Semi-signed prioritized neural fitting for surface reconstruction from unoriented point clouds

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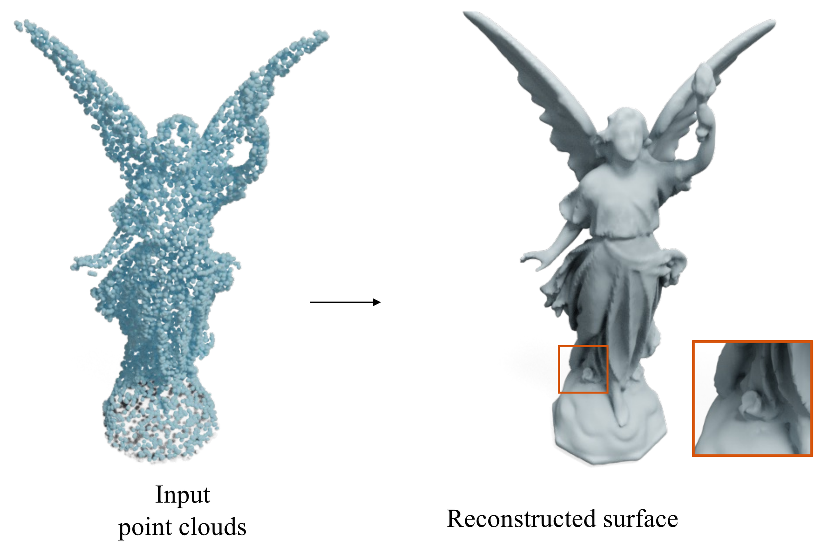
Goal

Given unoriented point clouds, we want to reconstruct the water-tight surface meshes.

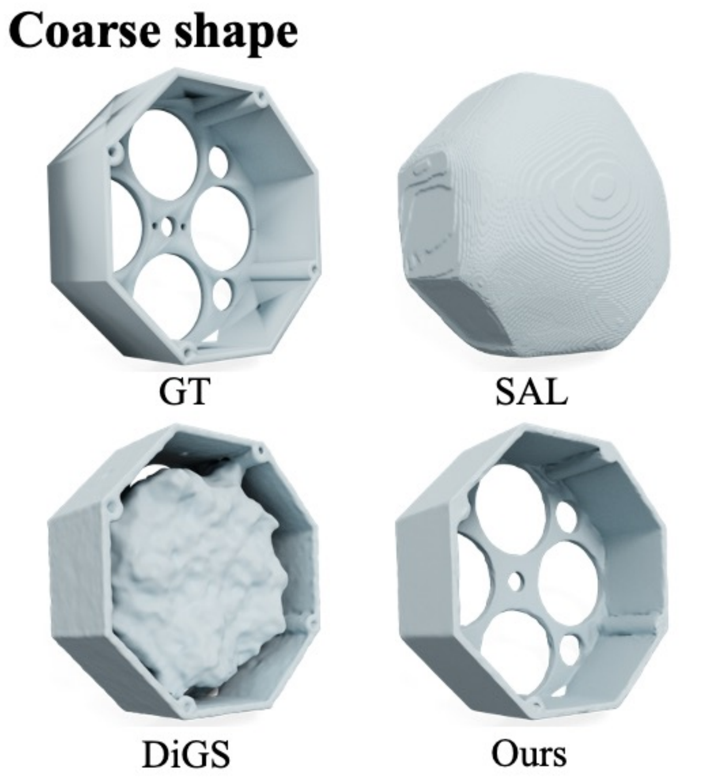


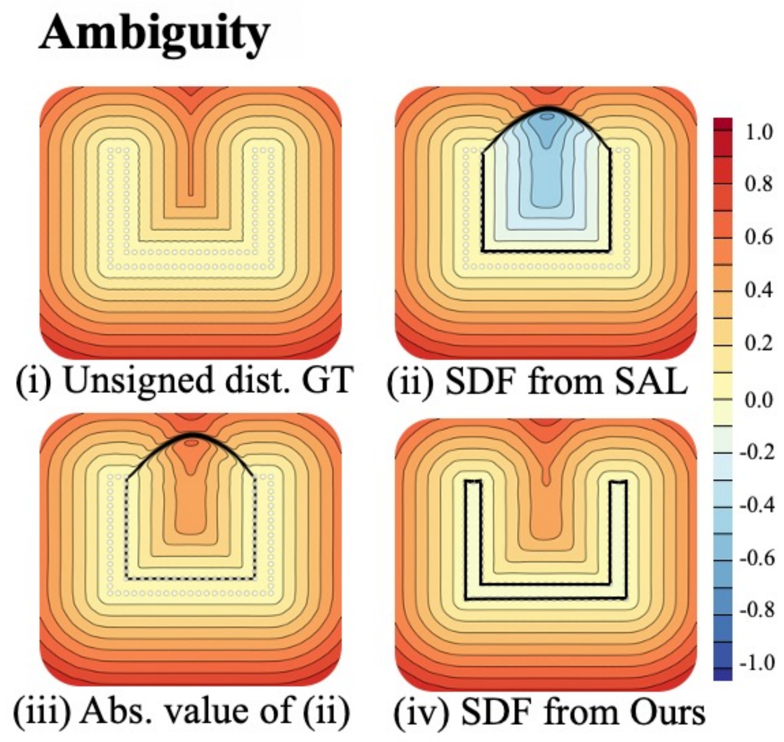
Desired properties

- ✓Reconstruct accurate surfaces for objects with various topology
- ✓Recover high-level details for complicated objects
- ✓Show robustness to noise and density variation

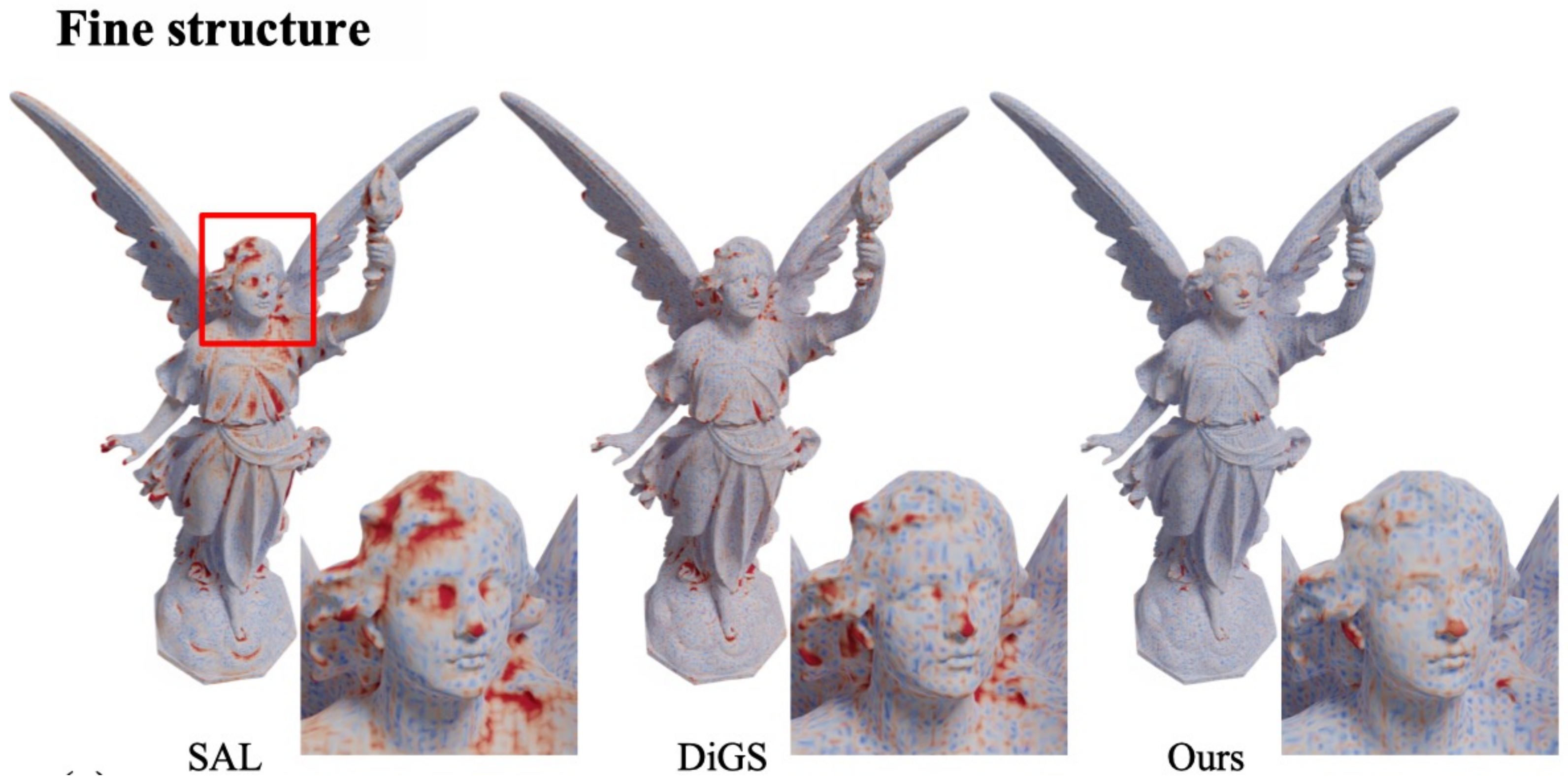
Challenges

- Existing methods have difficulty reconstructing the accurate surface for challenging topology.





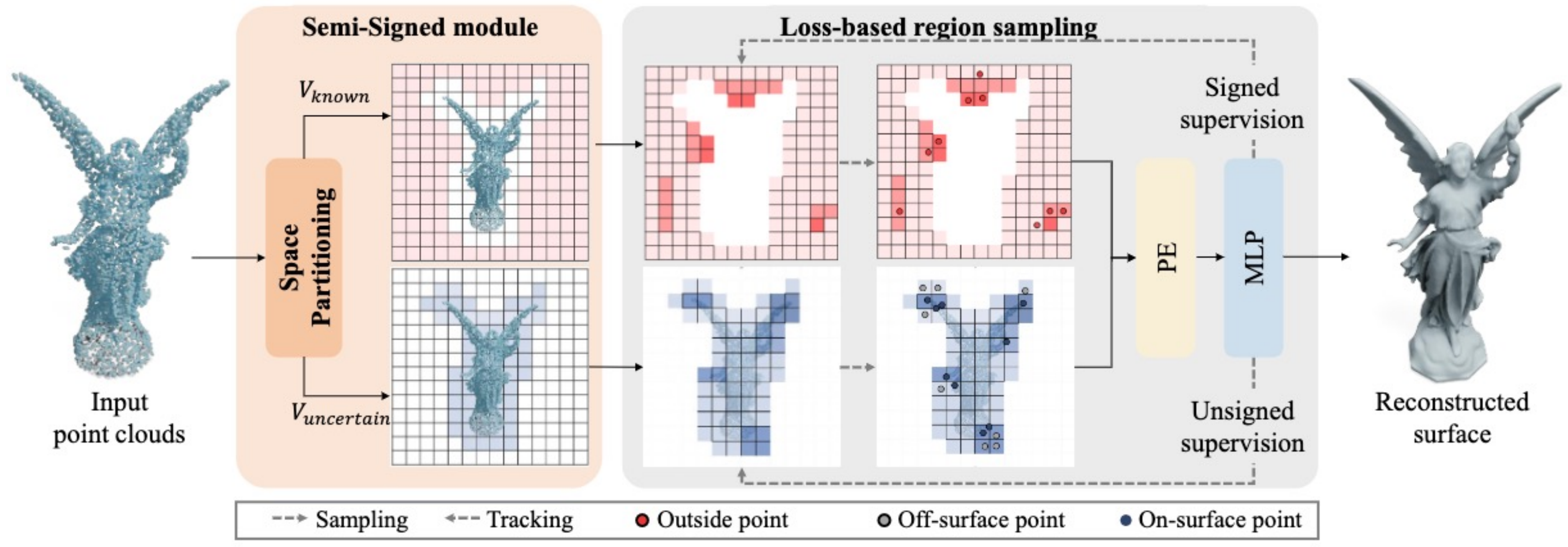
- Existing methods tend to generate over-smoothed surfaces.



Contribution

- We propose a new semi-signed fitting module that provides additional signed supervision, which significantly alleviates the difficulty in finding coarse shapes for complicated objects
- We introduce a loss-based per-region sampling and progressive PE, resulting in accurate surfaces with more details while generating fewer artifacts.
- We propose semi-signed prioritized (SSP) neural fitting, achieving improved performances compared to existing neural fitting methods on multiple datasets, especially with significant CD-L1 reduction.

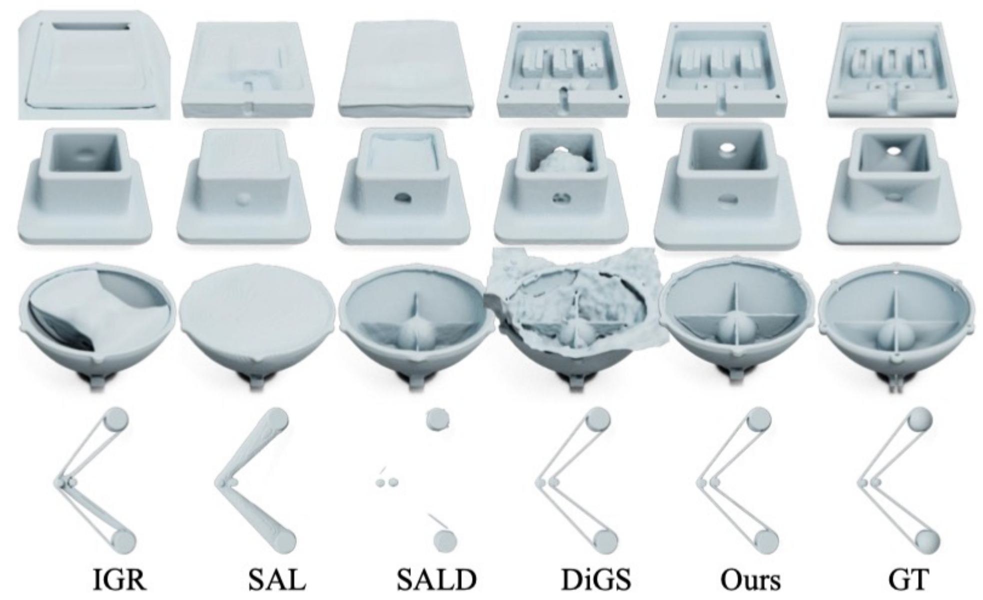
Architecture



Experiments

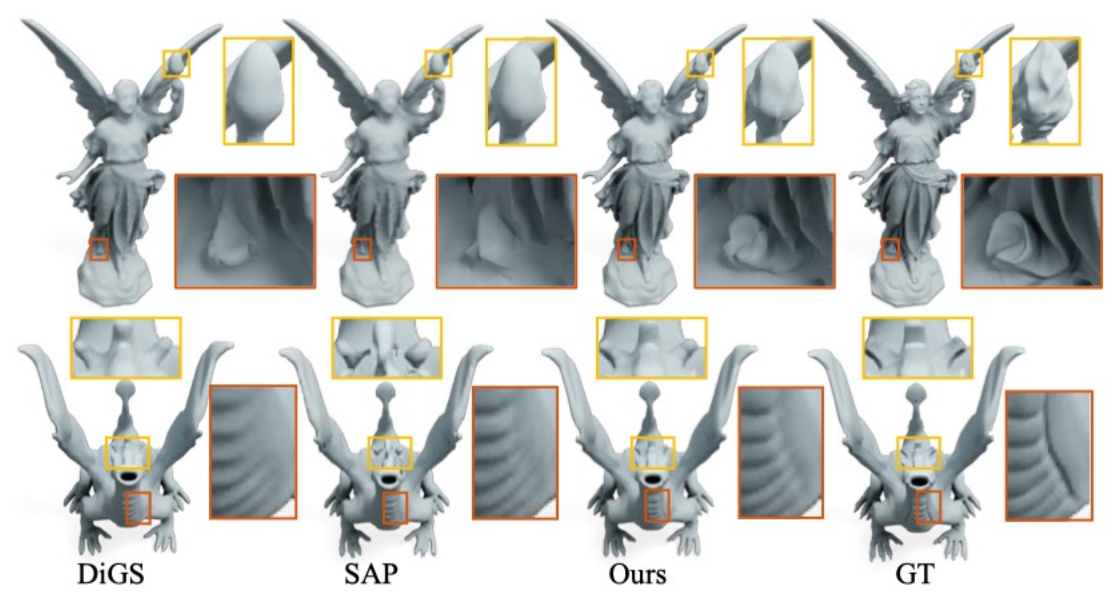
Results on ABC subset

Methods	F-score↑	CD-L_1 ↓ (×100)	NC↑
SPSR [25]	0.557	2.774	0.904
SAP [37]	0.660	1.368	0.915
IMLS [29]	0.626	1.245	0.923
POCO [9]	0.670	**1.148**	**0.943**
N-P [5]	0.370	2.071	0.912
SAL [2]	0.407	4.676	0.870
SALD [3]	0.560	1.719	0.919
IGR [17]	0.551	4.429	0.891
DiGS [6]	0.657	1.540	0.936
Ours	**0.675**	1.225	0.938



Results on Thingi10K

Methods	F-score↑	CD-L_1 ↓ (×100)	NC↑
SPSR [25]	0.787	2.230	0.896
SAP [37]	0.940	0.540	0.947
IMLS [29]	0.793	0.759	0.882
POCO [9]	0.902	0.610	0.939
N-P [5]	0.627	0.934	0.927
SAL [2]	0.884	0.779	0.925
SALD [3]	0.730	1.187	0.891
IGR [17]	0.308	6.471	0.631
DiGS [6]	0.942	0.529	0.954
Ours	**0.943**	**0.520**	**0.960**



Results on noisy input & density-variation input (in PCPNet)

	Density-variation			Noise		
Methods	F-score↑	CD-L_1 ↓ (×100)	NC↑	F-score↑	CD-L_1 ↓ (×100)	NC↑
SPSR [25]	0.789	2.007	0.938	**0.723**	2.216	0.833
SAP [37]	0.889	0.658	0.932	0.580	1.128	0.693
IMLS [29]	0.830	0.715	0.925	0.583	1.205	0.879
POCO [9]	0.867	0.845	0.943	0.510	1.721	0.911
N-P [5]	0.397	1.359	0.945	0.257	2.027	0.901
SAL [2]	0.767	1.823	0.937	0.328	8.467	0.880
SALD [3]	0.724	1.209	0.926	0.255	3.472	0.919
IGR [17]	0.714	7.316	0.918	0.697	3.480	0.889
DiGS [6]	0.877	0.868	0.951	0.544	1.273	0.717
Ours	**0.917**	**0.567**	**0.962**	0.685	**0.994**	**0.957**