Shape Completion using 3D-Encoder-Predictor CNNs and Shape Synthesis

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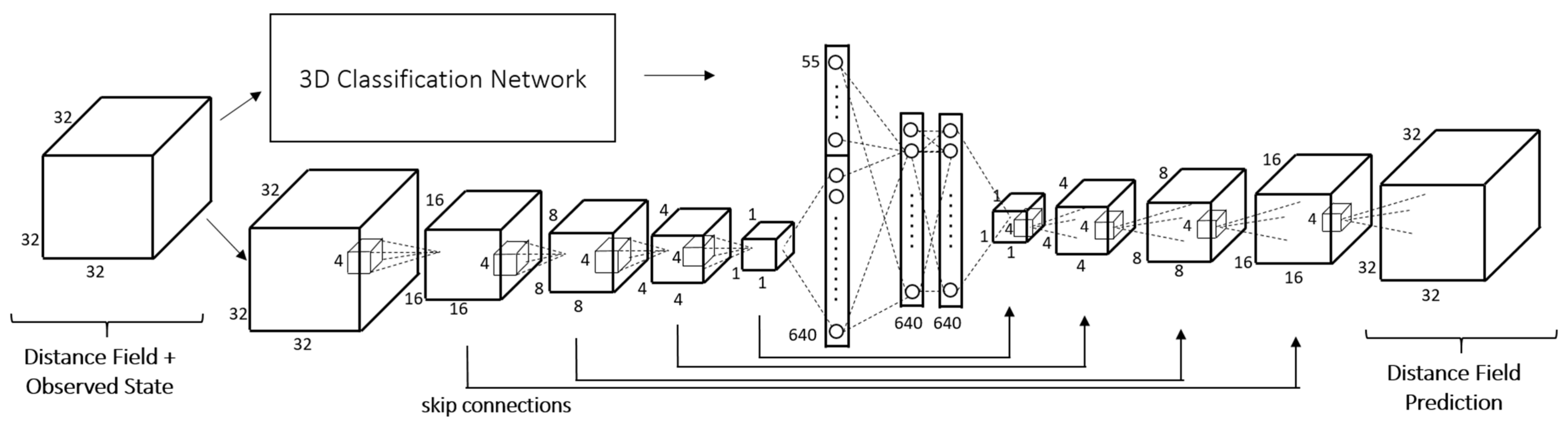
Introduction

State-of-the art reconstruction approaches are able to produce visually appealing 3D models scenes, but these models suffer from incompleteness, making them unusable in practical applications. We introduce a data-driven approach to complete partially scanned 3D shapes through a combination of volumetric deep neural networks and 3D shape synthesis to achieve both complete global structure and high-resolution fine detail.

http://graphics.stanford.edu/projects/cnncomplete

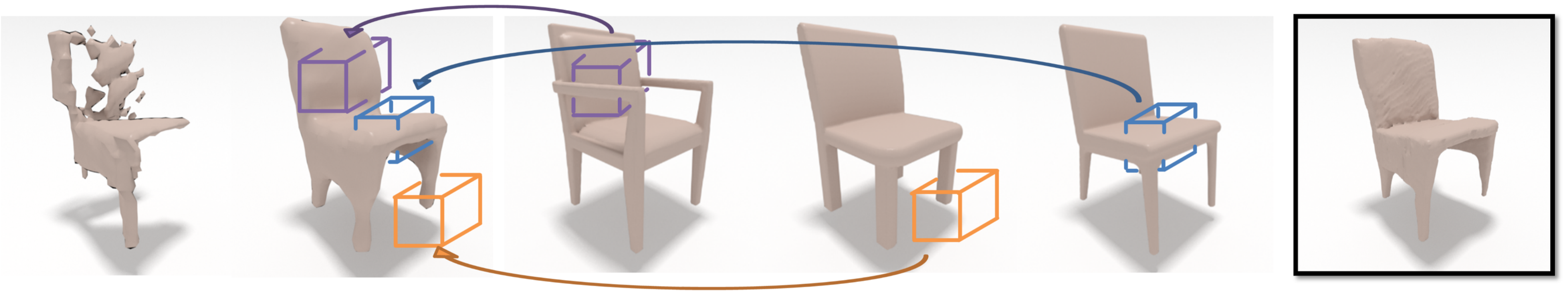
3D Encoder-Predictor Network

From a partially scanned input shape, our 3D-EPN infers a coarse but complete global structure.

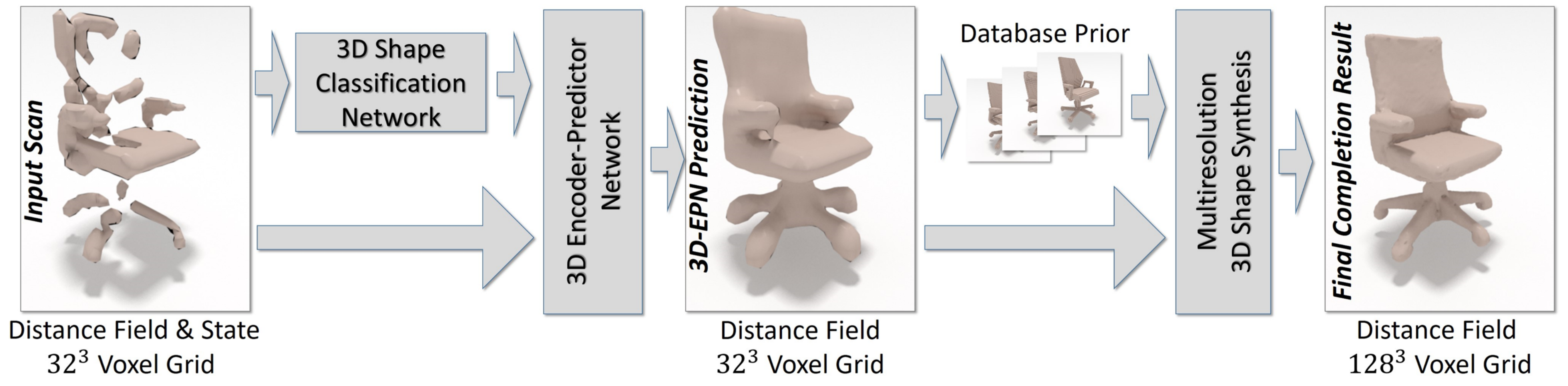


Patch-based Shape Synthesis

Our patch-based shape synthesis leverages database knowledge to attain fine detail at high resolution from the 3D-EPN prediction.

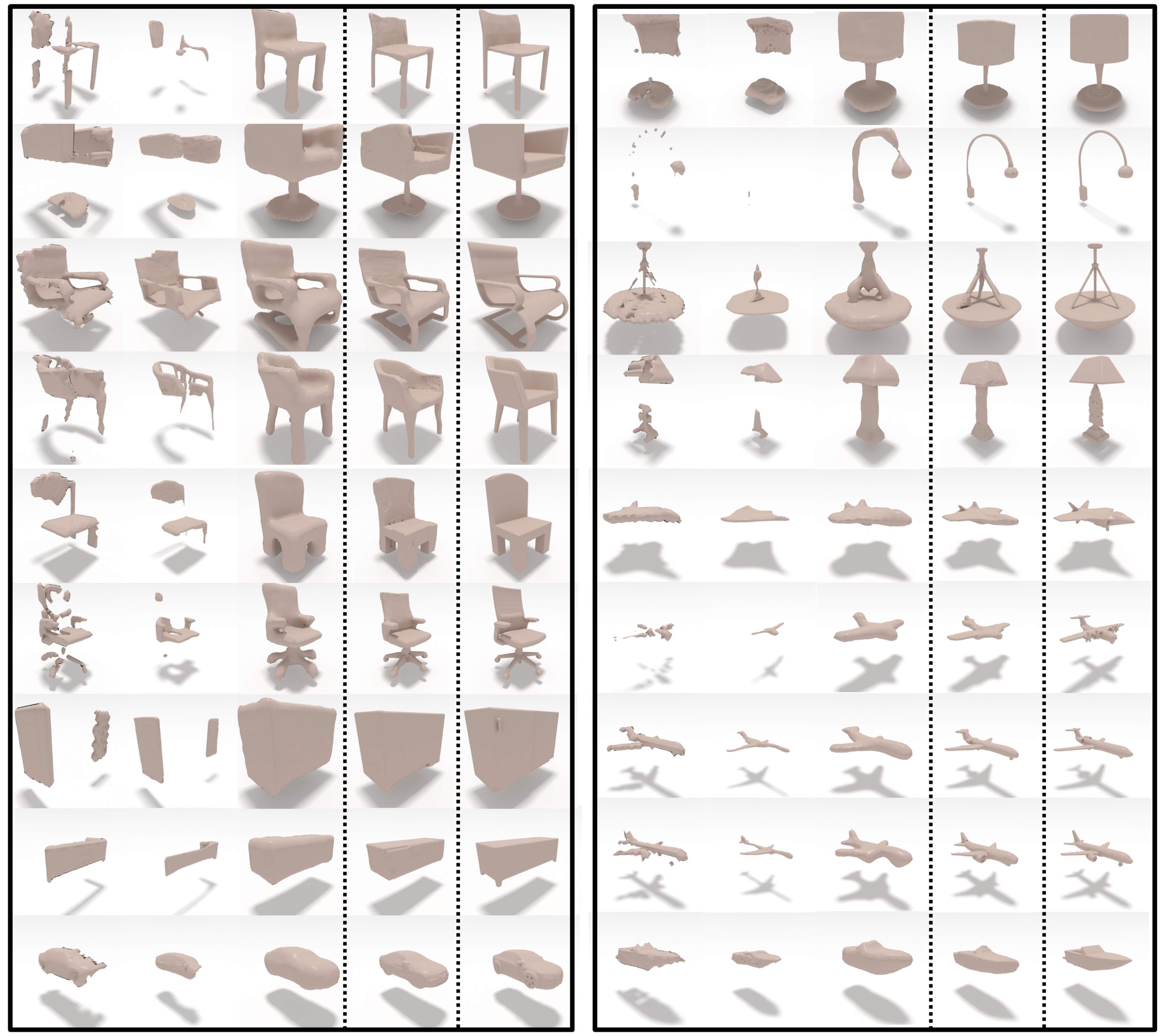


Input Scan **3D-EPN** **Database Neighbors** **Final Completion**



Results on Synthetic Data

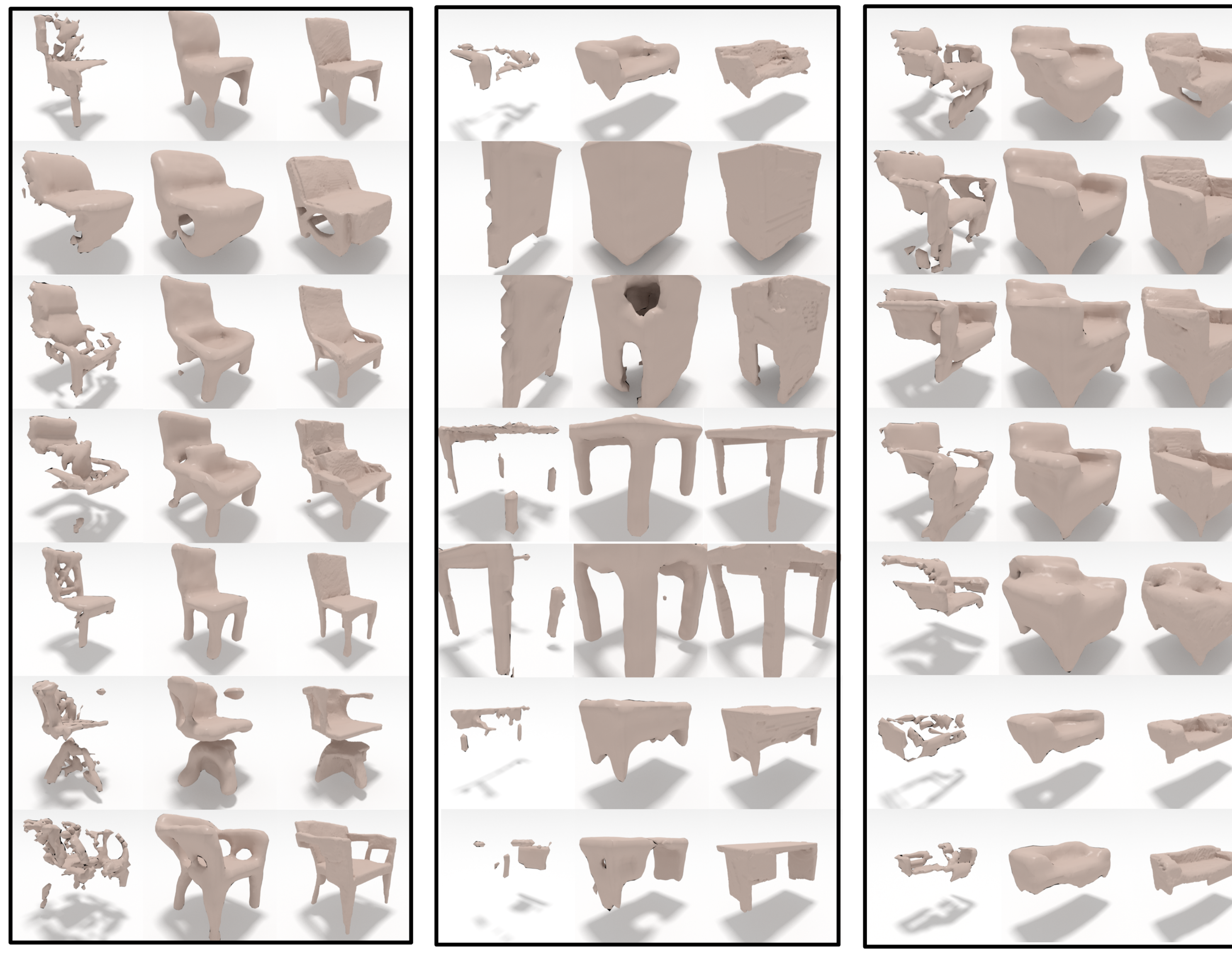
Virtual Scans of ShapeNet models



Input | Synth only (not used) | 3D-EPN only | **FINAL (3D-EPN + synth)** | Ground Truth

Results on Real Scans

Range Scans from [Qi et al. 2016]



Input | Ours (3D-EPN only) | **Ours (final)**

Evaluations

Method	ℓ_1-Err (32^3)	ℓ_1-Err (128^3)
Poisson	1.90	8.46
ShapeRecon	0.97	4.63
3D ShapeNets	0.91	3.70^{**}
Ours (synth-only)	1.20	6.92
Ours (3D-EPN)	0.37	2.29^{**}
Ours (final) 3D-EPN + synth	-	**1.89**

Surface Rep.	ℓ_1-Error (32^3)	ℓ_2-Error (32^3)
Binary Grid	0.653	1.160
Ternary Grid	0.567	0.871
Distance Field	0.417	0.483
Signed Distance Field	**0.379**	**0.380**

Acknowledgements

Google Tango

Check out our website for code and data!