DeepMend: Learning Occupancy Functions to Represent Shape for Repair

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https://github.com/Terascale-All-sensing-Research-Studio/DeepMend

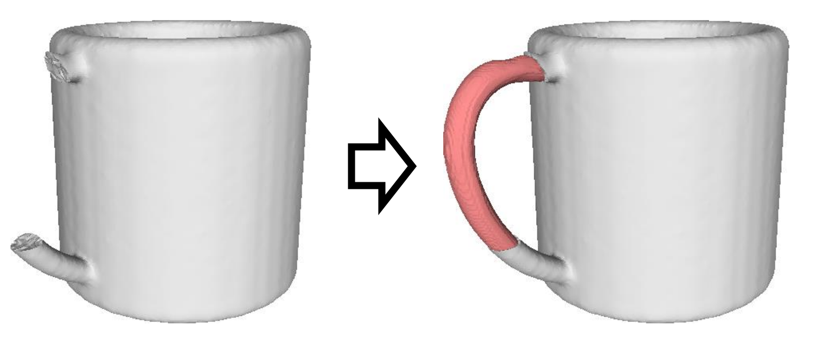
Motivation

Problem: Shape Repair

- Many common household objects are fractured during normal use.

Solution: DeepMend

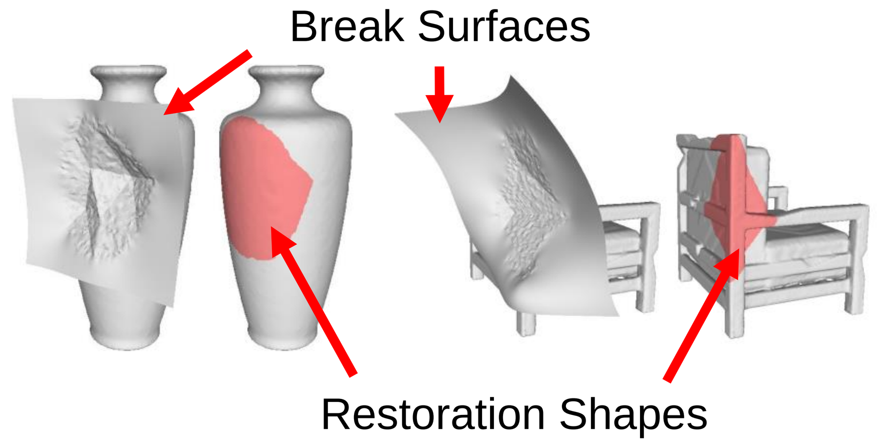
- We present DeepMend, an implicit shape based approach to automatically generate restorations to repair fractured shapes.



Fractured Shape DeepMend Repair

Fracture Dataset

- We generate synthetic fractures using shapes from ShapeNet [4].



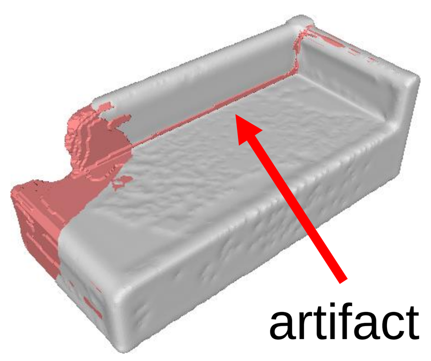
Metrics

Chamfer Distance (CD)

- Measure of bulk shape similarity. Lower is better.

Non-Fracture Region Error (NFRE)

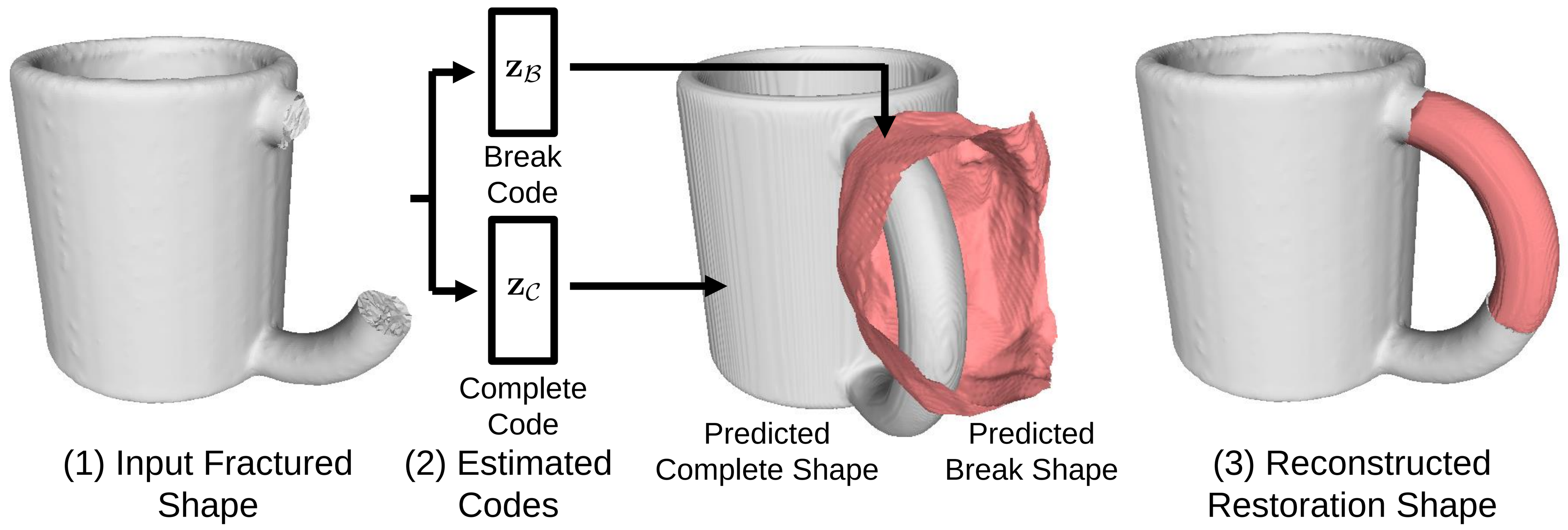
- Measure of artifacts that occur on the surface of the fractured shape. Lower is better.



Generating Shapes for Restoration

Our Approach

1. Input a novel fractured shape in need of restoration.
2. Deconstruct the fractured shape into a break code and complete code.
3. Reconstruct the restoration shape using the estimated complete and break codes.



Shape Representation

- We learn occupancy for a break shape and complete shape.
- We compute the fractured shape and restoration shape using the predicted break and complete occupancy, i.e.

$$o_F = o_C o_B \quad \leftarrow \text{Fractured Occupancy}$$

$$o_R = o_C(1 - o_B) \quad \leftarrow \text{Restoration Occupancy}$$

- During testing we optimize the following loss to obtain codes,

$$\mathcal{L}_{\text{infaug}} = \mathcal{L}_F + \lambda_{\text{ner}}\mathcal{L}_{\text{ner}} + \lambda_{\text{prox}}\mathcal{L}_{\text{prox}} + \lambda_{\text{reg}}\mathcal{L}_{\text{reg}}$$

where the loss terms are given as

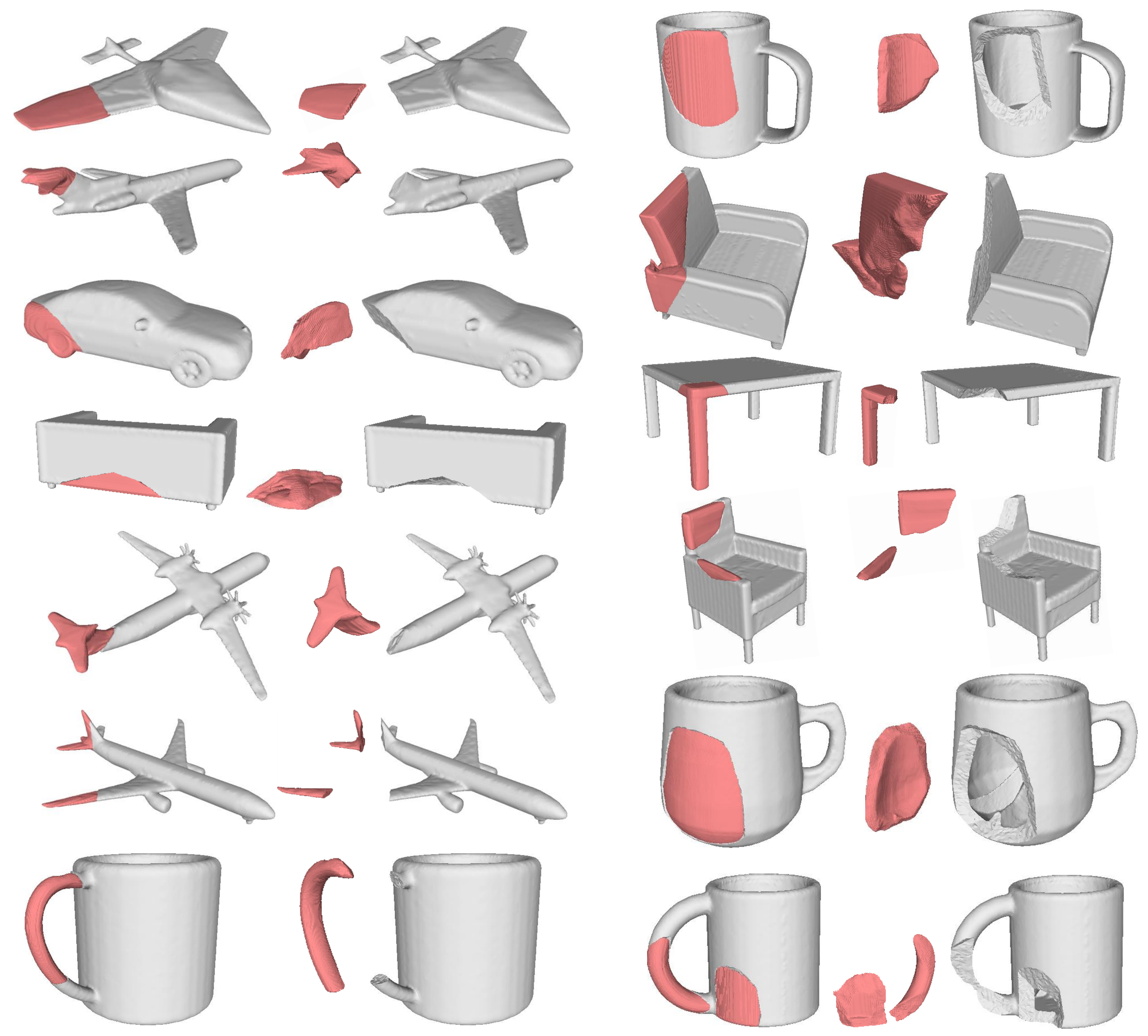
Fractured Shape Reconstruction Loss $\rightarrow$ $\mathcal{L}_F = (1/|X|)\sum_{\mathbf{x}\in X} BCE\left(o_C o_B, \hat{o}_F\right)$

Loss Preventing Empty Restorations $\rightarrow$ $\mathcal{L}_{\text{ner}} = -\log\left((1/|X|)\sum_{\mathbf{x}\in X} o_C(1 - o_B)\right)$

Loss Encouraging Proximity to Complete $\rightarrow$ $\mathcal{L}_{\text{prox}} = -\log\left(1 - (1/|X|)\sum_{\mathbf{x}\in X}(o_C - \hat{o}_F)^2\right)$

Code Regularization Loss $\rightarrow$ $\mathcal{L}_{\text{reg}} = \|\mathbf{z}_C\|_2 + \|\mathbf{z}_B\|_2$

Qualitative Results



Quantitative Results

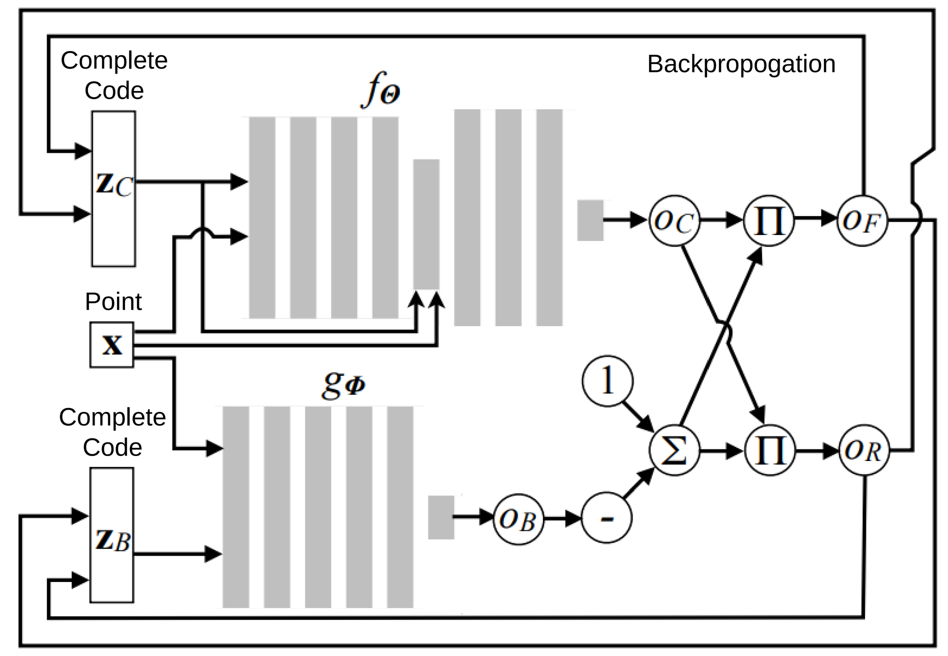
Approach	Metric	airplanes	bottles	cars	chairs	jars	mugs	sofas	tables	Mean
MendNet	CD	0.091	0.08	0.025	0.171	0.129	0.109	0.19	0.208	0.126
	NFRE	0.07	0.045	**0.017**	0.143	0.028	**0.008**	0.085	0.203	0.075
3D-ORGAN	CD	0.173	0.146	-	0.184	0.262	-	0.32	0.333	0.237
	NFRE	0.192	0.07	-	0.588	0.041	-	0.2	0.138	0.205
Sub-Occ	CD	0.05	0.041	**0.024**	0.112	0.119	**0.035**	0.066	0.122	0.071
	NFRE	0.099	0.076	0.142	0.262	0.183	0.07	0.17	0.175	0.147
Sub-Lamb	CD	0.075	0.039	0.05	**0.086**	0.082	0.1	**0.053**	**0.093**	0.072
	NFRE	0.302	0.12	0.272	0.33	0.289	0.452	0.192	0.204	0.27
DeepMend	CD	**0.037**	**0.022**	0.108	0.088	**0.065**	**0.035**	0.057	0.129	**0.068**
	NFRE	**0.009**	**0.012**	**0.017**	**0.009**	**0.007**	**0.008**	**0.012**	**0.012**	**0.011**

Chamfer distance (CD) and NFRE for MendNet, 3D-ORGAN, Sub-Occ, Sub-Lamb, and DeepMend. Bold values correspond to the lowest value within a class.

Baselines

- MendNet [1]: Prior implicit repair approach.
- 3D-ORGAN: 32^3 voxel-based approach.
- Sub-Occ: DeepSDF [2] complete + subtraction in occupancy space.
- Sub-Lamb: DeepSDF complete + subtraction in occupancy space + cleaning using Lamb et al. [3].

Architecture



Network Architecture

- We use the autodecoder architecture introduced by DeepSDF [2] as a backbone for DeepMend.
- The complete network f_Θ and break network g_Φ take a code and a point as input and predict complete occupancy o_C and break o_B occupancy.
- We compute fractured o_F and restoration occupancy o_R using the complete o_C and break o_B occupancies.

Conclusion

- We compute restoration and fractured shape occupancy by predicting complete and break shape occupancy.
- We contribute two novel loss functions that penalize voluminous or empty restorations respectively.
- Our work outperforms existing shape repair approaches and baselines based on complete prediction and subtraction.

Citations

[1] Lamb, et al. "MendNet: Restoration of Fractured Shapes Using Learned Occupancy Functions." *TOG 2022.*
[2] Park, et al. "Deepsdf: Learning continuous signed distance functions for shape representation." *CVPR 2019.*
[3] Lamb, et al. "Automated reconstruction of smoothly joining 3D printed restorations to fix broken objects." *Symposium on Computational Fabrication 2019.*
[4] Chang, et al. "Shapenet: An information-rich 3d model repository." *arXiv:1512.03012 2015.*