SepicNet: Sharp Edges Recovery by Parametric Inference of Curves in 3D Shapes

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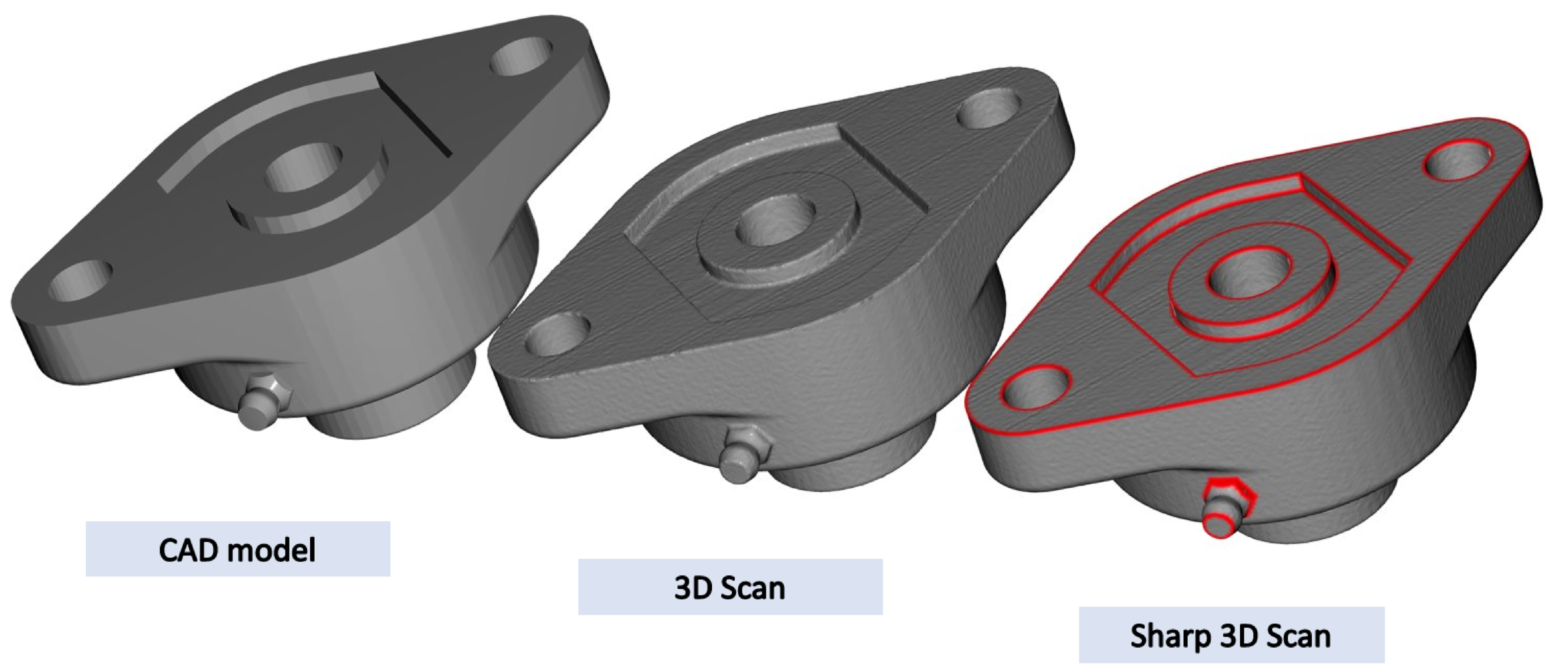
Dataset

Introduction



Motivation:

- **3D Reverse Engineering** (3D-RE) is the process of recreating **Computer-Aided Designs** (CAD) models from physical objects.
- 3D-RE allows for fast prototyping and industrial re-editing of objects.
- **3D scanning** opened a lot of doors for 3D-RE.

Challenges:

- 3D scans are **unstructured representations** in contrast to the **parametric nature** of CAD models.
- 3D scanning does not preserve sharp features of physical objects and tends to smooth them.

Contributions

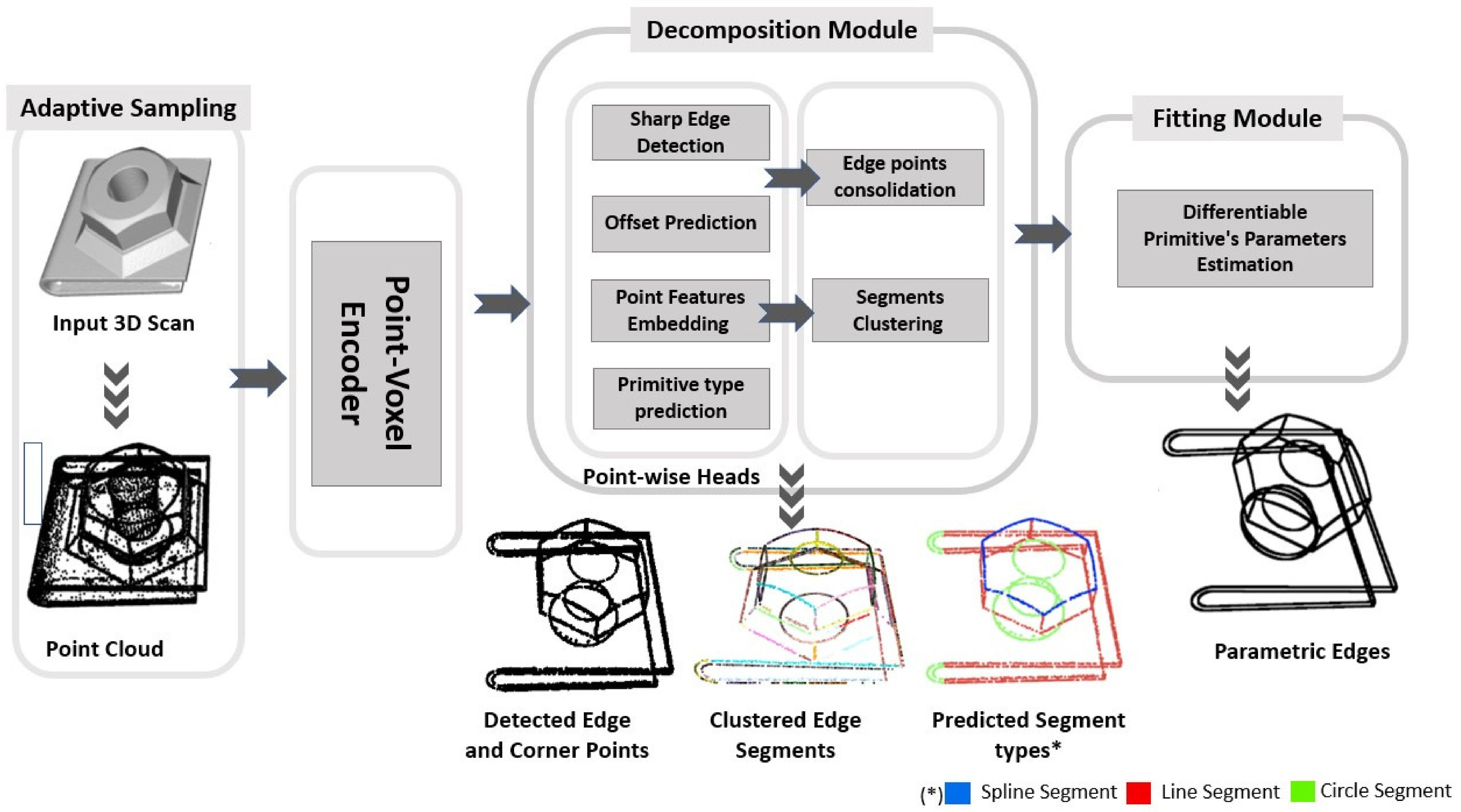
- CC3D-PSE dataset: 50k 3D scans labelled with parametric sharp edges (from CAD models).
- Automatic inference of parametric sharp edges from 3D scans.
- End-to-end neural network consisting of 3 modules (encoding, decomposition, and fitting).
- Better performance than related SOTA works [1,2].

The parametric sharp edges are not only important for **improving the quality of 3D scans**, BUT also for **re-creating parametric features of CAD models**.

CC3D-PSE Dataset:

- 50k+ 3D scans labelled with parametric sharp edges
- 11.6M+ sharp edges (62% lines, 19% circles, 19% splines)
- Benchmark for SHARP challenges @ CVPR 2022 [3]

Proposed Approach



Point encoding of 3D scans:

- Adaptive sampling based on principal curvatures.
- Point-Voxel encoder for pointwise encoding of sampled points.

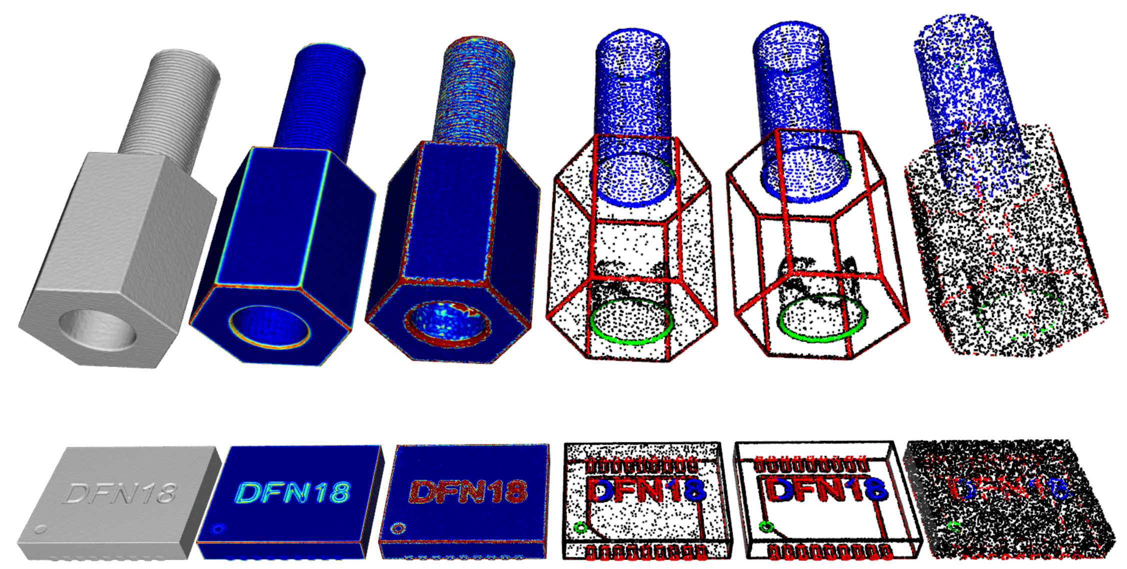
Decomposition module:

- Detection of sharp edge points (binary cross entropy loss).
- Prediction of pointwise edge consolidation offsets (L2 loss).
- Embedding of the sharp edge points (Triplet loss).
- Clustering into different segments (Hdbscan algorithm).
- Classification into circle, line, spline segments (categorical cross-entropy loss).

Differentiable fitting module:

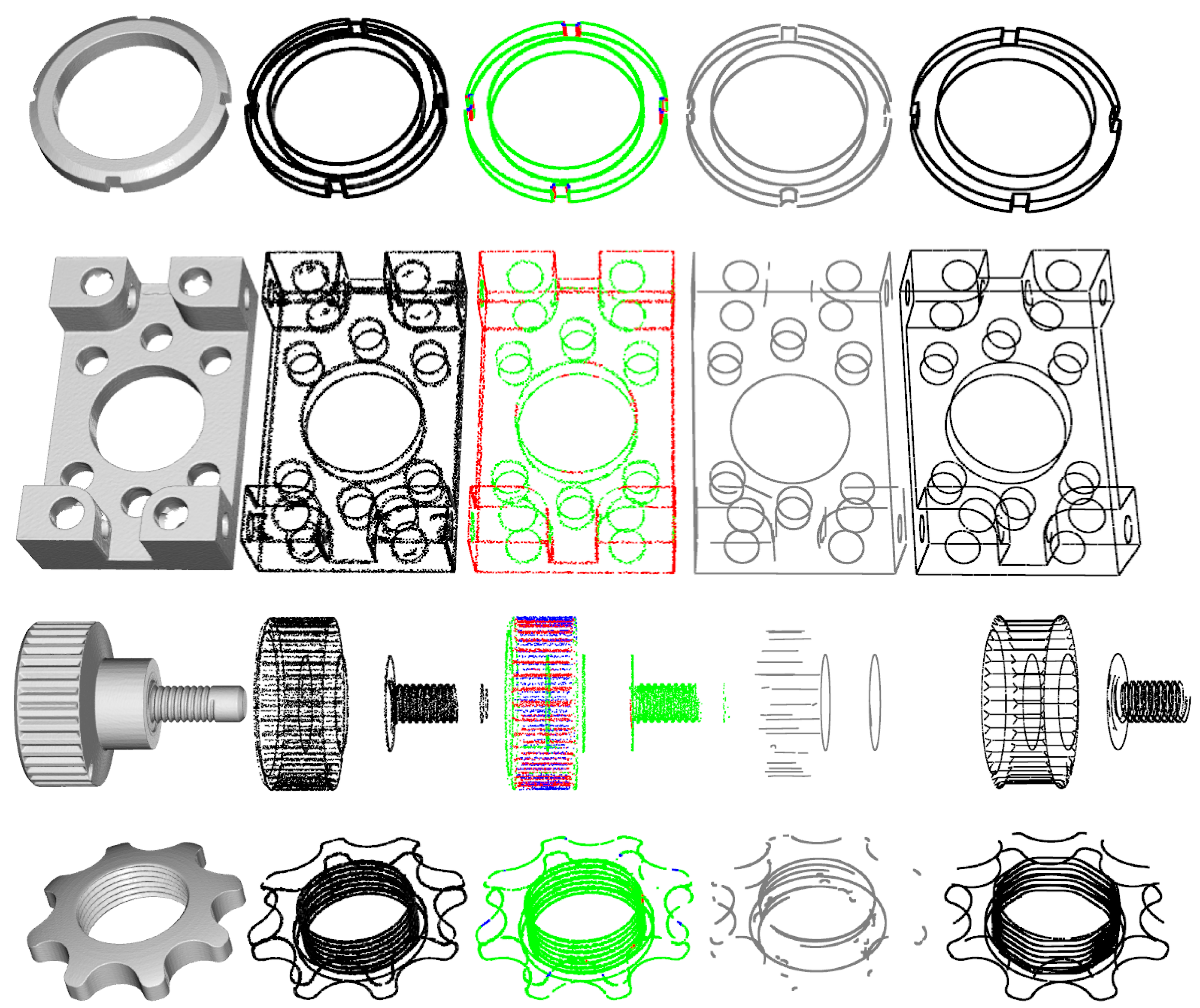
- Least-squares fitting for lines and circles.
- Differentiable interpolation method for splines.
- Edge point loss to enforce the fitting (sampling points and computing Chamfer loss).

Adaptive Sampling



Left-to-Right: original mesh, calculated mean and gaussian curvatures on the mesh, adaptively sampled point clouds with intensity factor γ = 1.0 and γ = 2.0, a uniformly sampled point cloud. The size of all point clouds is fixed to 10k points.

Experimental Results



Results of our SepicNet. From left to right: the original 3D scan, the sampled point cloud, the sharp segments detected, primitives fitted and ground truth edges.

Dataset	Model	*Precision* ↑	*Recall* ↑	*IoU* ↑	*ECD* ↓
CC3D-PSE	EC-Net [25]	0.333	0.345	0.371	0.172
	PIE-Net [23]	0.321	0.316	0.39	0.153
	SepicNet (ours)	**0.457**	**0.488**	**0.586**	**0.037**
ABC⋆	PIE-Net [23]	0.521	**0.516**	0.590	0.083
	SepicNet (ours)	**0.539**	0.501	**0.655**	**0.017**

Conclusion

- Dataset and data-driven approach for the automatic inference of sharp edges from 3D scans.
- How to leverage parametric sharp edges for re-creating CAD models and 3D-RE?

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References

[1] Wang, X., *et al.* (2020). Pie-net: Parametric inference of point cloud edges. Neurips.
[2] Yu, L., *et al.* (2018). Ec-net: an edge-aware point set consolidation network. ECCV.
[3] cvi2.uni.lu/sharp2022/challenge2

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