SuperFlex: Deformable Superquadrics for Point Cloud Decomposition

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ECCV 2026 | MALMÖ | SEPT 8–12

Introduction

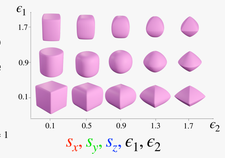
Motivation

1. Existing methods for 3D decomposition focus only on *rigid superquadrics*
2. Approaches which provide a compact decomposition *sacrifice reconstruction quality*
3. Previous approaches lack robustness to *partial point clouds*

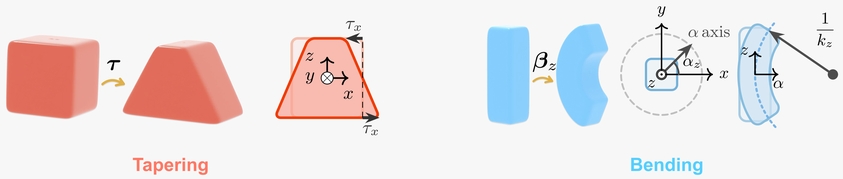
Task

Given a point cloud of a 3D object, we decompose it into a compact set of deformable *superquadrics*.

$$f(x,y,z) = \left(\left(\frac{|x|}{s_x}\right)^{\frac{2}{\epsilon_2}} + \left(\frac{|y|}{s_y}\right)^{\frac{2}{\epsilon_2}} \right)^{\frac{\epsilon_2}{\epsilon_1}} + \left(\frac{|z|}{s_z}\right)^{\frac{2}{\epsilon_1}} = 1$$



Deformations



Our contributions

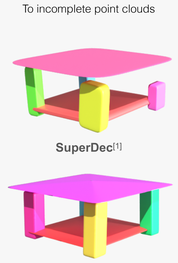
Expressiveness
Deformed Superquadrics



Reconstruction
Novel IoU-based loss

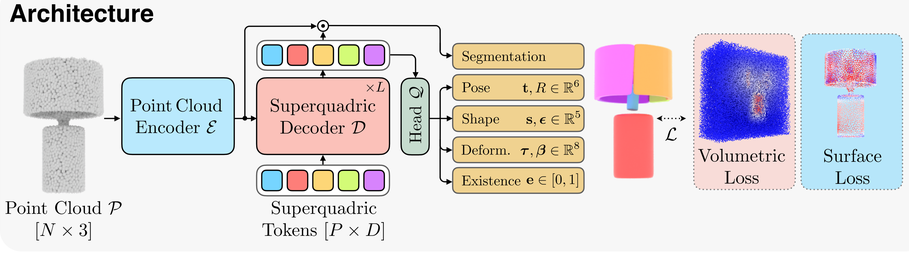


Robustness
To incomplete point clouds



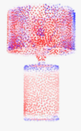
Method

Architecture

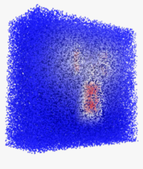


Loss Formulation

$$\mathcal{L} = \lambda_{\text{IoU}}\mathcal{L}_{\text{IoU}} + \lambda_{\text{SDF}}\mathcal{L}_{\text{SDF}} + \mathcal{L}_{\text{reg}}$$



Surface Loss
Minimize the *radial distance* over the input points



Volumetric Loss
Maximize the approximate *Intersection over Union*

$$\mathcal{I}_p(\mathbf{x}) = \sigma\left(-\frac{d(\mathbf{x};\Theta_p)}{\tau_{\text{IoU}}}\right)$$

$$IoU = \frac{\sum_{\mathbf{x}\in\mathcal{V}} \hat{\mathcal{O}}(\mathbf{x})\,\mathcal{O}(\mathbf{x})}{\sum_{\mathbf{x}\in\mathcal{V}} \left(\hat{\mathcal{O}}(\mathbf{x}) + \mathcal{O}(\mathbf{x}) - \hat{\mathcal{O}}(\mathbf{x})\,\mathcal{O}(\mathbf{x})\right)}$$

Partial Point Clouds

Occlusion Augmentations

We simulate realistic scanning artifacts by applying ***Hidden Point Removal*** to mimic viewpoint-dependent visibility and *random spherical masking* to simulate foreground occluders.



Training on occluded point clouds

***Unsupervised* Training**
We use the complete object as supervision. The model learns to decompose only the visible geometric fragments without assuming hidden data.



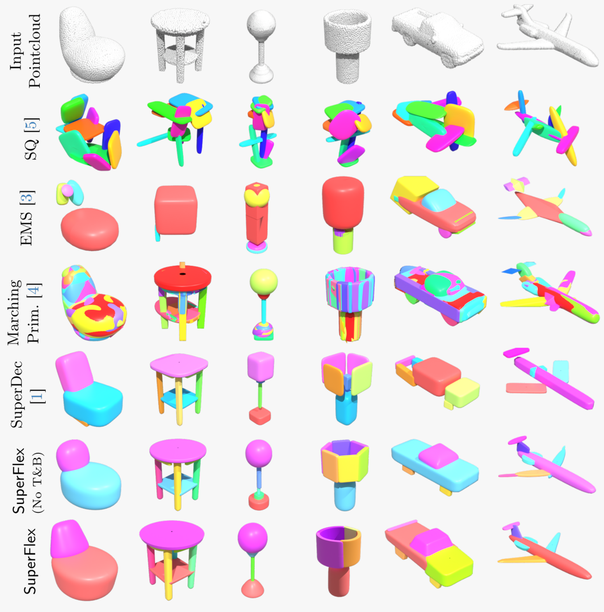
***Supervised* Training**
We use the pseudo ground truth superquadrics as supervision. The model learns to actively *complete missing and occluded geometry.*



Results

Results on ShapeNet

We compare our model to other baseline approaches on ShapeNet. T&B indicates whether tapering and bending are used.



Method	T&B	IoU↑	F [2]↑	L1↓	L2↓	# Prim.↓	Runtime↓
SQ [5]	✗	0.27	0.13	3.67	0.29	10	0.0065 s
EMS [3]	✗	0.40	0.29	4.40	1.06	5.67	7.82 s
March.Prim. [4]	✗	0.56	0.18	2.08	0.10	24.10	163.41 s
SuperDec [1]	✗	0.59	0.28	1.77	0.050	5.79	0.0075 s
SuperFlex (ours)	✗	0.70	0.35	1.75	0.049	6.04	0.0075 s
SuperFlex (ours)	✓	**0.72**	**0.37**	**1.54**	**0.043**	**5.64**	0.0082 s

Test-time Optimization

We can further refine the model outputs using the same losses and gradient descent.

Test-time Opt.	IoU↑	F [2]↑	L1↓	L2↓	Runtime↓
✗	0.72	0.37	1.54	0.043	**0.0082** s
✓	**0.87**	**0.49**	**1.32**	**0.036**	5 s



Results on Partial Point Clouds

We test our model on partial point clouds of objects extracted from the Aria Synthetic Dataset.



Method	Occ.	IoU↑	F [2]↑	L1↓	L2↓	# Prim.↓
SQ [5]	✗	0.13	0.10	8.62	3.00	10.0
EMS [3]	✗	0.20	**0.19**	10.96	6.05	4.47
SuperDec [1]	✗	0.20	0.14	5.98	2.45	6.0
SuperFlex	✗	0.20	0.16	5.85	2.09	6.3
SuperFlex	✓	0.48	0.16	4.49	1.62	4.9

Decomposition from RGB Frames

The robustness to partial point clouds allows us to obtain superquadric decompositions from just a single RGB frame.



Scene Decomposition

Tested on scenes from the **ScanNet++** dataset. Each object in the scene is passed and decomposed separately by our model.



References

[1] Fedele et al., SuperDec: 3D Scene Decomposition with Superquadric Primitives, ICCV 2025.
[2] Knapitsch et al., Tanks and temples: benchmarking large-scale scene reconstruction, ACM Trans. Graph. 2017.
[3] Liu et al., Robust and Accurate Superquadric Recovery: A Probabilistic Approach, CVPR 2022.
[4] Liu et al., Marching-primitives: Shape abstraction from signed distance function, CVPR 2023.
[5] Paschalidou et al., Superquadrics revisited: Learning 3D shape parsing beyond cuboids, CVPR 2019.