Neural RGB-D Surface Reconstruction

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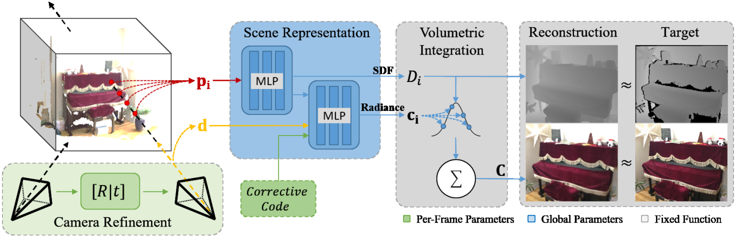
Introduction

Introduction

Typical nerf doesn’t reconstruct an actual surface, which may lead to artifacts. The paper proposes to use truncated signed distance function instead of direct depth , which is easy to be disturbed by noise, to represent the surface and leverages the RGB and depth information to reconstruct. In addition, the paper propose a pose and camera refinement technique which improves the overall reconstruction quality.

pipeline



the input of first mlp is position ,we use depth images as ground truth to train the SDF,the second mlp use the output of mlp and using direction as input to output the radiance,then combine them all,using the weight as a function of tsdf

Conclusion

Method	C-ℓ_1 ↓	IoU ↑	NC ↑	F-score ↑
BundleFusion	0.062	0.594	0.892	0.805
RoutedFusion	0.057	0.615	0.864	0.838
COLMAP + Poisson	0.057	0.619	0.901	0.839
Conv. Occ. Nets	0.077	0.461	0.849	0.643
SIREN	0.060	0.603	0.893	0.816
NeRF + Depth	0.065	0.550	0.768	0.782
Ours (w/o pose)	0.049	0.655	0.908	0.868
Ours	**0.044**	**0.747**	**0.918**	**0.924**

Table 1. Reconstruction results on a dataset of 10 synthetic scenes. The Chamfer ℓ_1 distance, normal consistency and the F-score [37] are computed between point clouds sampled with a density of 1 point per cm^2, using a threshold of 5 cm for the F-score. We voxelize the mesh to compute the intersection-over-union (IoU) between the predictions and ground truth.

Thank you!