Gaussian-Flow: 4D Reconstruction with Dynamic 3D Gaussian Particle

Supplementary Material

A. Implementation Details

In this paper, we focus exclusively on modeling three key attributes of the 3D Gaussian Splatting (3DGS) using our novel DDDM model. These attributes are: 1) the position of the Gaussian, 2) the rotation represented by a quaternion, and 3) the first three coefficients of the Spherical Harmonics (SHs). The learning approach employed for each of these attributes within the DDDM framework mirrors that of the corresponding 3DGS attribute, ensuring consistency in our modeling strategy.

We first train each scene with no deformation (as a 3DGS) for 2000 iterations, and then train the scene with deformation (with DDDM) for the remaining training phase. We stop the process of adding (through splitting and cloning as delineated in 3DGS) and pruning Gaussian points as 15K iterations. Then, We start using the KNN rigid loss at 5000 iterations, since the number of Gaussian points is fixed, which is more computationally efficient, because we can only compute the KNN index once instead of calculating the KNN for each iteration.

B. More Results

This section presents additional visual results. We present the qualitative results on the D-NeRF synthetic scenes in Figure 8. We also visualize a broader range of viewpoints and scenes, highlighting the capability of our method in rendering novel view variants across both spatial and temporal dimensions on HyperNeRF dataset and Plenoptic Video dataset dataset.

Hook Jumpingjacks Mutant

Figure 8. Qualitative Visualization on D-NeRF synthetic scenes.

As shown in Figure 9, we show more results on scene ***americano***, ***chickchicken*** and ***split cookie***. As shown in Figure 10, we show the rendering and depth map results on Plenoptic Video dataset rendered at more viewpoints and time.

Figure 9. **View Synthesis Results on HyperNeRF Dataset.**

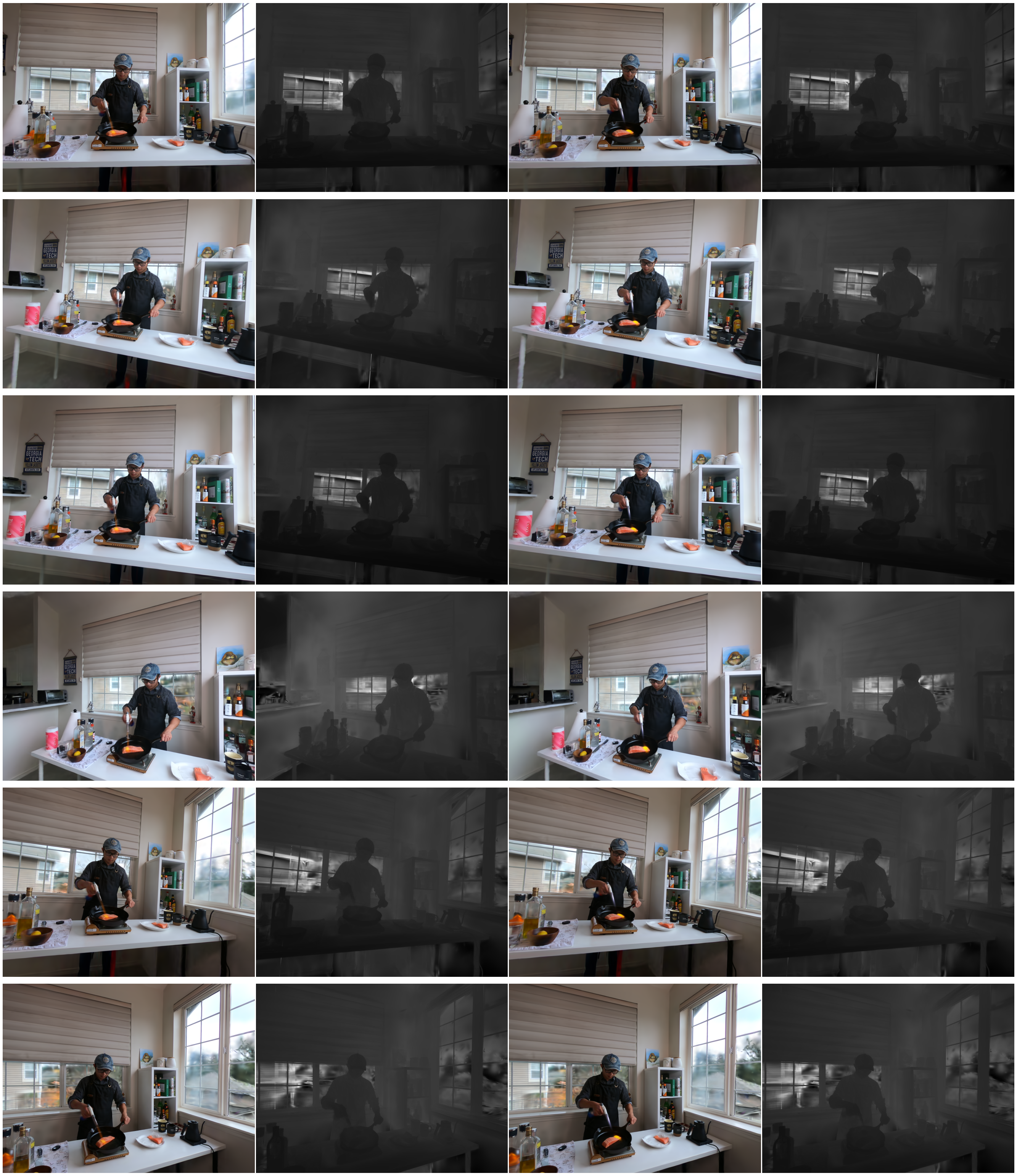

Figure 10. **View Synthesis Results and Depths on Plenoptic Video Dataset.**