FIRe: Fast Inverse Rendering using Directional and Signed Distance Functions

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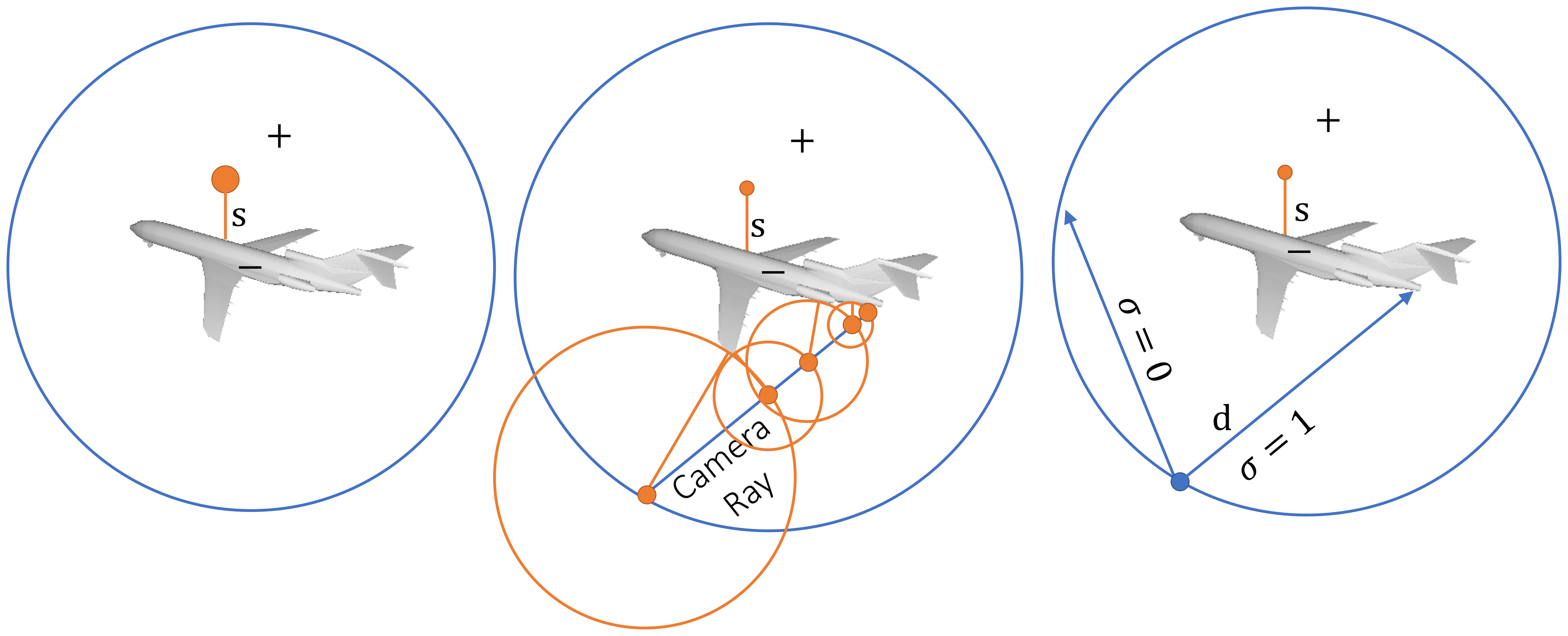
Highlights

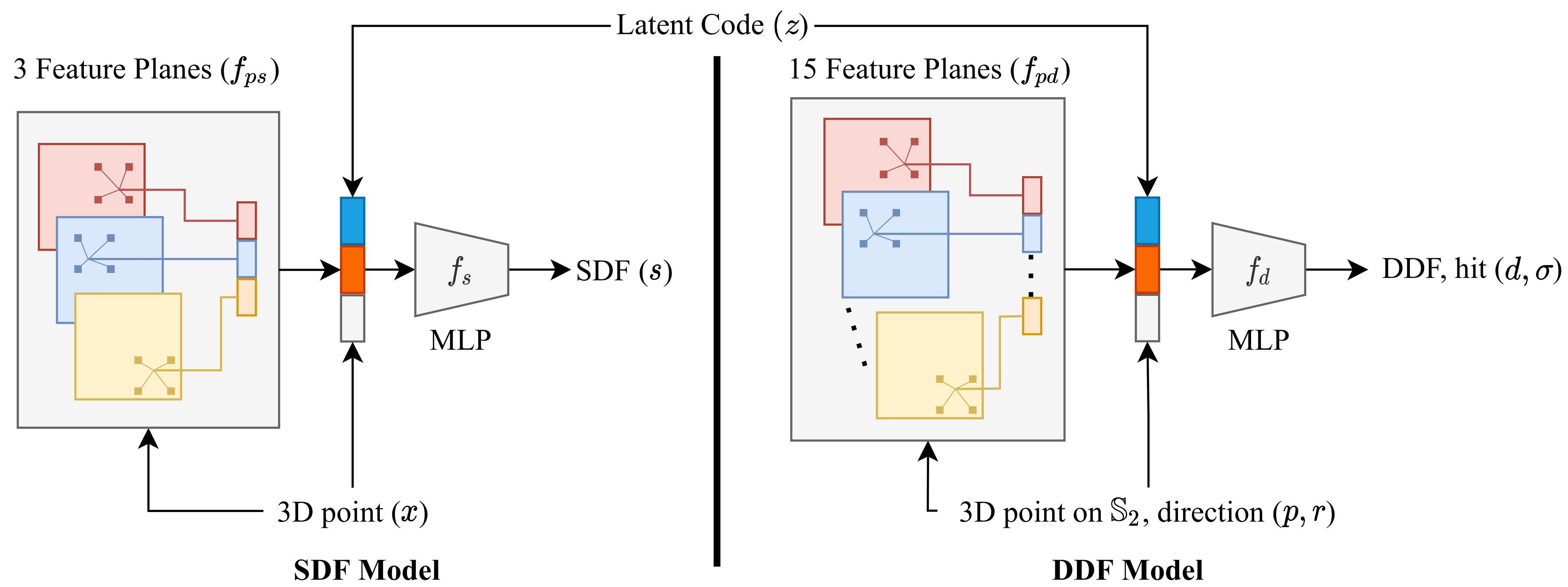
- We present a novel 3D neural scene representation called directional distance function (DDF)
- We learn a signed distance function (SDF) along with DDF to represent a class of shapes
- We propose a novel inverse rendering algorithm that is 15.5x (per iteration) faster than **the state of the art** while more accurately reconstructing 3D shapes from single-view depth maps

Motivation



SDF representation | Sphere tracing for rendering an object represented using SDF | Our representation combines DDFs and SDFs for faster rendering

Models



Training

Loss = L1 SDF Supervision	$\lVert SDF - SDF_{GT} \rVert_1$
+ L1 DDF Supervision	$\lVert DDF - DDF_{GT} \rVert_1$
+ DDF Mask	$BCE(RayHit, RayHit_{GT})$
+ TrackSDF	$\lVert SDF(p + DDF.r) \rVert_1$
+ TVL1 feature plane regularizer	
+ Latent code regularizer	

Trained per class of the ShapeNet[8] dataset

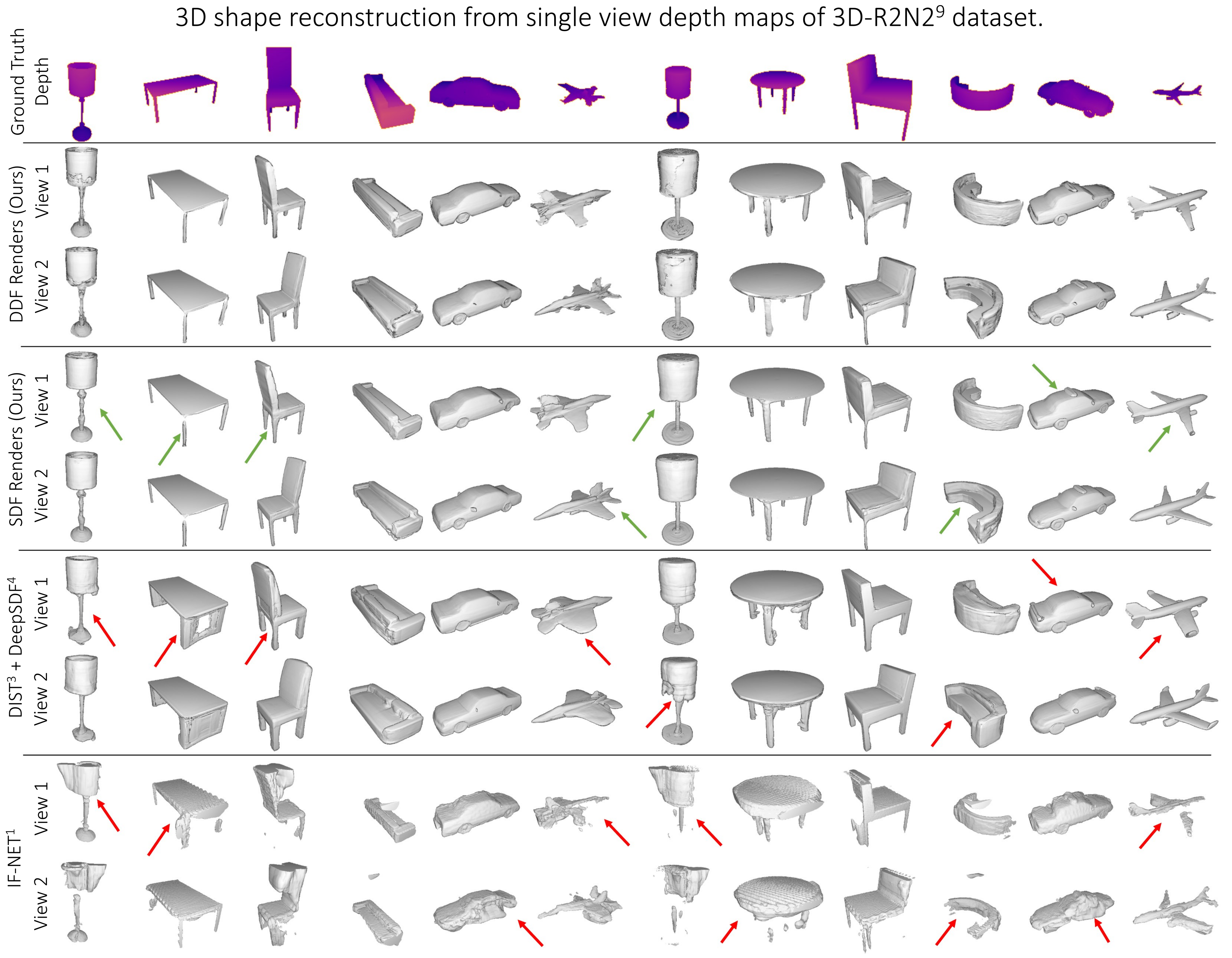
Inference: Optimization for latent code from a given depth map

Loss = Depth	$\lVert depth - depth_{GT} \rVert_1$
+ DDF Mask	$BCE(RayHit, RayHit_{GT})$
+ SDF Mask (hit)	$\lVert SDF(p + DDF.r) \rVert_1$
+ SDF Mask (miss) τ is SDF truncation thresh.	$\lVert SDF(p + DDF.r) - \tau \rVert_1$
+ Latent code regularizer	

Shapes are reconstructed from a given single-view depth map

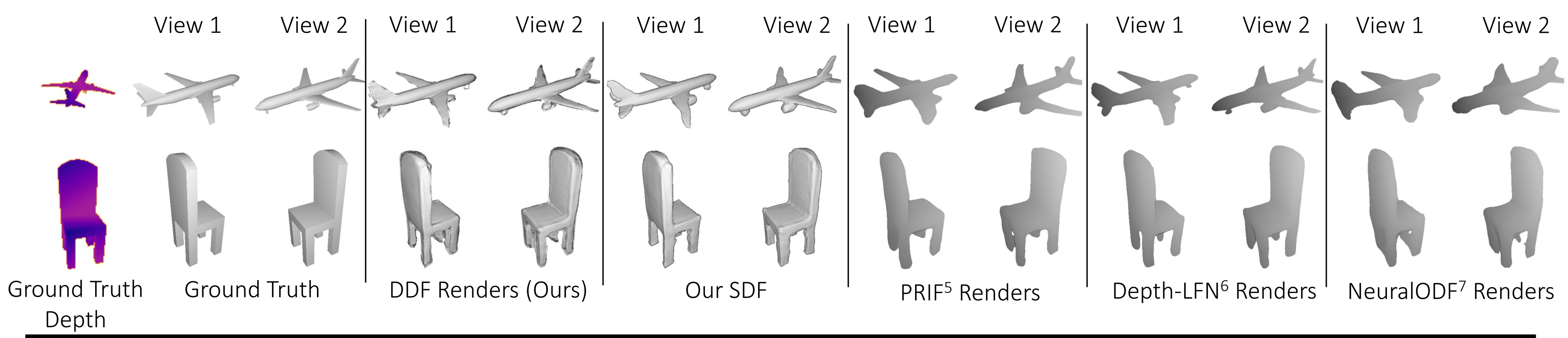
Shape from Depth

3D shape reconstruction from single view depth maps of 3D-R2N2[9] dataset.



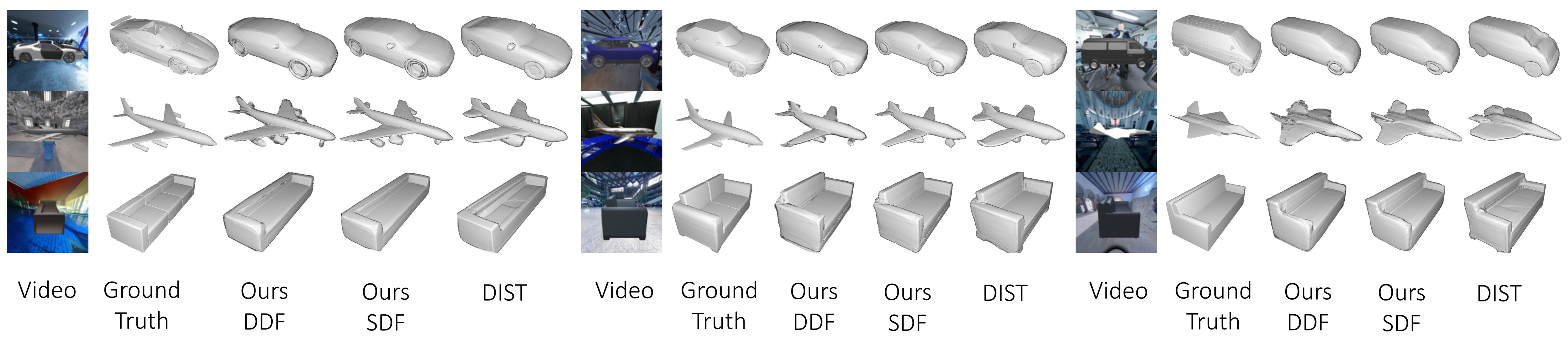
Shape from Depth

Comparison with other DDF models



Shape from Videos

3D reconstruction from videos from the PMO dataset[2].



Summary

We propose a novel neural scene representation, DDF defined on the unit sphere, for rendering images from our SDF model during inference with **1 forward pass** through the model. We present an algorithm to reconstruct 3D shapes from single view depth maps using our DDF and SDF models, which is **15.5× per iteration faster** than competing methods.

References

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