# Supplemental: Codebook-Condensed and Trainable Gaussian Splatting for Fast, Memory-Efficient Reconstruction (ContraGS)

## A. Acceptance Probability Derivation

### A.1. Proposal and Acceptance Probabilities

To determine whether a split, merge or parameter update step proposed is accepted to be taken or not - we compute the acceptance probability as follows:

$$A(S \to S') = \min\left(1, \frac{P(S')q(S|S')}{P(S)q(S'|S)}\right) \tag{1}$$

For the parameter update transition that uses the SGLD update, $A = 1$. For the merge and split transitions, the acceptance probability is given by:

$$A(S \to S_{\text{merge}}) = \min\left(1, \frac{P(S_{\text{merge}})q_{\text{split}}(S_{\text{merge}} \to S)}{P(S)q_{\text{merge}}(S \to S_{\text{merge}})}\right) \tag{2}$$

$$A(S \to S_{\text{split}}) = \min\left(1, \frac{P(S_{\text{split}})q_{\text{merge}}(S_{\text{split}} \to S)}{P(S)q_{\text{split}}(S \to S_{\text{split}})}\right) \tag{3}$$

We now derive the acceptance distribution.

#### A.1.1. Parameter update choice

The proposal distribution for a parameter update, $q_{update}$, is identical to the SGLD parameter update. Thus we express the parameter update state transition using $q_{update}$ as follows:

$$\boldsymbol{p}_{t+1} \sim \mathcal{N}\left(\boldsymbol{p}_t + \frac{\epsilon_p}{2}\nabla_p \log(p(S)), \epsilon_p I\right) \tag{4}$$

$$o_{t+1} \sim \mathcal{N}\left(o_t + \frac{\epsilon_o}{2}\nabla_o \log(p(S)), \epsilon_o I\right) \tag{5}$$

$$\text{SH}_{t+1} \sim \mathcal{N}\left(\text{SH}_t + \frac{\epsilon_{\text{SH}}}{2}\nabla_{\text{SH}} \log(p(G,C)), \epsilon_{\text{SH}} I\right) \tag{6}$$

$$\text{SR}_{t+1} \sim \mathcal{N}\left(\text{SR}_t + \frac{\epsilon_{\text{SR}}}{2}\nabla_{\text{SR}} \log(p(G,C)), \epsilon_{\text{SR}} I\right) \tag{7}$$

Where $\epsilon_p, \epsilon_o, \epsilon_{\text{SH}}, \epsilon_{\text{SR}}$ are small hyperparameters. The acceptance probability $A = 1$.

#### A.1.2. Split Codebook Vectors

During the split transition, we split its codebook vector into a new entry. A 3DG mapped to codebook vector $c$ is remapped into a new codebook vector entry row $c''$. The original codebook vector becomes $c'$.

$$c' = c \qquad c'' = c + u \tag{8}$$

$$q_{split}(u) = \mathcal{N}(0, \epsilon_{\text{split}} I) \tag{9}$$

The acceptance probability of this state transition is given by:

$$A(S \to S_{\text{split}}) = \min\left(1, \frac{p(S_{\text{split}})q_{merge}(c - c')}{p(S)q_{split}(c - c')}\right) \tag{10}$$

The ratio $\frac{p(S_{\text{split}})}{p(S)} \approx e^{-\lambda_{\text{SH}}}$ if we choose to split the SH codebook, and $e^{-\lambda_{\text{SR}}}$ if we choose to split the SR codebook. We thus have the acceptance probability given by:

$$A(S \to S_{\text{split}}) = \min\left(1, e^{-\lambda_{\text{SH}}}/q_{sm}(u)\right) \tag{11}$$

#### A.1.3. Merge Codebook Vectors

Two codebook vectors $c, c'$ can be merged into one codebook vector of value $c$. Two rows to be merged are selected with a transition distribution defined by:

$$q_{\text{merge}}(S \to S_{\text{merge}}) = \mathcal{N}(c - c'|\mu = 0, \sigma = \epsilon_{\text{merge}} I) \tag{12}$$

The acceptance probability of a merge transition is:

$$A(S \to S_{\text{merge}}) = \min\left(1, \frac{p(S_{\text{merge}})q_{split}(c - c')}{p(S)q_{merge}(c - c')}\right) \tag{13}$$

$\frac{p(S)}{p(S_{\text{merge}})} \approx e^{\lambda_{\text{SH}}}$ if it leads to a reduction in the number of rows, or 1 otherwise, as merging a small set of rows of codebook vectors does not affect the overall accuracy.

$$A(S \to S_{\text{merge}}) = \min\left(1, e^{\lambda_{\text{SH}}} q_{sm}(c - c')\right) \tag{14}$$

Where

$$q_{sm}(u) = \exp\left(\frac{u^2}{2}\left(\frac{1}{\epsilon^2_{merge}} - \frac{1}{\epsilon^2_{split}}\right)\right) \tag{15}$$

## B. Reconstruction using an SfM Initialized Point Cloud

| | DeepBlending | MipNerf360 | | | | | | | Tanks and Temples | |
|---|---|---|---|---|---|---|---|---|---|---|
| | playroom | bicycle | bonsai | counter | garden | kitchen | room | stump | train | truck |
| 3DGS | 30.10 | 25.18 | 31.98 | 29.13 | 27.38 | 31.54 | 31.77 | 26.67 | 22.03 | 25.39 |
| EAGLES | 30.38 | 25.02 | 31.45 | 28.42 | 26.94 | 30.79 | 31.64 | 26.67 | 22.34 | 25.04 |
| Reduced-GS | 29.96 | 25.12 | 32.10 | 29.13 | 27.28 | 31.33 | 31.68 | 26.58 | 22.01 | 25.42 |
| Scaffold-GS | 30.89 | 25.02 | 32.50 | 29.43 | 27.30 | 31.42 | 32.13 | 26.72 | 22.54 | 25.74 |
| SpeedySplat | 30.02 | 25.10 | 31.20 | 28.28 | 26.68 | 29.65 | 30.78 | 26.64 | 21.68 | 25.23 |
| Taming3DGS | 30.11 | 24.86 | 32.93 | 29.63 | 27.59 | 32.16 | 32.40 | 26.17 | 22.58 | 26.00 |
| ContraGS-2M | 33.73 | 27.02 | 31.59 | 30.60 | 27.49 | 30.54 | 32.34 | 30.83 | 24.35 | 26.93 |

Table 1. PSNR on evaluation datasets

| | DeepBlending | MipNerf360 | | | | | | | Tanks and Temples | |
|---|---|---|---|---|---|---|---|---|---|---|
| | playroom | bicycle | bonsai | counter | garden | kitchen | room | stump | train | truck |
| 3DGS | 0.909 | 0.748 | 0.946 | 0.916 | 0.858 | 0.916 | 0.916 | 0.768 | 0.821 | 0.885 |
| EAGLES | 0.913 | 0.750 | 0.942 | 0.907 | 0.840 | 0.928 | 0.927 | 0.774 | 0.798 | 0.876 |
| Reduced-GS | 0.906 | 0.747 | 0.947 | 0.915 | 0.856 | 0.932 | 0.926 | 0.768 | 0.810 | 0.882 |
| Scaffold-GS | 0.913 | 0.740 | 0.948 | 0.917 | 0.850 | 0.929 | 0.931 | 0.766 | 0.829 | 0.887 |
| SpeedySplat | 0.907 | 0.747 | 0.926 | 0.877 | 0.815 | 0.891 | 0.904 | 0.764 | 0.773 | 0.868 |
| Taming3DGS | 0.910 | 0.706 | 0.950 | 0.922 | 0.856 | 0.937 | 0.934 | 0.738 | 0.830 | 0.893 |
| ContraGS-2M | 0.925 | 0.813 | 0.943 | 0.938 | 0.848 | 0.922 | 0.933 | 0.896 | 0.861 | 0.904 |

Table 2. SSIM on evaluation datasets

| | DeepBlending | MipNerf360 | | | | | | | Tanks and Temples | |
|---|---|---|---|---|---|---|---|---|---|---|
| | playroom | bicycle | bonsai | counter | garden | kitchen | room | stump | train | truck |
| 3DGS | 0.241 | 0.242 | 0.180 | 0.182 | 0.122 | 0.116 | 0.196 | 0.242 | 0.197 | 0.141 |
| EAGLES | 0.251 | 0.244 | 0.191 | 0.199 | 0.154 | 0.127 | 0.200 | 0.243 | 0.237 | 0.164 |
| Reduced-GS | 0.243 | 0.244 | 0.180 | 0.183 | 0.123 | 0.117 | 0.197 | 0.243 | 0.206 | 0.147 |
| Scaffold-GS | 0.244 | 0.260 | 0.179 | 0.185 | 0.133 | 0.122 | 0.187 | 0.261 | 0.190 | 0.136 |
| SpeedySplat | 0.269 | 0.244 | 0.227 | 0.258 | 0.213 | 0.197 | 0.257 | 0.289 | 0.289 | 0.190 |
| Taming3DGS | 0.251 | 0.314 | 0.172 | 0.171 | 0.129 | 0.110 | 0.181 | 0.309 | 0.191 | 0.125 |
| ContraGS-2M | 0.252 | 0.230 | 0.186 | 0.150 | 0.160 | 0.148 | 0.187 | 0.163 | 0.187 | 0.124 |

Table 3. LPIPS on evaluation datasets

| | Blender | | | | | | | | DeepBlending | MipNerf360 | | | | | | | Tanks and Temples | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | chair | drums | ficus | hotdog | lego | materials | mic | ship | playroom | bicycle | bonsai | counter | garden | kitchen | room | stump | train | truck |
| ContraGS-2M | 158.30 | 127.17 | 236.28 | - | 103.08 | 149.54 | 257.87 | 115.33 | 134.57 | 130.04 | 101.38 | 99.03 | 139.62 | 135.20 | 128.97 | 131 | 128.07 | 96.07 |
| 3DGS | 190.27 | 149.03 | 67.31 | 70.85 | 140.61 | 58.35 | 83.00 | 115.99 | 817.16 | 2,089.36 | 482.08 | 467.02 | 1,858.58 | 690.12 | 553.89 | 1,772.67 | 480.17 | 901.40 |
| EAGLES | 10.78 | 8.44 | 4.80 | 6.38 | 12.35 | 4.80 | 5.17 | 7.36 | 63.14 | 159.47 | 50.91 | 44.77 | 116.03 | 82.74 | 52.33 | 156.55 | 33.40 | 57.96 |
| Reduced-GS | 121.14 | 96.92 | 65.94 | 46.87 | 85.20 | 40.21 | 49.72 | 68.60 | 572.14 | 1,432.41 | 321.76 | 295.36 | 1,406.55 | 443.20 | 371.62 | 1,099.43 | 269.20 | 636.50 |
| Scaffold-GS | 31.66 | 31.66 | 31.66 | 31.66 | 31.66 | 31.66 | 31.66 | 31.96 | 95.11 | 304.83 | 135.45 | 91.52 | 246.28 | 107.76 | 89.25 | 252.44 | 114.89 | 192.21 |
| SpeedySplat | 72.30 | 57.09 | 43.51 | 32.94 | 61.88 | 32.71 | 32.45 | 50.27 | 393.28 | 895.20 | 314.86 | 264.14 | 1,043.39 | 406.80 | 286.05 | 803.08 | 188.92 | 494.39 |
| Taming3DGS | - | - | - | - | - | - | - | - | 325.63 | 477.60 | - | 631.04 | 1,221.08 | 797.98 | 756.10 | 282.02 | 743.60 | 1,189.74 |

Table 4. Peak memory during training

# C. Random Parameter Initialization

| | Tanks and Temples | | MipNerf360 | | | | | | | DeepBlending | Blender | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | train | truck | bicycle | bonsai | counter | garden | kitchen | room | stump | playroom | chair | drums | ficus | hotdog | lego | materials | mic |
| 3DGS | 19.49 | 18.41 | 17.69 | 16.46 | 23.46 | 21.71 | 24.61 | 27.69 | 20.74 | 14.41 | 31.93 | 24.91 | 29.05 | 36.48 | 32.37 | 29.69 | 34.58 |
| EAGLES | 18.91 | 18.43 | 19.30 | 17.79 | 23.25 | 24.82 | 25.52 | 25.27 | 20.08 | 20.82 | 34.42 | 25.68 | 33.67 | 37.05 | 34.92 | 28.95 | 35.12 |
| Reduced-GS | 18.74 | 18.02 | | 15.59 | 23.85 | 24.15 | 25.82 | 25.11 | 19.67 | 12.95 | 35.59 | 26.28 | 35.48 | 38.07 | 36.06 | 30.50 | 36.71 |
| Scaffold-GS | 19.69 | 18.32 | 20.58 | 17.77 | 21.06 | 18.45 | 23.08 | 23.35 | 18.73 | 13.99 | 34.85 | 26.17 | 35.04 | 37.81 | 35.42 | 30.60 | 36.69 |
| SpeedySplat | 19.24 | 18.15 | 15.90 | 19.54 | 23.84 | 0.00 | 0.00 | 24.40 | 0.00 | 13.39 | 33.95 | 25.96 | 35.18 | 36.13 | 32.12 | 29.33 | 35.86 |
| Taming3DGS | 19.78 | 18.46 | 19.64 | 20.08 | - | - | 26.73 | - | 20.86 | - | - | - | - | - | - | - | - |
| ContraGS-2M | 24.35 | 26.93 | 27.02 | 31.59 | 30.60 | 27.49 | 30.54 | 32.34 | 30.83 | 33.73 | 38.48 | 29.05 | 38.79 | 36.48 | 39.34 | 36.20 | 41.56 |

Table 5. PSNR measured on evaluation dataset

| | Tanks and Temples | | MipNerf360 | | | | | | | DeepBlending | Blender | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | train | truck | bicycle | bonsai | counter | garden | kitchen | room | stump | playroom | chair | drums | ficus | hotdog | lego | materials | mic |
| 3DGS | 0.737 | 0.722 | 0.487 | 0.658 | 0.827 | 0.710 | 0.878 | 0.870 | 0.606 | 0.682 | 0.983 | 0.941 | 0.953 | 0.984 | 0.975 | 0.950 | 0.987 |
| EAGLES | 0.726 | 0.719 | 0.562 | 0.690 | 0.835 | 0.784 | 0.890 | 0.846 | 0.600 | 0.808 | 0.984 | 0.950 | 0.982 | 0.983 | 0.980 | 0.949 | 0.989 |
| Reduced-GS | 0.717 | 0.712 | - | 0.620 | 0.840 | 0.762 | 0.891 | 0.838 | 0.567 | 0.646 | 0.988 | 0.955 | 0.987 | 0.985 | 0.983 | 0.960 | 0.992 |
| Scaffold-GS | 0.727 | 0.696 | 0.467 | 0.697 | 0.780 | 0.455 | 0.830 | 0.803 | 0.396 | 0.669 | 0.985 | 0.948 | 0.985 | 0.984 | 0.980 | 0.960 | 0.992 |
| SpeedySplat | 0.706 | 0.701 | 0.422 | 0.713 | 0.816 | - | - | 0.817 | - | 0.657 | 0.979 | 0.949 | 0.985 | 0.975 | 0.958 | 0.947 | 0.990 |
| Taming3DGS | 0.743 | 0.722 | 0.525 | 0.735 | - | - | 0.895 | 0.000 | 0.588 | - | - | - | - | - | - | - | - |
| ContraGS-2M | 0.861 | 0.904 | 0.813 | 0.943 | 0.938 | 0.848 | 0.922 | 0.933 | 0.896 | 0.925 | 0.993 | 0.977 | 0.994 | 0.984 | 0.992 | 0.989 | 0.997 |

Table 6. SSIM measured on evaluation dataset

| | Tanks and Temples | | MipNerf360 | | | | | | | DeepBlending | Blender | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | train | truck | bicycle | bonsai | counter | garden | kitchen | room | stump | playroom | chair | drums | ficus | hotdog | lego | materials | mic |
| 3DGS | 0.286 | 0.291 | 0.481 | 0.469 | 0.289 | 0.251 | 0.182 | 0.279 | 0.398 | 0.549 | 0.023 | 0.059 | 0.043 | 0.030 | 0.031 | 0.064 | 0.026 |
| EAGLES | 0.306 | 0.305 | 0.422 | 0.443 | 0.273 | 0.203 | 0.174 | 0.312 | 0.406 | 0.387 | 0.015 | 0.045 | 0.018 | 0.025 | 0.020 | 0.053 | 0.011 |
| Reduced-GS | 0.307 | 0.308 | - | 0.498 | 0.277 | 0.219 | 0.168 | 0.320 | 0.441 | 0.308 | 0.010 | 0.036 | 0.012 | 0.020 | 0.016 | 0.037 | 0.006 |
| Scaffold-GS | 0.291 | 0.317 | 0.505 | 0.456 | 0.353 | 0.508 | 0.262 | 0.368 | 0.571 | 0.573 | 0.014 | 0.047 | 0.014 | 0.023 | 0.019 | 0.041 | 0.008 |
| SpeedySplat | 0.349 | 0.359 | 0.567 | 0.427 | 0.327 | - | - | 0.352 | 0.000 | 0.581 | 0.023 | 0.048 | 0.014 | 0.044 | 0.060 | 0.061 | 0.011 |
| Taming3DGS | 0.282 | 0.292 | 0.454 | 0.404 | - | - | 0.161 | - | 0.406 | - | - | - | - | - | - | - | - |
| ContraGS-2M | 0.187 | 0.124 | 0.230 | 0.186 | 0.150 | 0.160 | 0.148 | 0.187 | 0.163 | 0.252 | 0.007 | 0.026 | 0.007 | 0.030 | 0.009 | 0.019 | 0.003 |

Table 7. LPIPS measured on evaluation dataset

## D. Training and Rendering Speeds

| | T and T | | MipNerf360 | | | | | | | DeepBlending |
|---|---|---|---|---|---|---|---|---|---|---|
| | train | truck | bicycle | bonsai | counter | garden | kitchen | room | stump | playroom |
| Taming3DGS | 263.40 | 240.66 | 224.62 | 211.51 | 170.02 | 178.84 | 163.10 | 174.79 | 374.40 | 468.09 |
| Ours 5M | 129.00 | 96.00 | 89.00 | 58.00 | 46.00 | 118.00 | 101.00 | 107.00 | 88.00 | 141.00 |
| Ours | 206.00 | 209.00 | 159.00 | 217.00 | 219.00 | 249.19 | 210.00 | 242.00 | 220.00 | 319.00 |
| MCMC 5M | 75.50 | 85.90 | 72.00 | 68.50 | 56.10 | 91.70 | 59.49 | 71.24 | 41.00 | 114.00 |
| MCMC 2M | 94.00 | 173.32 | 77.00 | 75.69 | 62.78 | 185.00 | 70.16 | 143.58 | 142.79 | 251.8 |

Table 8. Frames per second (FPS) measured on differnt datasets

| | DeepBlending | MipNerf360 | | | | | | | T and T | |
|---|---|---|---|---|---|---|---|---|---|---|
| | playroom | bicycle | bonsai | counter | garden | kitchen | room | stump | train | truck |
| MCMC 2M | 31.66 | 24.00 | 24.00 | 20.00 | 27.00 | 22.87 | 23.70 | 24.00 | 29.19 | 31.49 |
| MCMC 5M | 13.10 | 11.99 | 11.99 | 10.09 | 13.08 | 10.81 | 11.28 | 12.76 | 12.25 | 13.65 |
| Ours | 46.33 | 31.63 | 27.07 | 32.82 | 36.33 | 29.48 | 34.80 | 32.00 | 38.50 | 43.00 |
| Ours 5M | 21.65 | 15.09 | 13.55 | 11.59 | 17.80 | 13.14 | 17.45 | 17.33 | 19.87 | 18.48 |
| Taming3DGS | 93.12 | 71.35 | 50.09 | 48.59 | 40.02 | 40.70 | 49.09 | 102.78 | 67.08 | 47.11 |

Table 9. Training Iterations per second

### D.1. Comparison of Training Speeds with Taming-GS at Different Gaussian Counts

Table 10 compares training speeds with TamingGS.

| Model-numGS | PSNR | Training time | Memory |
|---|---|---|---|
| ContraGS-2M | 30.06 | 14 mins | 130 MB |
| ContraGS-530K | 29.31 | 6.5 mins | 59 MB |
| TamingGS | 29.39 | 8 mins | 477 MB |

Table 10. Performance comparison of TamingGS and ContraGS for the same number of Gaussians

## E. Qualitative Results

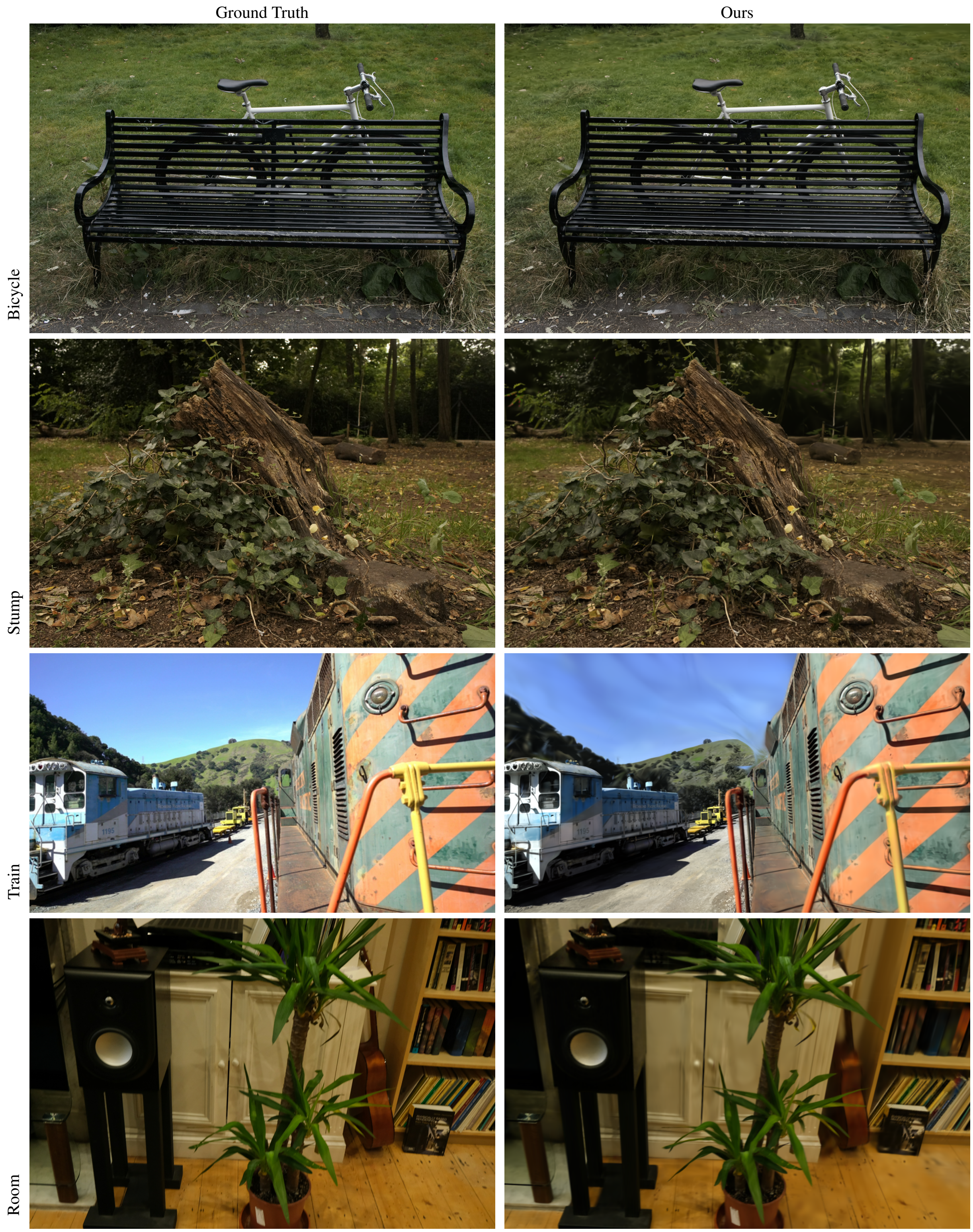


Figure 1. Qualitative results of ContraGS compared to ground truth reconstruction

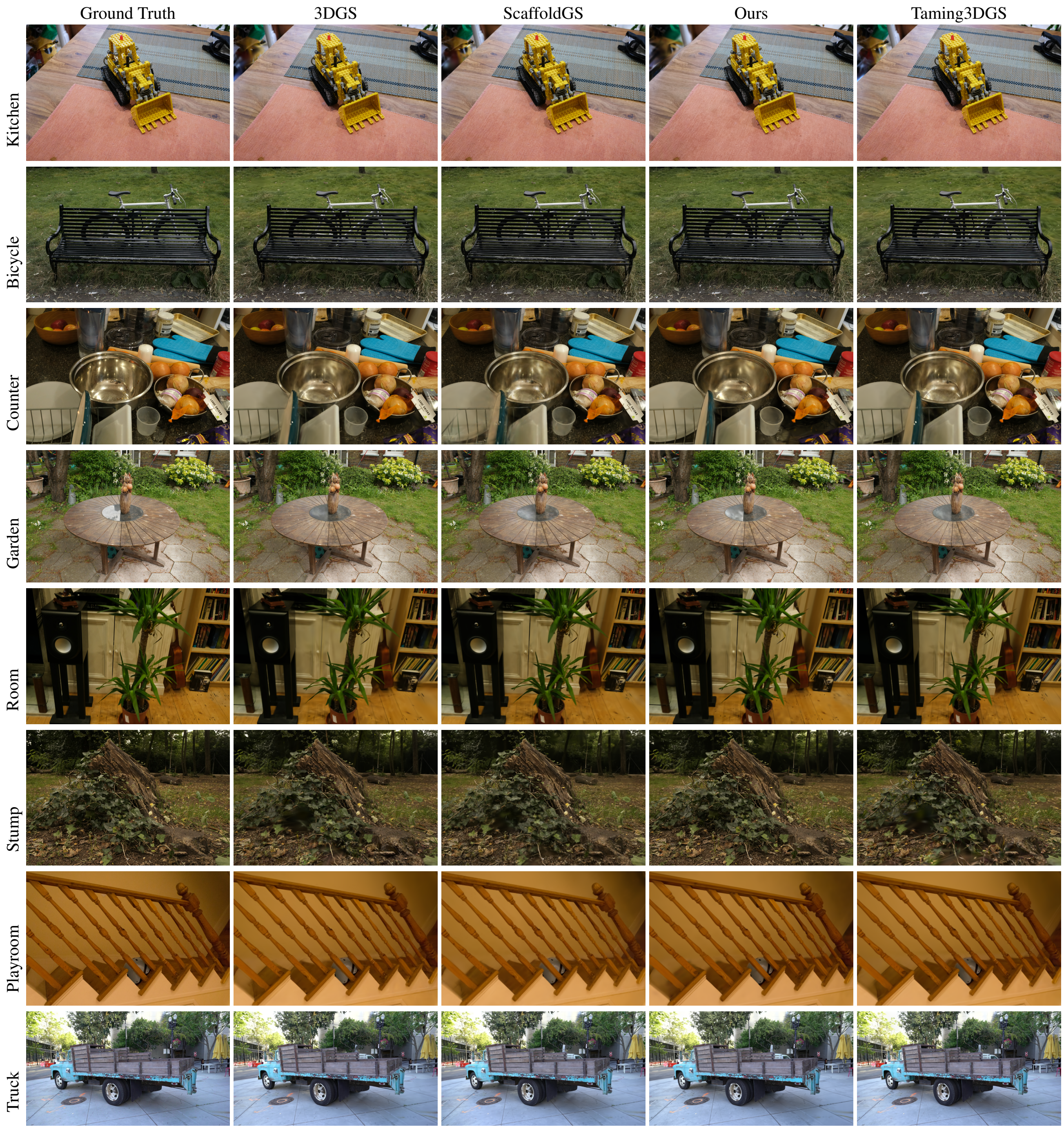


Figure 2. Qualitative results of ContraGS compared to prior work and ground truth reconstruction