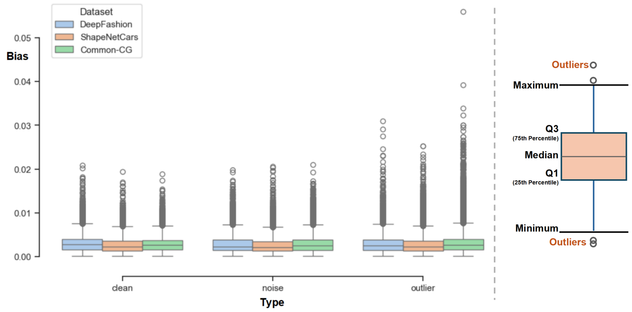
A Lightweight UDF Learning Framework for 3D Reconstruction Based on Local Shape Functions

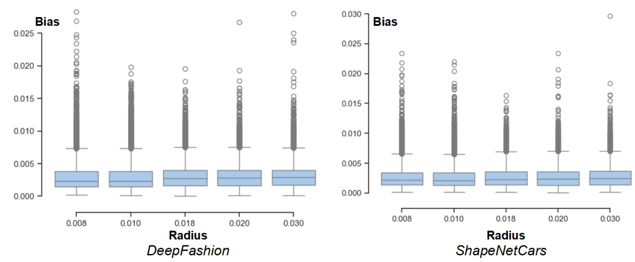
Supplementary Material

1. Bias analysis

To illustrate the effectiveness of generalizing from our synthetic dataset to general point clouds, we conduct a bias analysis comparing our synthetic local patches with local geometries extracted from test data. We obtain the feature vectors $\mathbf{f}_p^i$ for all patches in the training dataset (totaling 131,064 data points), processed by Points-Net in our network, and then extract local geometries with a radius $r = 0.018$ from point clouds in three categories: DeepFashion3D, ShapeNetCars, and 10 common computer graphics models (Bunny, Bimba, etc). We compute the corresponding feature vectors $\hat{\mathbf{f}}_p^i$, and measure the distances between $\mathbf{f}_p^i$ and $\hat{\mathbf{f}}_p^i$ as the bias. The same analysis is also applied to point clouds with noise and outliers. As illustrated in Fig. 1 (a), we employ boxplots to visualize the bias distribution. The results indicate that bias remains low under conditions that are clean, noisy, or affected by outliers. The radius impacts the size of extracted local geometries and thus influences the observed bias. We performed experiments with different radii using the aforementioned analysis method. Fig. 1 (b) shows a radius of $r = 0.018$ (our default setting) results in relatively fewer outliers.



(a) Bias analysis for point clouds from three datasets



(b) Joint analysis with radius

Figure 1. We statistically analyze the feature bias between local geometries extracted from test data and local patches from our synthetic training dataset, illustrating the bias distributions with box plots. (a) The bias remains low across three different datasets.(b) A radius of 0.018 results in relatively fewer outliers in most scenarios.

2. Radius and point cloud density

Given that our method learns UDF values from locally extracted patches in input point clouds, the density and radius of these clouds can affect the reconstruction results. To evaluate the applicability of our method's parameters, we conduct performance evaluation experiments under varying point cloud densities and radii. Figure 2 presents several examples from our experiments. We observed that the maximum applicable radius is $r = 0.05$. This means that when r exceeds 0.05, the feature information within the local geometry surpasses our network's ability to evaluate, preventing accurate reconstruction of the geometry, as illustrated in the upper right area of Fig. 2. In order to standardize the point cloud density scale, we count the number of points within a circle of radius 0.05 as the density value. Experiments demonstrate that our method cannot successfully reconstruct when the density is approximately less than 30 , as shown in the lower left area of Fig. 2. Therefore, for user-inputted point clouds, the density of the point cloud is first assessed. If it is below the algorithm's requirements, upsampling can be used to densify the point cloud. For general models, a radius setting of 0.018 is feasible in most cases. Users can also quickly perform bias analysis and make appropriate adjustments within a range of less than 0.05.

3. More results

As shown in Fig. 5 and Fig. 6, we provide more visual comparisons on the DeepFashion3D and ShapeNetCars dataset, using point clouds containing noise and outliers. Our framework is able of reconstructing reasonable surfaces even with 50% outliers, as shown in Fig. 3. Furthermore, our approach can reconstruct high-quality geometry from point clouds containing both noise and outliers. We also conduct experiments on large scanned scenes to evaluate our algorithm as shown in Fig. 4.

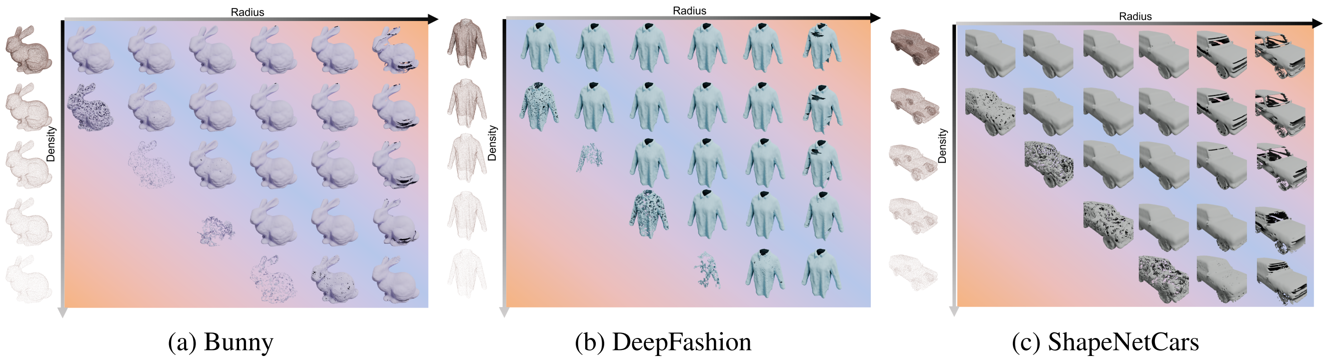


Figure 2. We evaluate the performance of our algorithm across varying point cloud densities and radii.

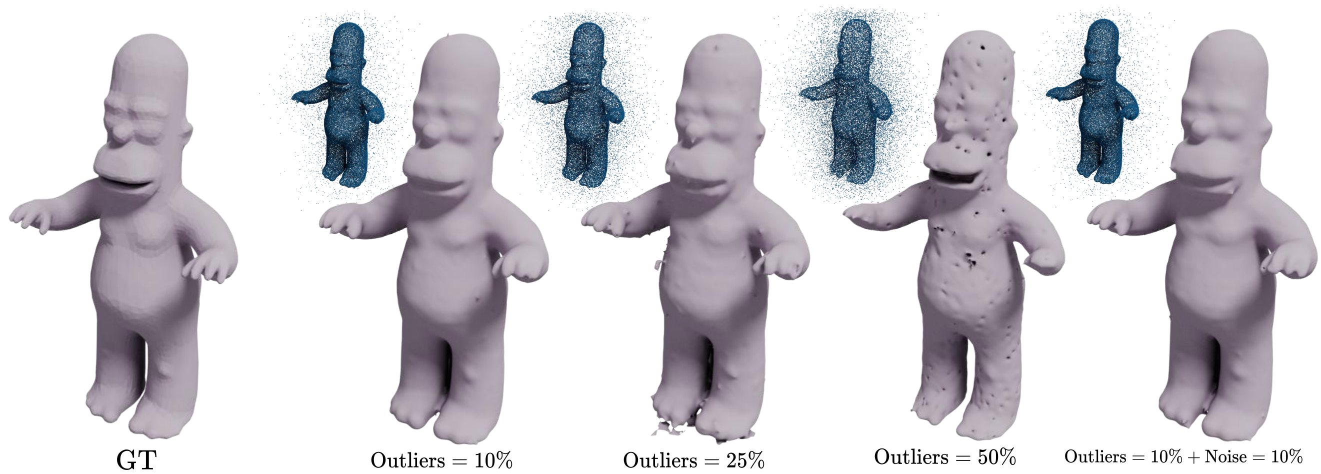


Figure 3. Our model demonstrates robustness to more outliers.

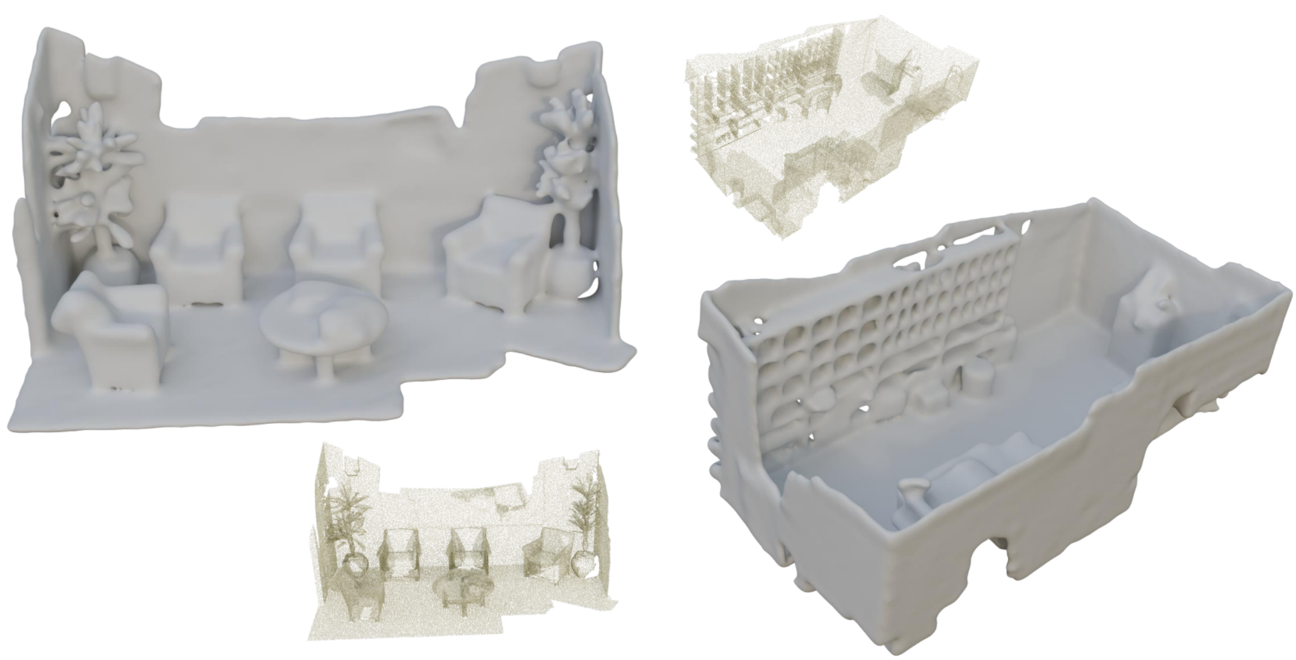


Figure 4. Reconstruction result on large scene dataset

Figure 5. More visual results on the DeepFashion3D dataset. Top three rows: Reconstruction results under noise-free conditions. Bottom three rows: Reconstruction results under noise condition.

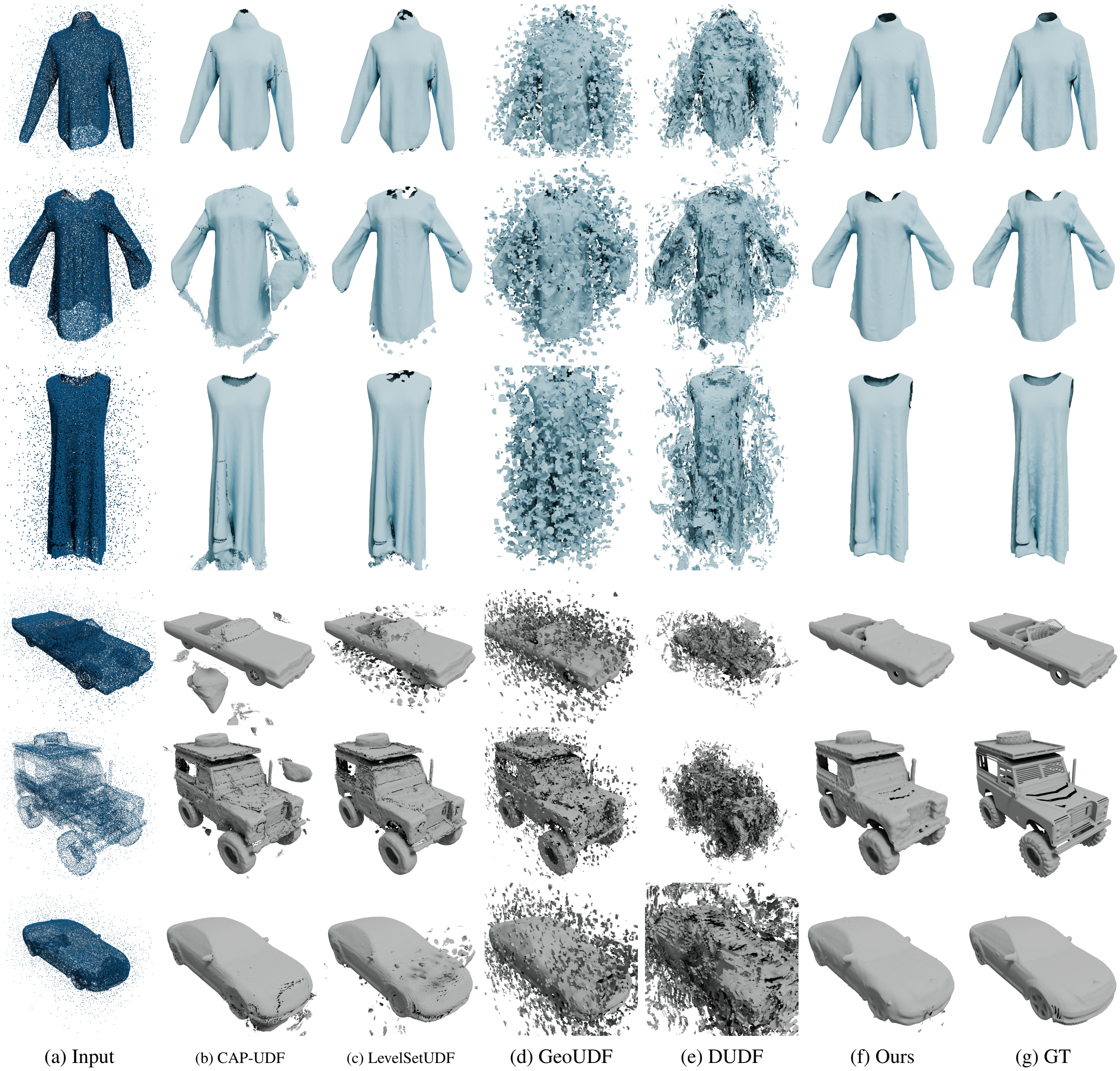


Figure 6. More visual results on the synthetic datasets with outliers.