HYBRID INPAINTING OF 3D MESHES

Final Presentation

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INTRODUCTION

- Real-world data is often incomplete due to occlusion, sensor limitations, or surface reflectivity, leading to holes in 3D meshes.
- Just like restoring a broken sculpture, 3D mesh inpainting aims to digitally repair lost or damaged structure.
- Traditional hole-filling trades off accuracy vs. efficiency. (MVS and SfM)
- There's a growing need for data-driven, robust approaches that can intelligently reconstruct missing geometry — beyond interpolation and naive fitting.
- Thus, we present a Hybrid NeRF-based pipeline that fuses partial meshes with radiance field predictions to reconstruct watertight 3D geometry using the Objaverse Dataset, with a focus on improving performance through a comparison with existing models like PCN.

PREVIOUSLY

Baseline Methods for Mesh Reconstruction

MeshFix

Methodology:

- Uses geometry-based topological reconstruction
- Creates watertight meshes by sealing gaps and ensuring connectivity
- Focuses on repairing mesh inconsistencies

Results:

- Output mesh appears physically complete, but error mapping reveals discrepancies
- Performs well for simple geometries, achieving good volume and surface scores
- Complex models pose challenges—fails to recover correct surface geometry
- Fills gaps generically, ignoring object-specific structures

(Left) Meshfix Reconstruction (Right) Error Map

Poisson Reconstruction

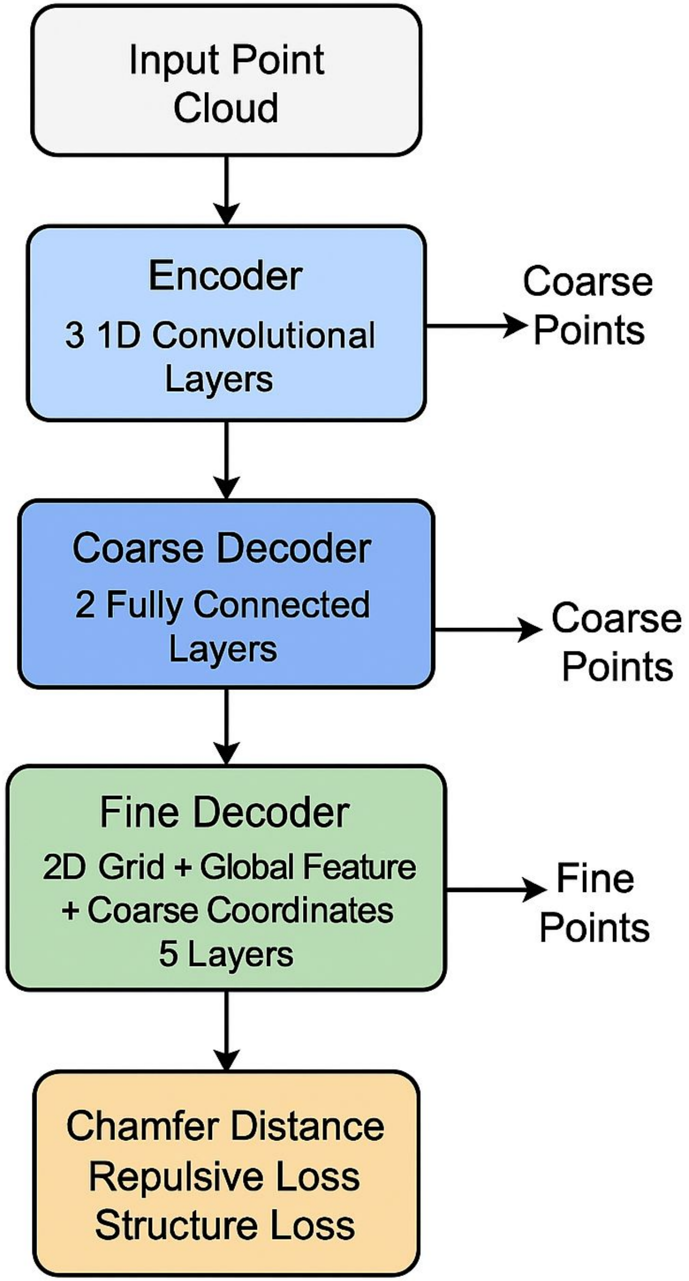
Methodology:

- Converts the mesh into point clouds
- Applies density-based outlier removal and depth-adaptive filtering
- Uses Poisson equation to generate a smooth, continuous surface from point clouc

Results:

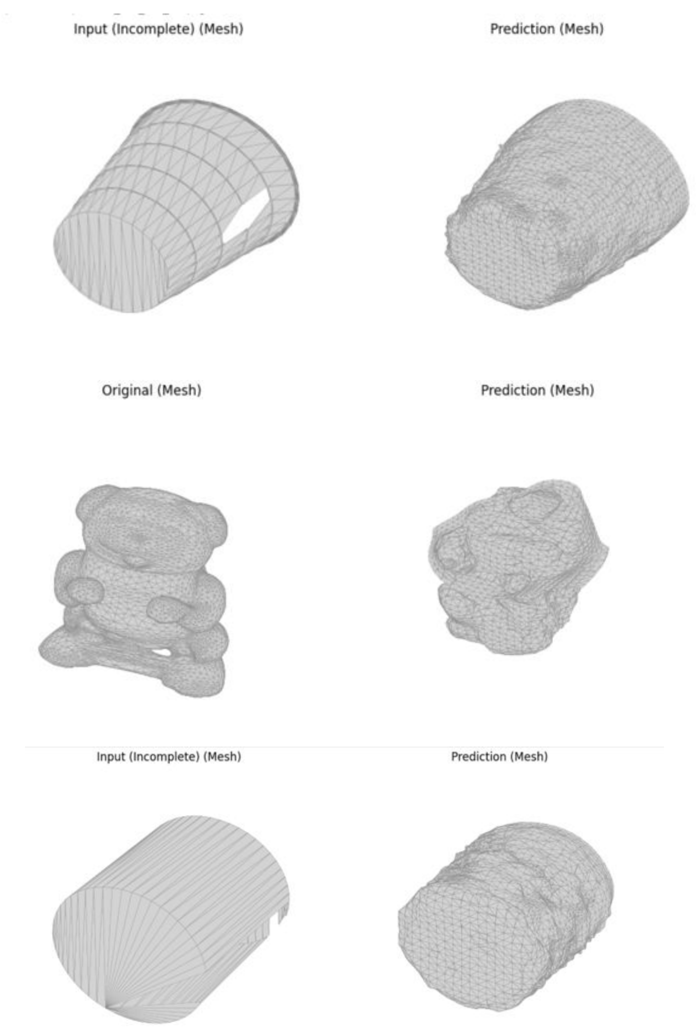
- Mesh holes are physically complete, but lack accuracy
- Point-cloud to mesh conversion ignores object structure, creating noisy, distorted output

(Left) Holed Mesh (Right) Poisson Reconstruction



PCN

- Encoder (Global Feature Extraction)
  - Input: Partial 3D Point Cloud (N x 3)
  - 3 × 1D Conv Layers + ReLU, Max Pooling → Global Feature Vector
  - Permutation invariant shape summary
- Coarse Decoder (Initial Shape Prediction)
  - 2 Fully Connected Layers → 1024 Coarse Points
  - Reshaped from final FC output; first guess of full shape
- Fine Decoder (FoldingNet-based Refinement)
  - 2D Grid + Coarse Points + Global Feature
  - 5-Layer MLP with Skip Connections
  - Learns detailed surface around coarse shape
- Training Setup
  - Losses: Chamfer Distance, Repulsion, Structure Loss
  - Epochs: 50 | Dataset: ~200 inputs



PCN

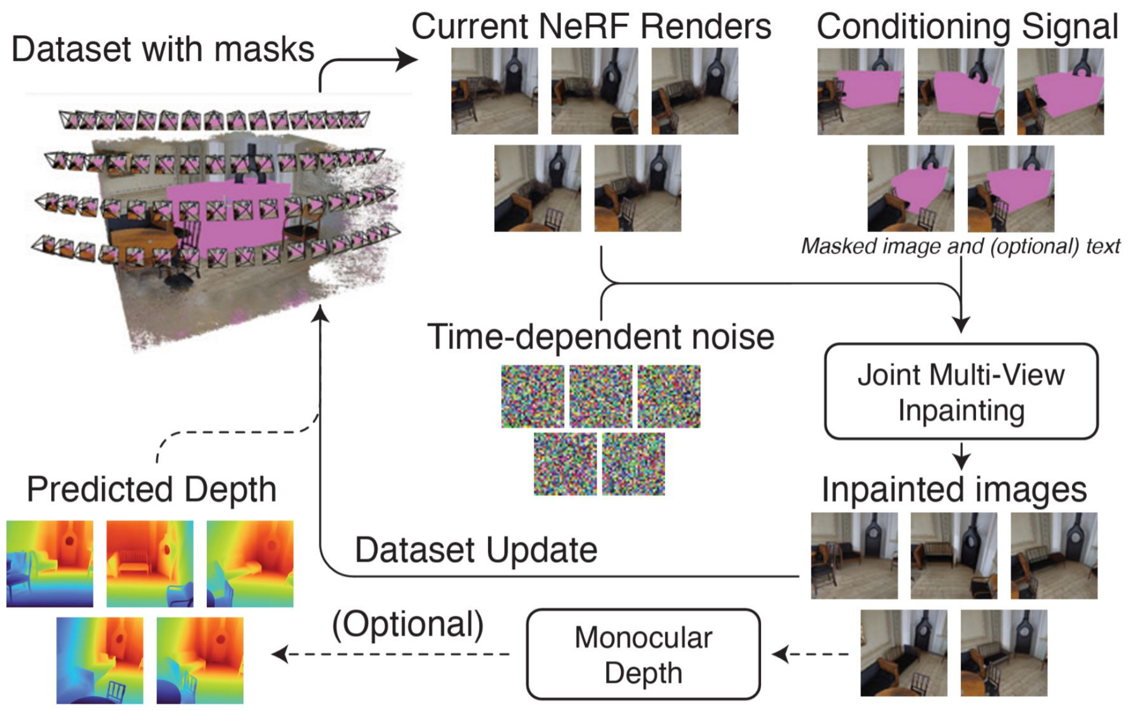
- Key Insights:
  - Modular pipeline improves consistency and detail
  - Folding decoder enables surface generation from grid
  - Skip connections maintain structural alignment
  - Multi-loss training balances geometry + uniformity
- Limitations & Future Work:
  - Small dataset (~200 samples) limits generalization
  - Folding decoder is compute-heavy
  - Explore: Mixed precision, encoder pretraining, larger datasets

Reference:

- Qinglew. "Qinglew/PCN-PyTorch: Implementation of PCN(Point Completion Network) in PYTORCH." *GitHub*, github.com/qinglew/PCN-PyTorch.git. Accessed 7 May 2025.
- Wentaoyuan. "Wentaoyuan/PCN: Code for PCN: Point Completion Network in 3DV'18 (Oral)." *GitHub*, github.com/wentaoyuan/pcn.git. Accessed 7 May 2025.

NERFILLER

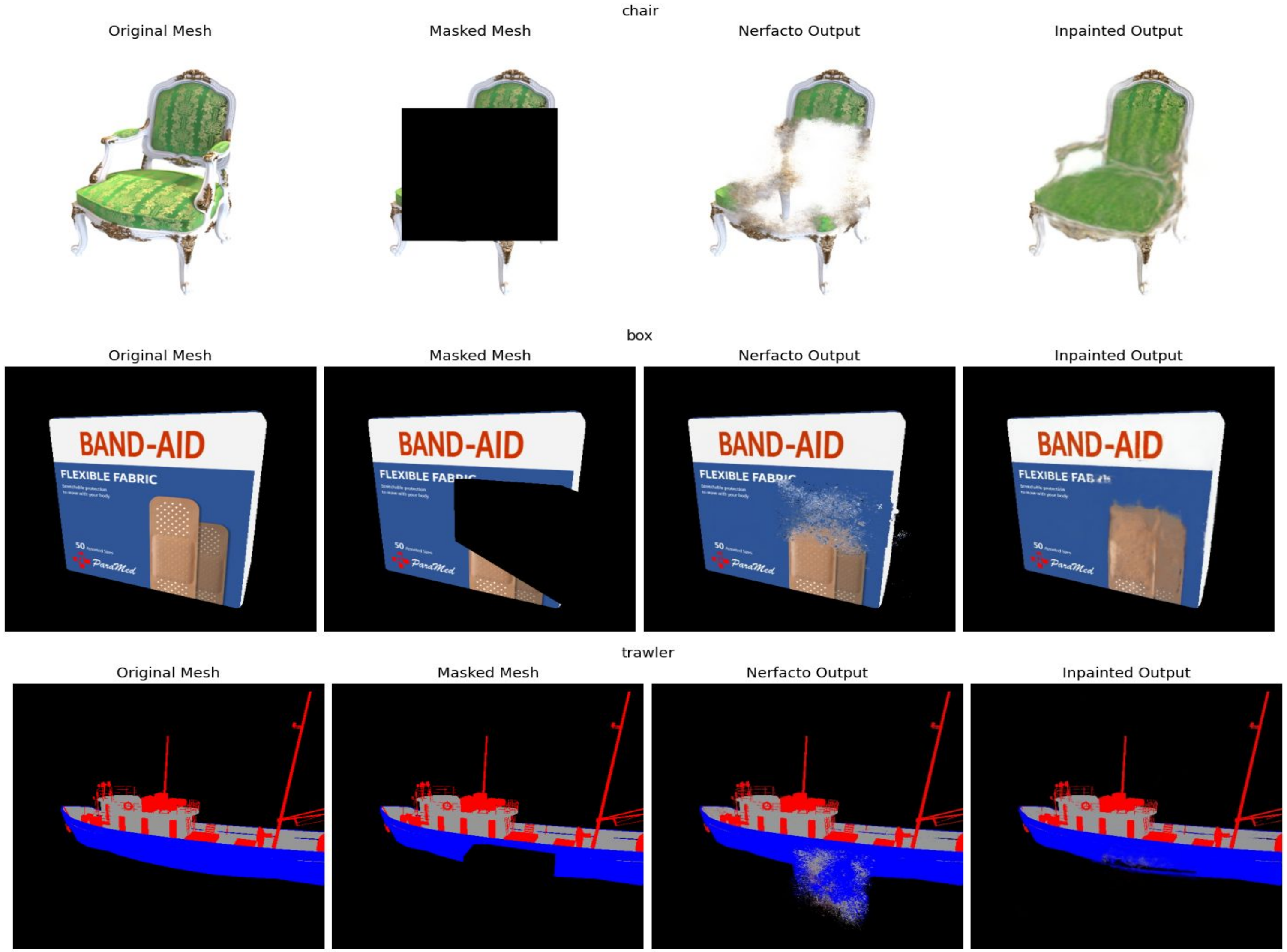
- 3D generative inpainting framework using 2D view-based inpainting to complete 3D texture and geometry.
- Uses a dense grid structure of 40 multi-view images for joint multi-view consistent inpainting for every iteration.
- Starts with training the base NeRF model (Nerfacto) on the partial mesh views for 30k iterations.
- With a trained Nerfacto, it iteratively inpaints the rendered views to fill in occluded regions and missing geometry.
- These inpainted views are used to then estimate the depth and subsequently update the NeRF dataset, creating a fine-tuned NeRF representation.
- Inpainting occurs every 1k iterations for a total of 30k iterations, following the initial 30k Nerfacto iterations.
- Slow runtime with large memory and graphics requirements.



Weber, Ethan, et al. "NeRFiller: Completing Scenes via Generative 3D Inpainting." *2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, 2024.

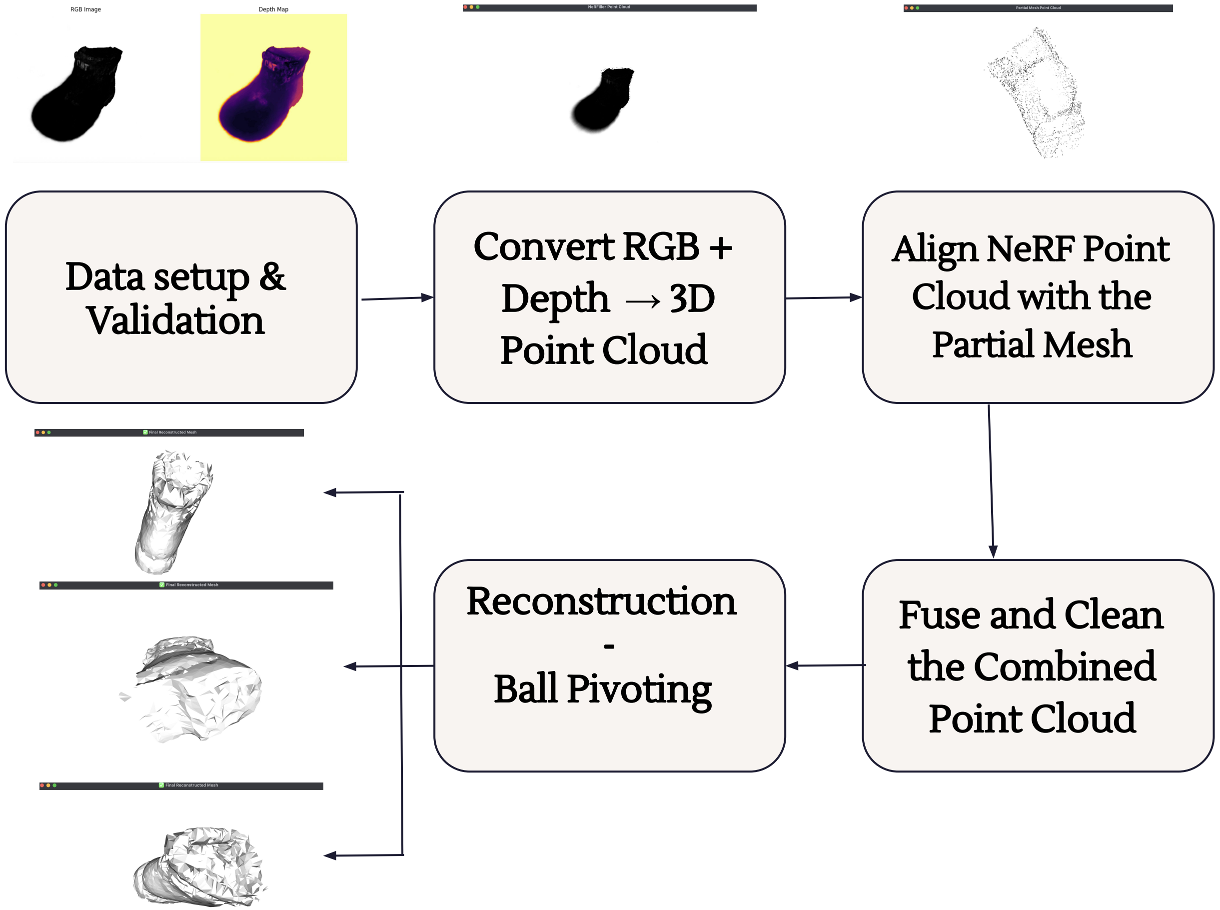
NERFILLER

Mesh	Method	PSNR	SSIM
Chair	Nerfacto	6.95	0.733
	Grid Prior	**21.42**	**0.879**
Box	Nerfacto	17.95	0.907
	Grid Prior	**31.57**	**0.974**
Trawler	Nerfacto	22.59	0.912
	Grid Prior	**33.81**	**0.978**



HYBRID MODEL

- **Data Preparation**
  Load RGB + depth maps and camera metadata from NeRF-Filler outputs for 3D sampling.
- **Point Cloud Generation**
  Convert RGB-depth pairs into point clouds using Open3D and intrinsic camera parameters.
- **Partial Mesh Sampling**
  Load the holed mesh and uniformly sample 3,000 surface points for alignment.
- **Fusion & Cleaning**
  Merge NeRF and mesh point clouds, align centers, downsample, and estimate normals.
- **Mesh Reconstruction**
  Use Ball Pivoting Algorithm (BPA) to reconstruct a watertight mesh from the cleaned point cloud.



1. Weber, Ethan, et al. *"NeRFiller: Completing Scenes via Generative 3D Inpainting." 2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, 2024.
2. Bernardini, Fausto, et al. *"The ball-pivoting algorithm for surface reconstruction." IEEE Transactions on Visualization and Computer Graphics (TVCG)* 5.4 (1999): 349–359.

CONCLUSION

- Our hybrid NeRF-based pipeline effectively combines partial meshes with radiance field predictions to improve the reconstruction quality, addressing some limitations of traditional methods like MeshFix.
- The implemented approach leverages the strengths of both geometric (Point Cloud Fusion) and data-driven (NeRF) techniques.
- While still a work in progress, the approach shows strong potential for digital restoration, robotics, and AR/VR applications.

THANK YOU