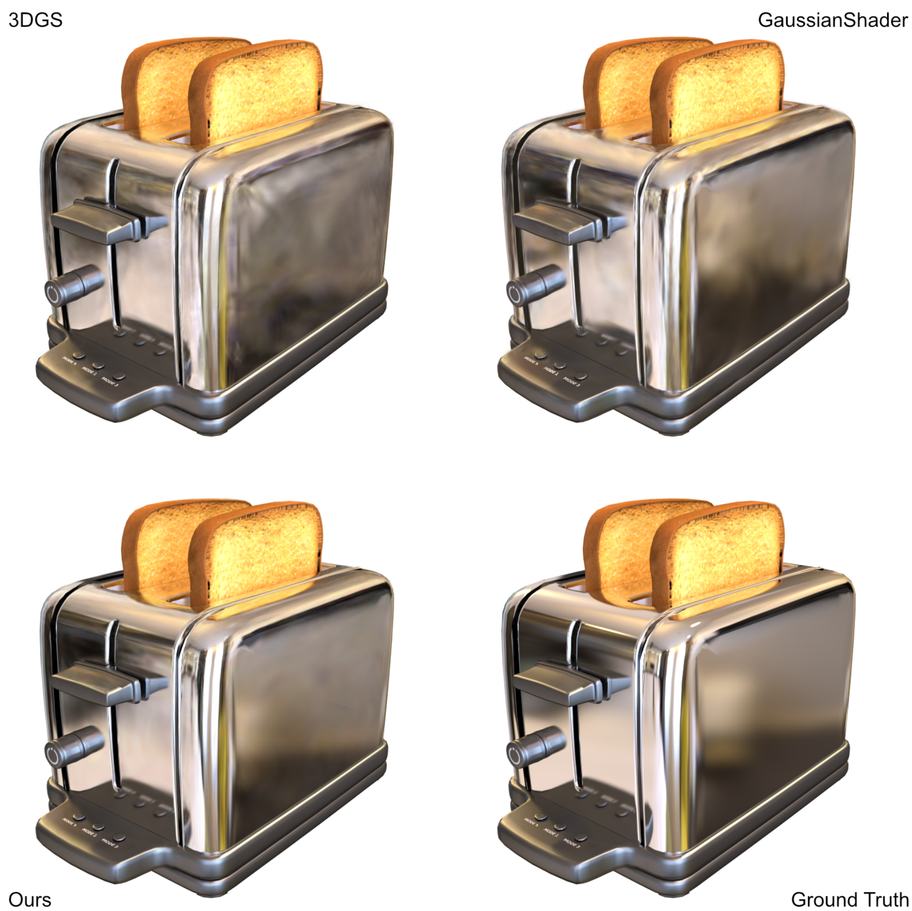


**Fig. C.2:** Comparison of Toaster scene rendering

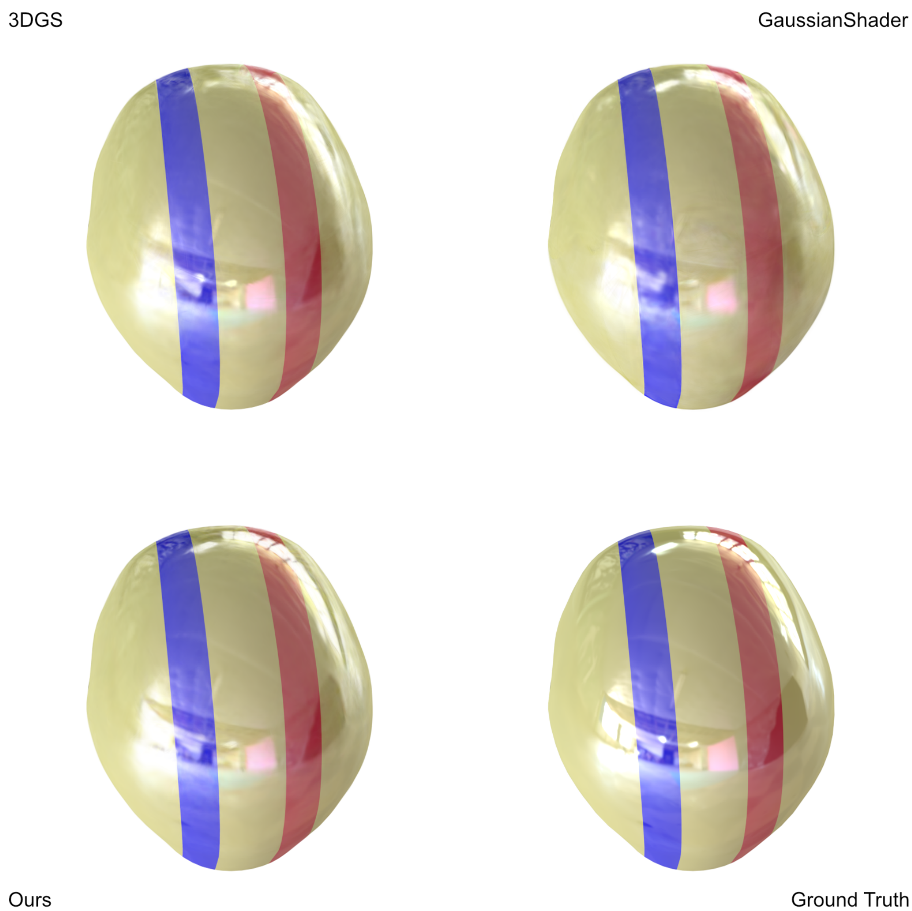


**Fig. C.3:** Comparison of Helmet scene rendering

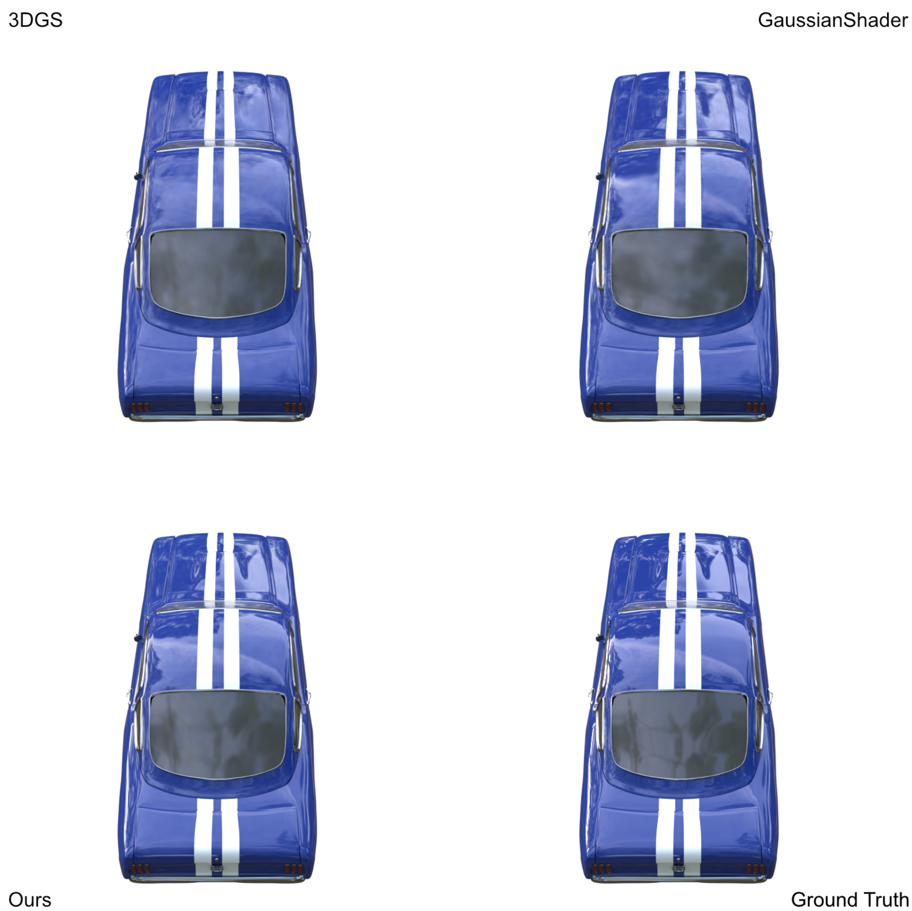


**Fig. C.4:** Comparison of Car scene rendering


**Fig. C.5:** Comparison of Coffee scene rendering