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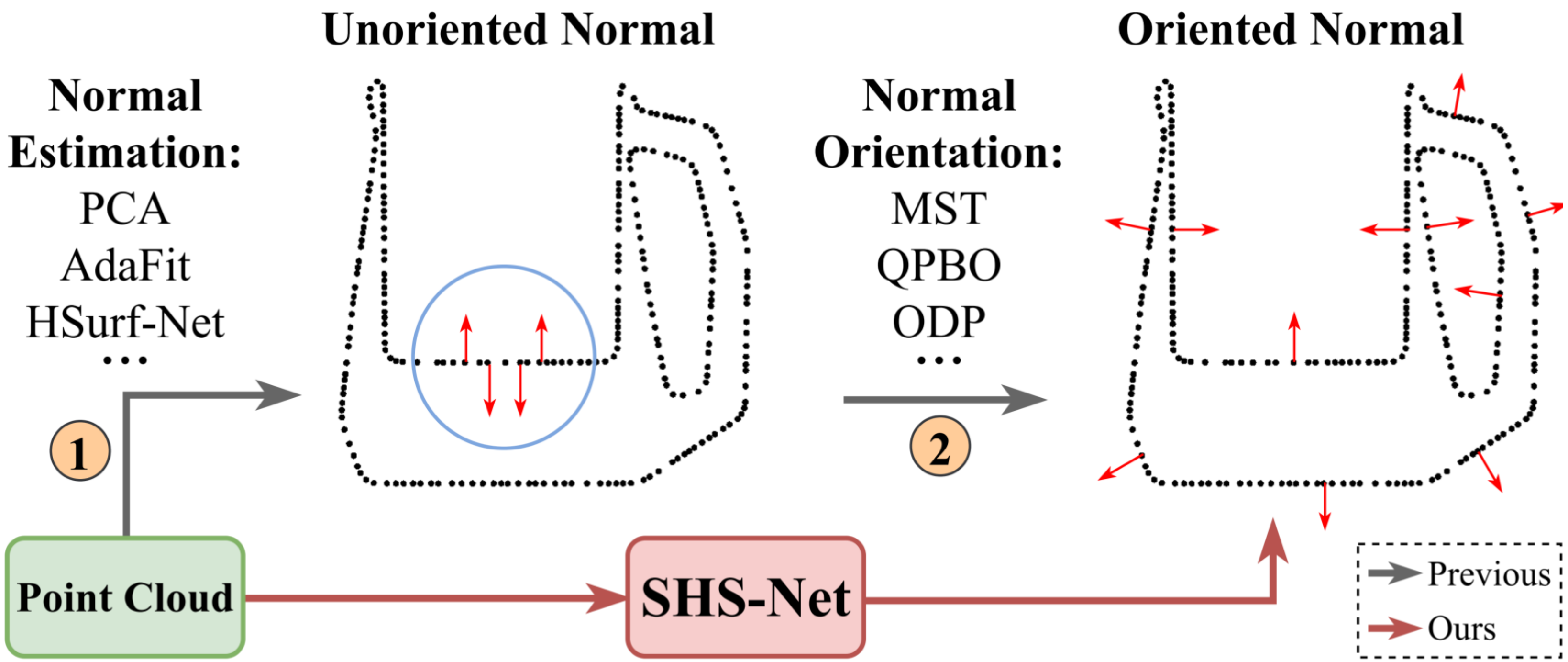
SHS-Net: Learning Signed Hyper Surfaces for Oriented Normal Estimation of Point Clouds

Qing Li[1], Huifang Feng[2], Kanle Shi[3], Yue Gao[1],
Yi Fang[4], Yu-Shen Liu[1], Zhizhong Han[5]

1. School of Software, BNRist, Tsinghua University, Beijing, China
2. School of Informatics, Xiamen University, Xiamen, China
3. Kuaishou Technology, Beijing, China
4. Center for Artificial Intelligence and Robotics, New York University Abu Dhabi, Abu Dhabi, UAE
5. Department of Computer Science, Wayne State University, Detroit, USA

0 Introduction

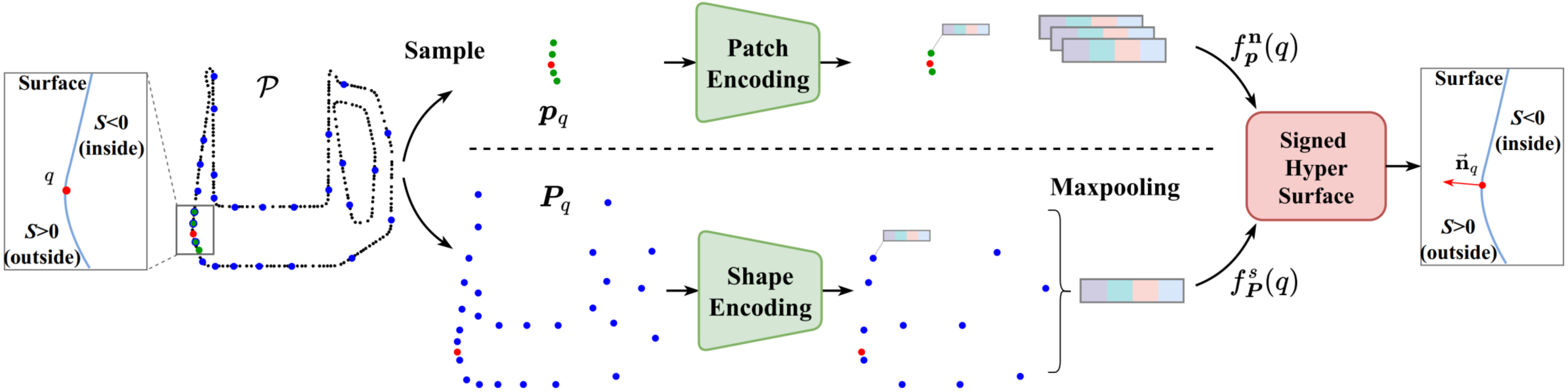


- We propose SHS-Net to estimate oriented normals directly from point clouds.
- In contrast, previous works usually implement this process through a two-stage paradigm using different algorithms, i.e., (1) unoriented normal estimation (e.g., PCA, AdaFit and HSurf-Net) and (2) normal orientation (e.g., MST, QPBO and ODP).

1. Method

1 Learning Signed Hyper Surface

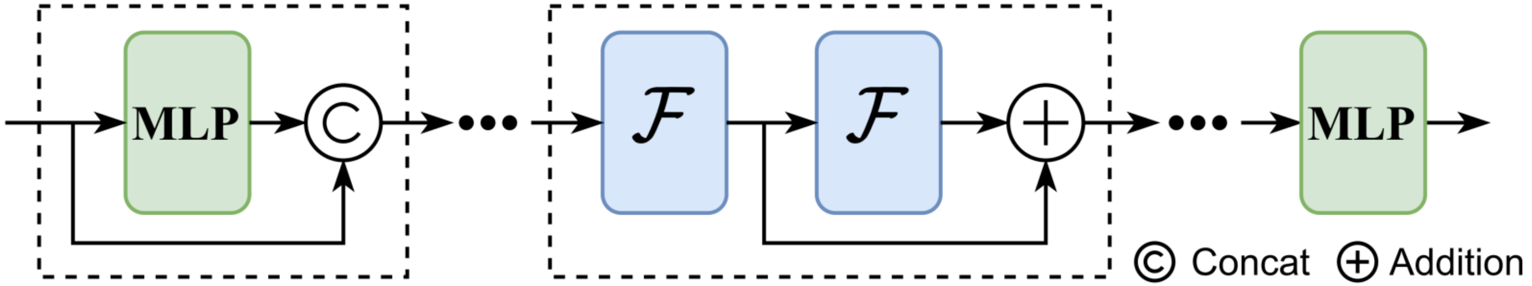
$$f_{\boldsymbol{p}}^{\mathbf{n}}(q) = \mathcal{E}_{\theta}^{\mathbf{n}}(q|z_q^{\mathbf{n}}), \;\; z_q^{\mathbf{n}} = e_{\varphi}(\boldsymbol{p}_q)$$



$$f_{\boldsymbol{P}}^{s}(q) = \operatorname{sgn}\big(g^s(q)\big) = \operatorname{sgn}\big(\mathcal{E}_{\theta}^{s}(q|z_q^{s})\big), \;\; z_q^{s} = e_{\psi}(\boldsymbol{P}_q)$$

$$f_{\boldsymbol{S}}(q) = f_{\boldsymbol{p}}^{\mathbf{n}}(q) \cdot f_{\boldsymbol{P}}^{s}(q) = \mathcal{E}_{\theta}^{\mathbf{n},s}(q|z_q^{\mathbf{n}}, z_q^{s})$$

1 Feature Encoding Module

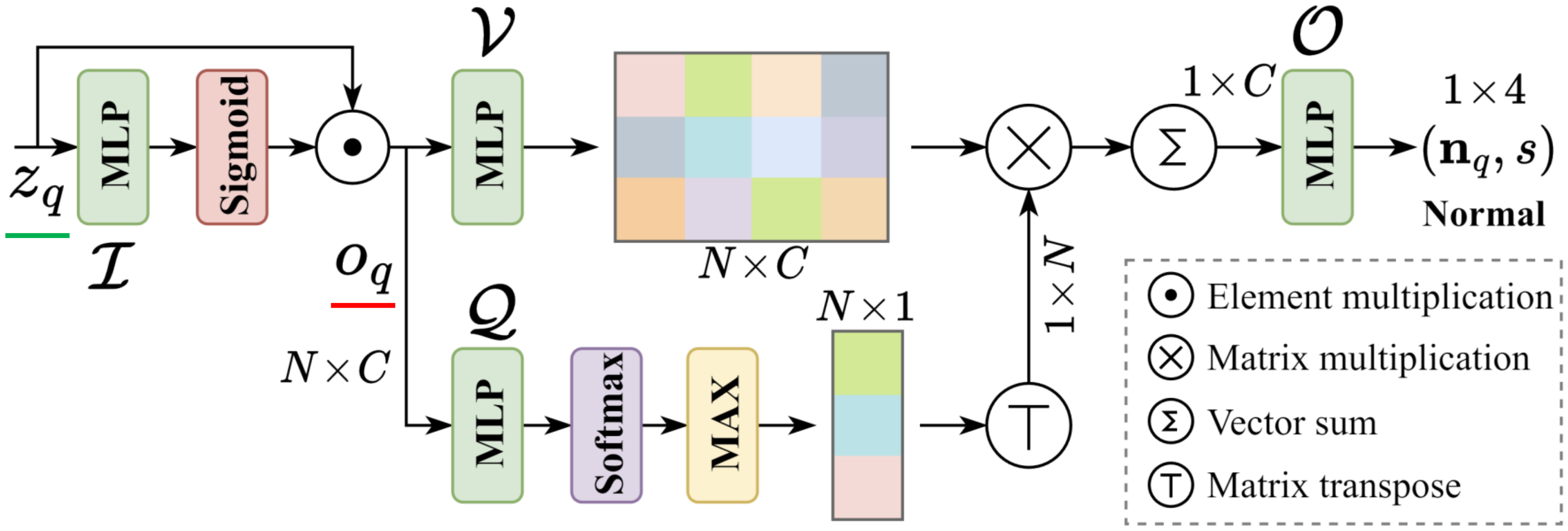


$\mathcal{F}$ is formulated as:

$$\dot{z}_i = \mathcal{A}\left(\mathcal{B}\left(\mathrm{MAX}\{\mathcal{C}(w_j \cdot z_j)\}_{j=1}^{N_l}\right), z_i\right)$$

$\mathcal{A}, \mathcal{B}$ and $\mathcal{C}$ are MLPs, w is a distance-based weight.

1 Attention-weighted Normal Prediction Module



$$(\dot{\mathbf{n}}_q, s) = \mathcal{O}\Big(\mathcal{V}(o_q) \otimes \mathrm{MAX}\big\{\mathrm{softmax}_{\mathcal{N}_q}\big(\mathcal{Q}_j(o_q)_{j=1}^{m}\big)\big\}\Big)$$

$$o_q = \tau \cdot z_q, \quad \tau = \mathrm{sigmoid}(\mathcal{I}(z_q))$$

$\mathcal{O}, \mathcal{V}, \mathcal{Q}$ and $\mathcal{I}$ are MLPs.

1 Loss Functions

- Sin loss: $\mathcal{L}_{sin} = \|\mathbf{n}_q \times \hat{\mathbf{n}}_q\|$
- MSE loss: $\mathcal{L}_{mse} = \frac{1}{N}\sum_{i=1}^{N} \tau_i \|\vec{\mathbf{n}}_i - \hat{\vec{\mathbf{n}}}_i\|^2$
- Sign loss: $\mathcal{L}_{sgn} = H\Big(\sigma\big(g^s(q)\big),\ [f_{\boldsymbol{S}}(q) > 0]\Big)$
- Weight loss: $\mathcal{L}_\tau = \frac{1}{N}\sum_{i=1}^{N} (\tau_i - \hat{\tau}_i)^2, \quad \hat{\tau}_i = \exp\left(-\frac{(p_i \cdot \hat{\mathbf{n}}_q)^2}{\xi^2}\right)$
- **Final loss:** $\mathcal{L} = \lambda_1 \mathcal{L}_{sin} + \lambda_2 \mathcal{L}_{sgn} + \lambda_3 \mathcal{L}_{mse} + \lambda_4 \mathcal{L}_\tau$

$$\lambda_1 = 0.1,\ \lambda_2 = 0.1,\ \lambda_3 = 0.5 \text{ and } \lambda_4 = 1.0$$

2. Experiments

2 FamousShape Dataset

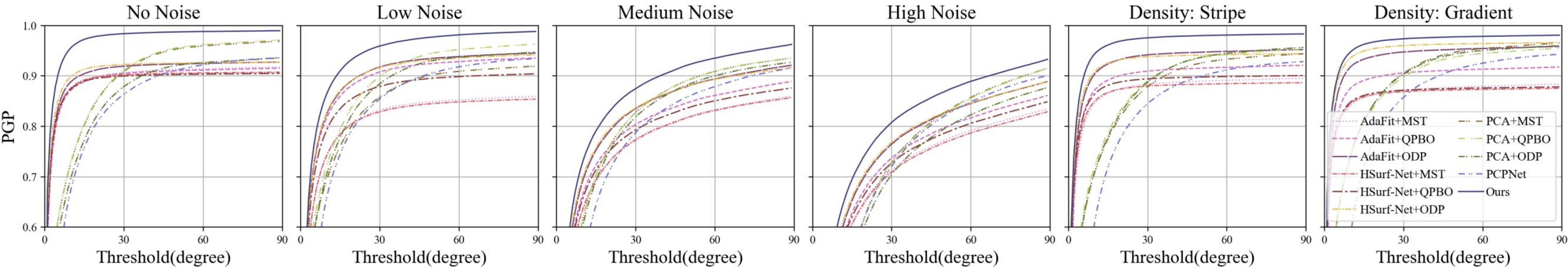
We follow the same preprocessing steps as the PCPNet dataset to conduct data augmentation, *e.g.*, adding Gaussian noise with different levels (0.12%, 0.6% and 1.2%) and uneven sampling (stripe and gradient).
This dataset is publicly available online.

2 Oriented Normal Evaluation

RMSE of oriented normal on datasets PCPNet and FamousShape.

Category	PCPNet Dataset							FamousShape Dataset						
	Noise				Density		Average	Noise				Density		Average
	None	0.12%	0.6%	1.2%	Stripe	Gradient		None	0.12%	0.6%	1.2%	Stripe	Gradient	
PCA [19]+MST [19]	19.05	30.20	31.76	39.64	27.11	23.38	28.52	35.88	41.67	**38.09**	60.16	31.69	35.40	40.48
PCA [19]+QPBO [45]	18.55	21.61	30.94	39.54	23.00	25.46	26.52	32.25	39.39	41.80	61.91	36.69	35.82	41.31
PCA [19]+ODP [38]	28.96	25.86	34.91	51.52	28.70	23.00	32.16	30.47	31.29	41.65	84.00	39.41	30.72	42.92
AdaFit [59]+MST [19]	27.67	43.69	48.83	54.39	36.18	40.46	41.87	43.12	39.33	62.28	60.27	45.57	42.00	48.76
AdaFit [59]+QPBO [45]	26.41	24.17	40.31	48.76	27.74	31.56	33.16	27.55	37.60	69.56	62.77	27.86	29.19	42.42
AdaFit [59]+ODP [38]	26.37	24.86	35.44	51.88	26.45	20.57	30.93	41.75	39.19	44.31	72.91	45.09	42.37	47.60
HSurf-Net [32]+MST [19]	29.82	44.49	50.47	55.47	40.54	43.15	43.99	54.02	42.67	68.37	65.91	52.52	53.96	56.24
HSurf-Net [32]+QPBO [45]	30.34	32.34	44.08	51.71	33.46	40.49	38.74	41.62	41.06	67.41	62.04	45.59	43.83	50.26
HSurf-Net [32]+ODP [38]	26.91	24.85	35.87	51.75	26.91	20.16	31.07	43.77	43.74	46.91	72.70	45.09	43.98	49.37
PCPNet [17]	33.34	34.22	40.54	44.46	37.95	35.44	37.66	40.51	41.09	46.67	54.36	40.54	44.26	44.57
DPGO* [50]	23.79	25.19	35.66	43.89	28.99	29.33	31.14	-	-	-	-	-	-	-
Ours	**10.28**	**13.23**	**25.40**	**35.51**	**16.40**	**17.92**	**19.79**	**21.63**	**25.96**	41.14	**52.67**	**26.39**	**28.97**	**32.79**

PGP curves of oriented normal on the PCPNet dataset.

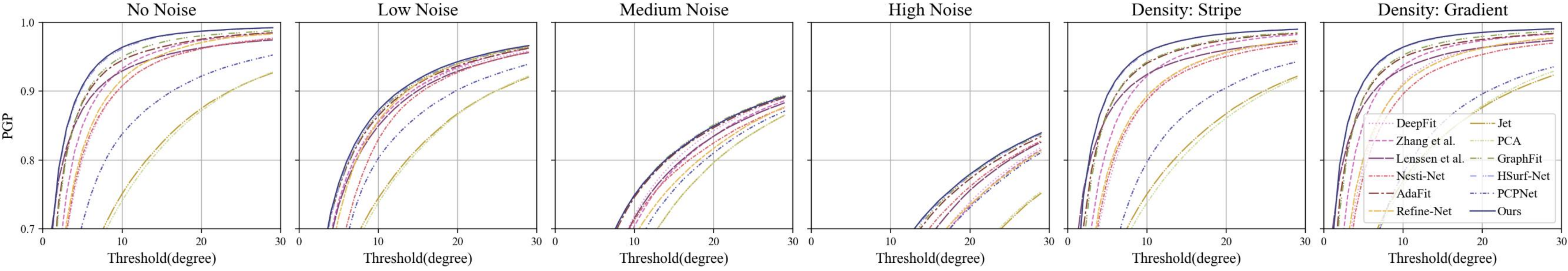


2 Unoriented Normal Evaluation

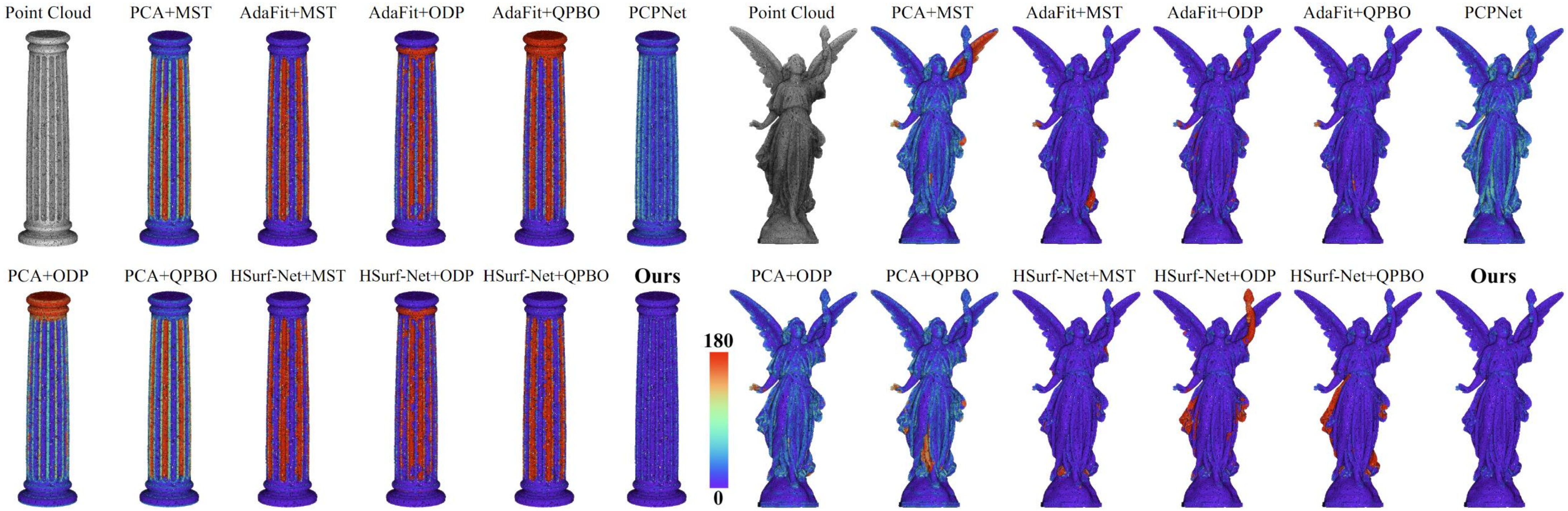
RMSE of unoriented normal on datasets PCPNet and FamousShape.

Category	PCPNet Dataset Noise None	PCPNet Noise 0.12%	PCPNet Noise 0.6%	PCPNet Noise 1.2%	PCPNet Density Stripe	PCPNet Density Gradient	PCPNet Average	FamousShape Dataset Noise None	FamousShape Noise 0.12%	FamousShape Noise 0.6%	FamousShape Noise 1.2%	FamousShape Density Stripe	FamousShape Density Gradient	FamousShape Average
Jet [10]	12.35	12.84	18.33	27.68	13.39	13.13	16.29	20.11	20.57	31.34	45.19	18.82	18.69	25.79
PCA [19]	12.29	12.87	18.38	27.52	13.66	12.81	16.25	19.90	20.60	31.33	45.00	19.84	18.54	25.87
PCPNet [17]	9.64	11.51	18.27	22.84	11.73	13.46	14.58	18.47	21.07	32.60	39.93	18.14	19.50	24.95
Zhou *et al.* * [57]	8.67	10.49	17.62	24.14	10.29	10.66	13.62	-	-	-	-	-	-	-
Nesti-Net [6]	7.06	10.24	17.77	22.31	8.64	8.95	12.49	11.60	16.80	31.61	39.22	12.33	11.77	20.55
Lenssen *et al.* [29]	6.72	9.95	17.18	21.96	7.73	7.51	11.84	11.62	16.97	30.62	39.43	11.21	10.76	20.10
DeepFit [5]	6.51	9.21	16.73	23.12	7.92	7.31	11.80	11.21	16.39	29.84	39.95	11.84	10.54	19.96
MTRNet* [9]	6.43	9.69	17.08	22.23	8.39	6.89	11.78	-	-	-	-	-	-	-
Refine-Net [56]	5.92	9.04	16.52	22.19	7.70	7.20	11.43	-	-	-	-	-	-	-
Zhang *et al.* * [54]	5.65	9.19	16.78	22.93	6.68	6.29	11.25	9.83	16.13	29.81	39.81	9.72	9.19	19.08
Zhou *et al.* * [58]	5.90	9.10	16.50	22.08	6.79	6.40	11.13	-	-	-	-	-	-	-
AdaFit [59]	5.19	9.05	16.45	21.94	6.01	5.90	10.76	9.09	15.78	29.78	38.74	8.52	8.57	18.41
GraphFit [31]	5.21	8.96	**16.12**	21.71	6.30	5.86	10.69	8.91	15.73	29.37	38.67	9.10	8.62	18.40
HSurf-Net [32]	4.17	8.78	16.25	21.61	4.98	4.86	10.11	7.59	15.64	29.43	**38.54**	**7.63**	7.40	17.70
Ours	**3.95**	**8.55**	16.13	**21.53**	**4.91**	**4.67**	**9.96**	**7.41**	**15.34**	**29.33**	38.56	7.74	**7.28**	**17.61**

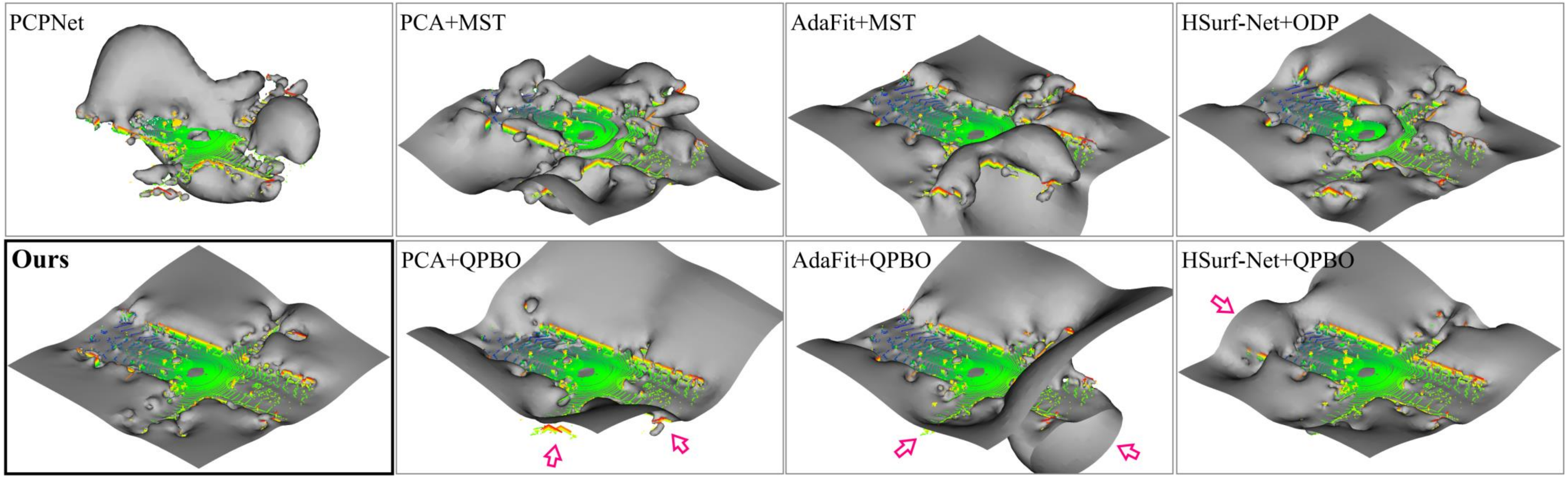
PGP curves of unoriented normal on the PCPNet dataset.



Visualization of the oriented normal error



Surface reconstruction using estimated normals on the KITTI dataset.



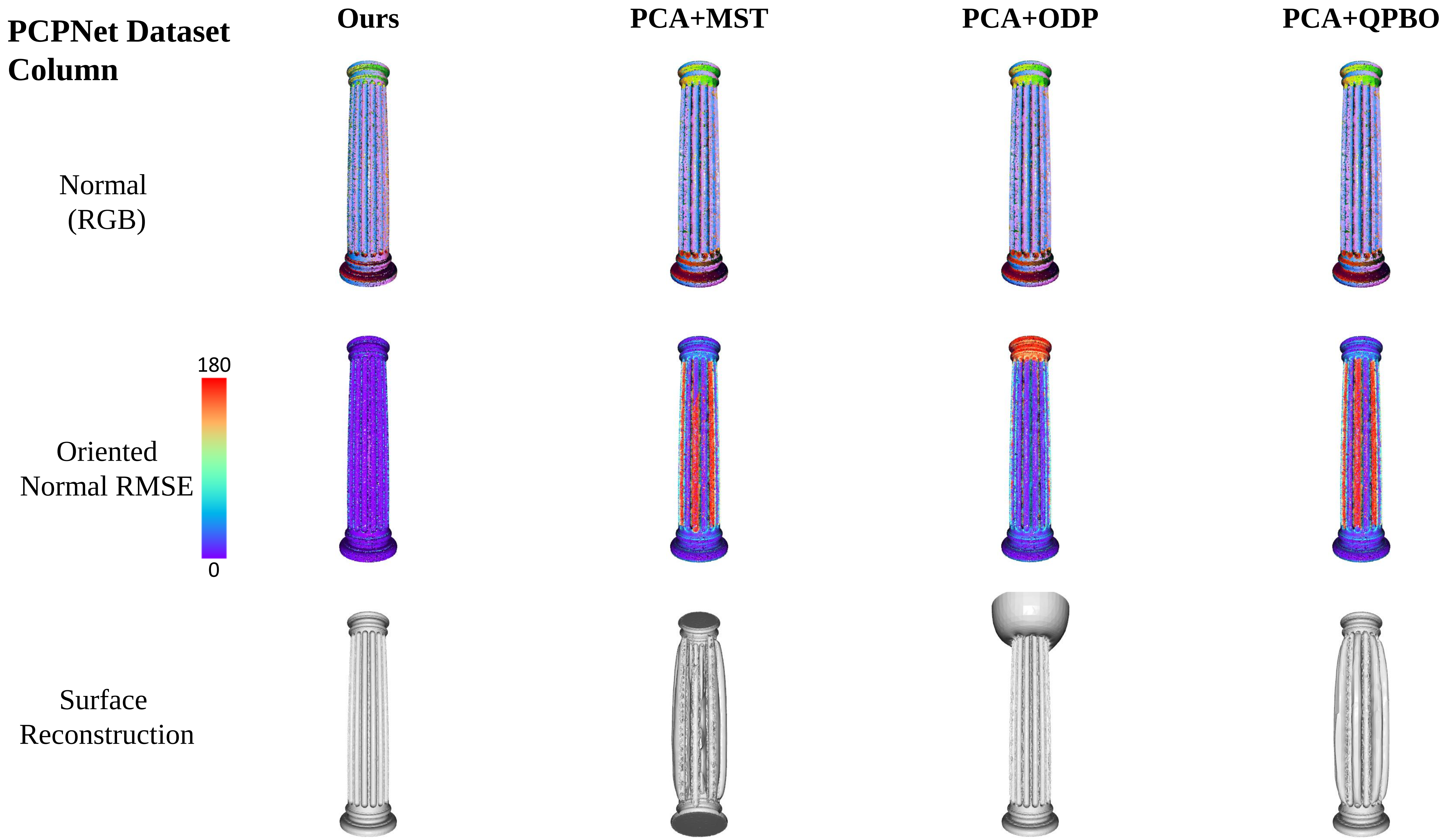
2 Ablation Studies

	Ablation	Feat. Enco.	Module $\mathcal{H}$	Loss	Point Samp.	Noise None	Noise 0.12%	Noise 0.6%	Noise 1.2%	Density Stripe	Density Gradient	Oriented Average	Unoriented Average
(a)	w/o patch encoding		✓	✓	✓	35.19	42.23	55.59	61.38	38.92	41.49	45.80	18.83
	w/o shape encoding		✓	✓	✓	69.72	64.37	81.87	77.07	74.84	90.35	76.37	14.94
	w/o weight w		✓	✓	✓	11.15	14.32	26.49	36.03	17.99	26.03	22.00	10.48
(b)	w/o module $\mathcal{H}$	✓		✓	✓	12.08	14.53	25.87	35.88	18.45	31.84	23.11	10.24
(c)	w/o $\mathcal{L}_{sin}, \mathcal{L}_{sgn}$	✓	✓		✓	23.86	25.55	34.13	42.48	32.42	41.30	33.29	20.23
(d)	w/o density gradient	✓	✓	✓		12.10	18.25	28.05	38.15	19.79	28.09	24.07	10.00
	w/o random sample	✓	✓	✓		11.01	13.79	25.64	35.86	17.22	25.71	21.54	9.94
	$\zeta=1/2$	✓	✓	✓		10.99	14.04	25.66	35.78	17.73	37.82	23.67	**9.92**
	$\zeta=1/3$	✓	✓	✓		13.27	15.42	26.82	37.16	17.52	28.11	23.05	9.95
	$N_{\boldsymbol{P}}=1100$	✓	✓	✓		10.67	14.21	25.54	35.97	16.80	26.98	21.69	9.99
	$N_{\boldsymbol{P}}=1300$	✓	✓	✓		12.44	14.53	25.93	35.79	18.40	19.85	21.16	9.98
	Final	✓	✓	✓	✓	**10.28**	**13.23**	**25.40**	**35.51**	**16.40**	**17.92**	**19.79**	9.96

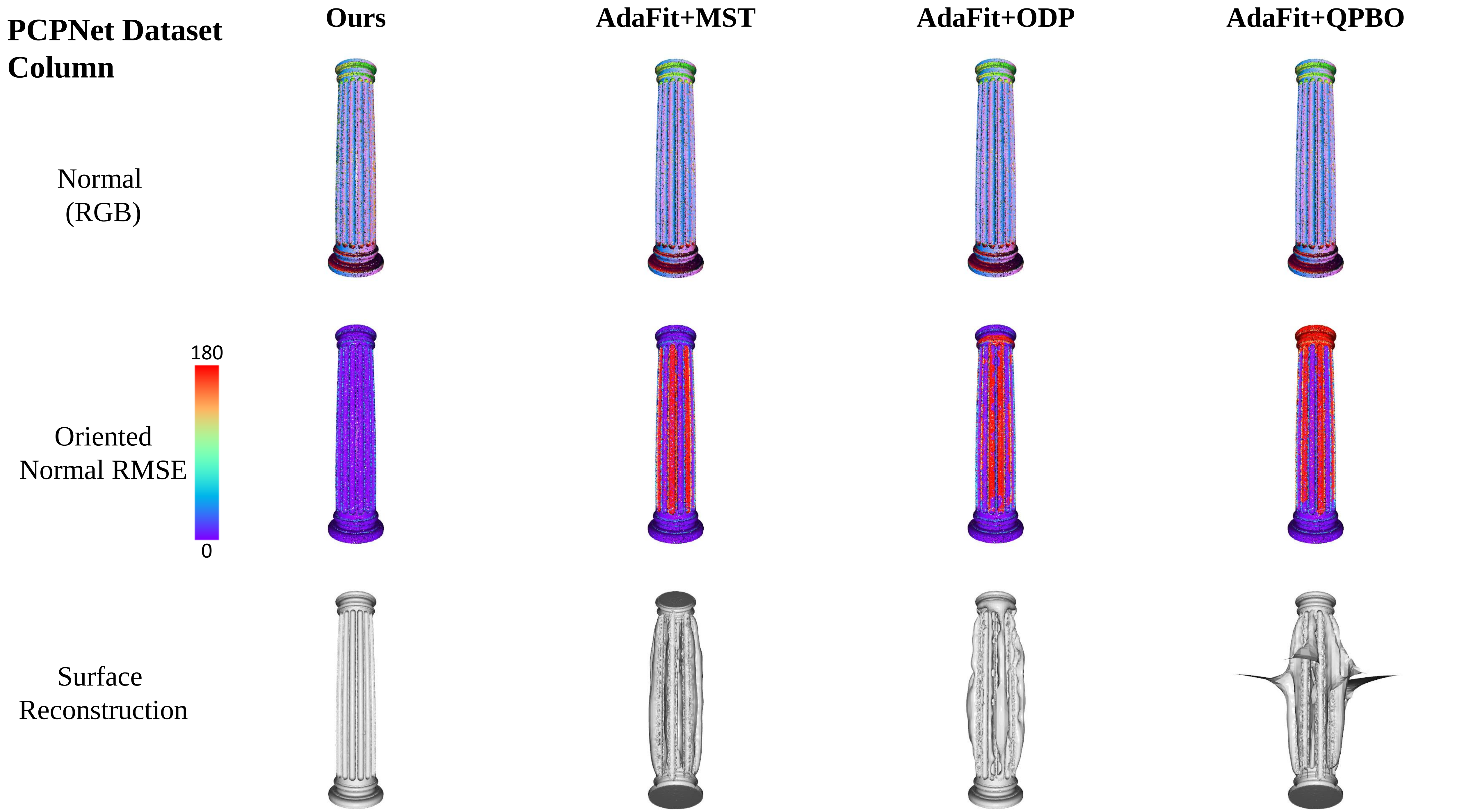
Oriented normal RMSE of ablation studies on the PCPNet dataset.

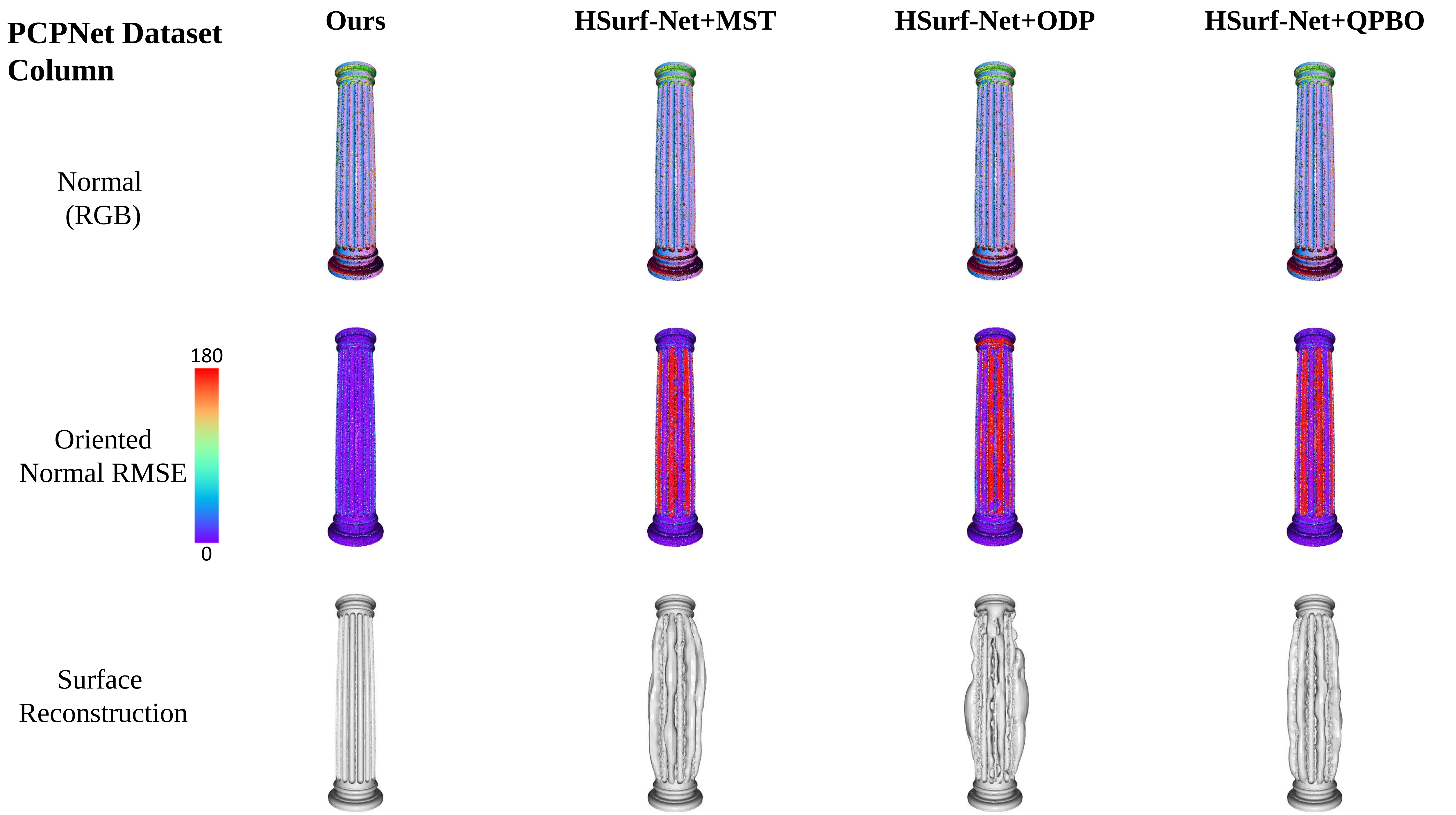
- The last column is the average results under the unoriented normal metric.
- The ablation experiments include: (a) the feature encoding modules and the weight, (b) the attention-weighted normal prediction module, (c) sin loss and sign loss, (d) the point sampling strategies and other hyperparameters.

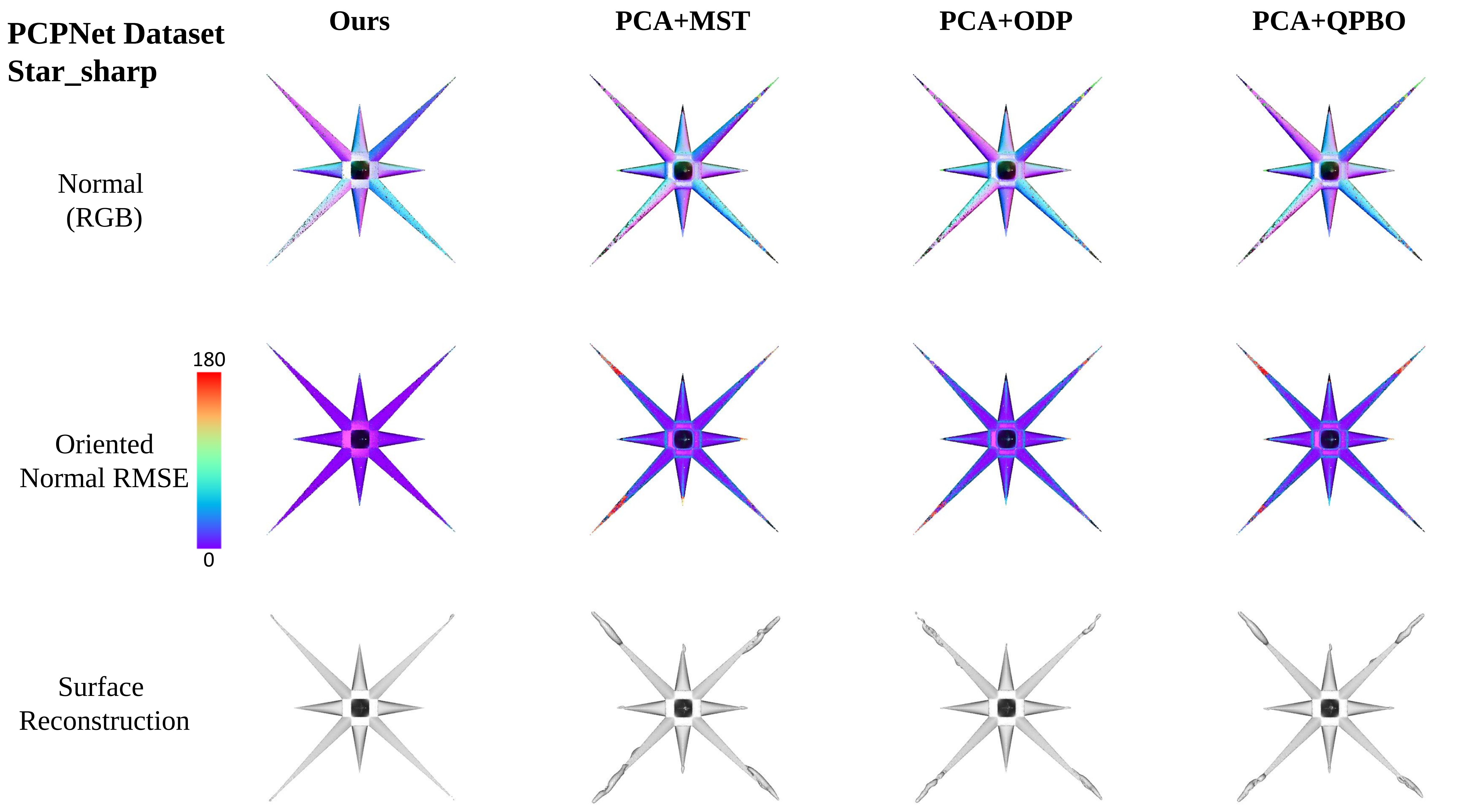
3. Demo and Application

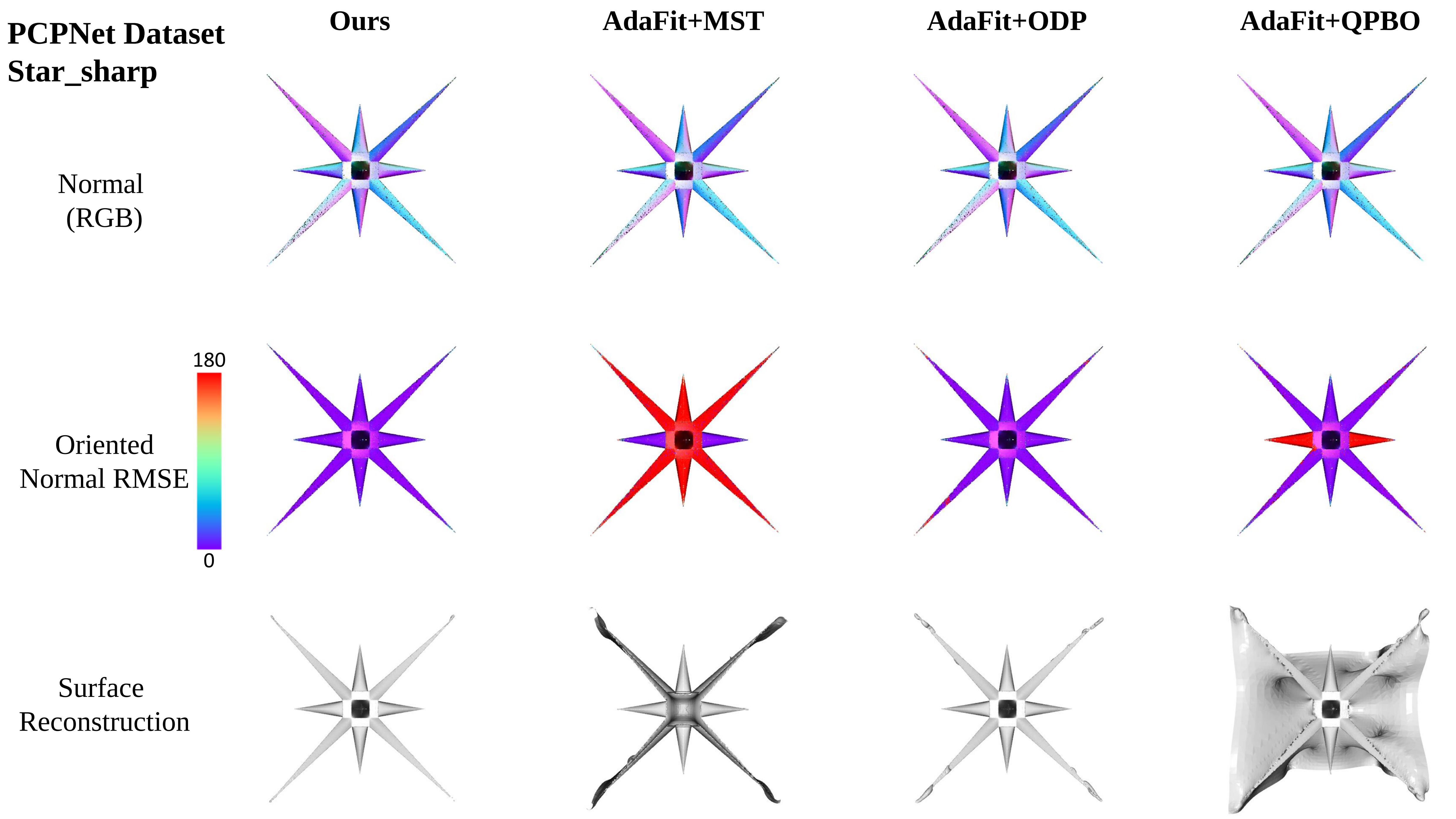


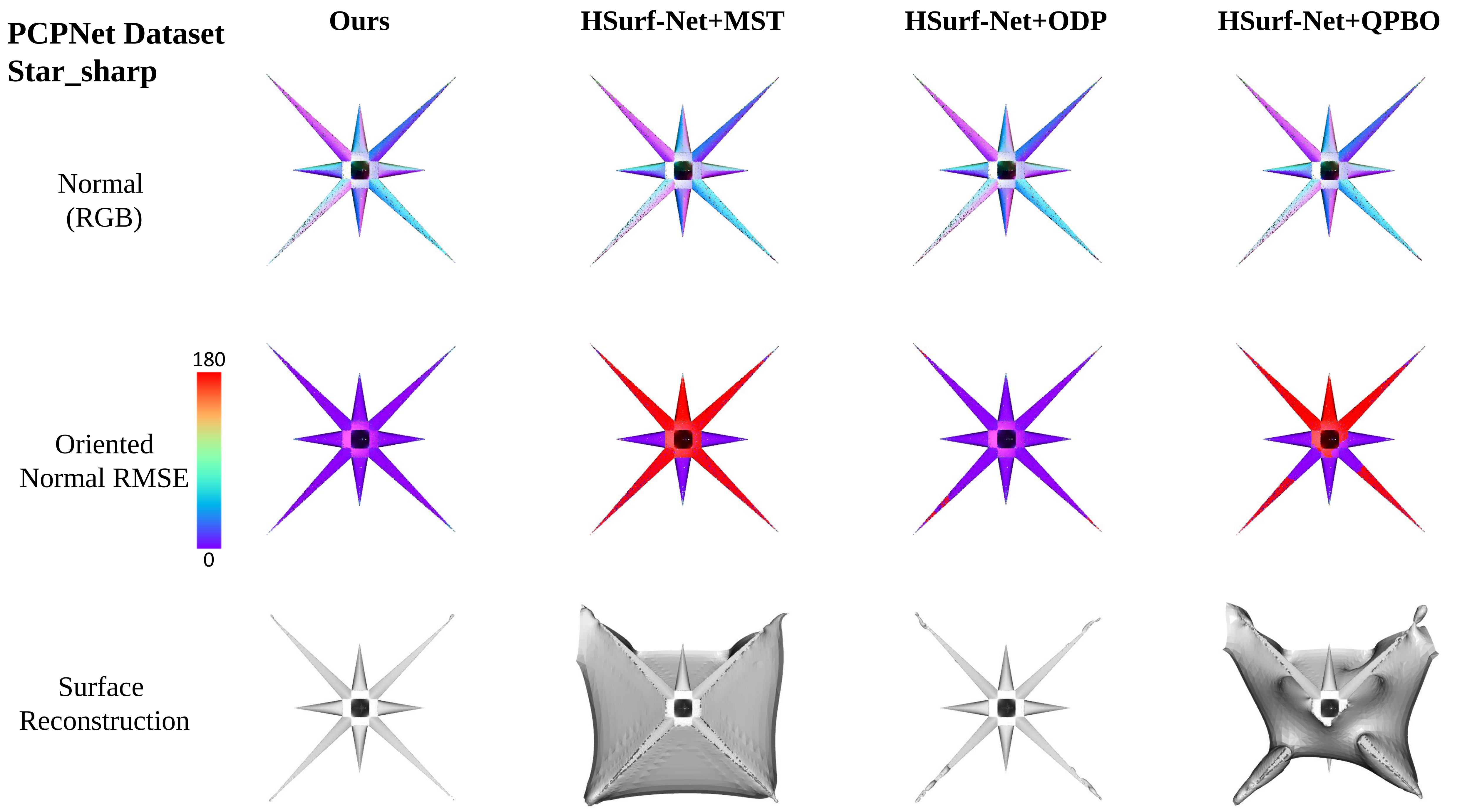
PCPNet Dataset
Column
Ours
PCA+MST
PCA+ODP
PCA+QPBO
Normal
(RGB)
Oriented
Normal RMSE
180
0
Surface
Reconstruction


PCPNet Dataset
Column
Ours
AdaFit+MST
AdaFit+ODP
AdaFit+QPBO
Normal
(RGB)
Oriented
Normal RMSE
180
0
Surface
Reconstruction

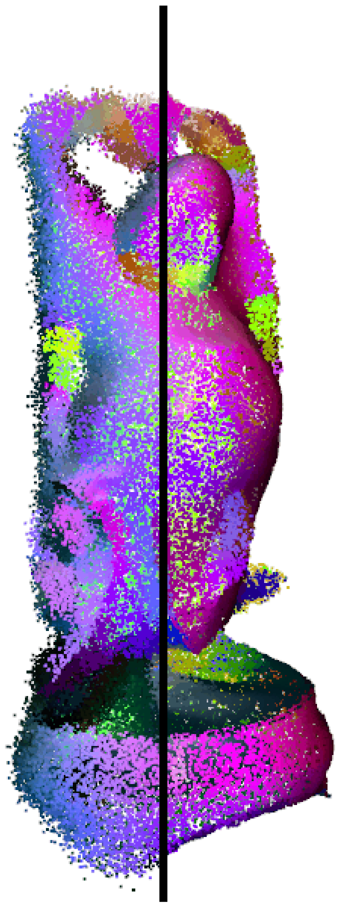

PCPNet Dataset
Column
Ours
HSurf-Net+MST
HSurf-Net+ODP
HSurf-Net+QPBO
Normal
(RGB)
Oriented
Normal RMSE
180
0
Surface
Reconstruction

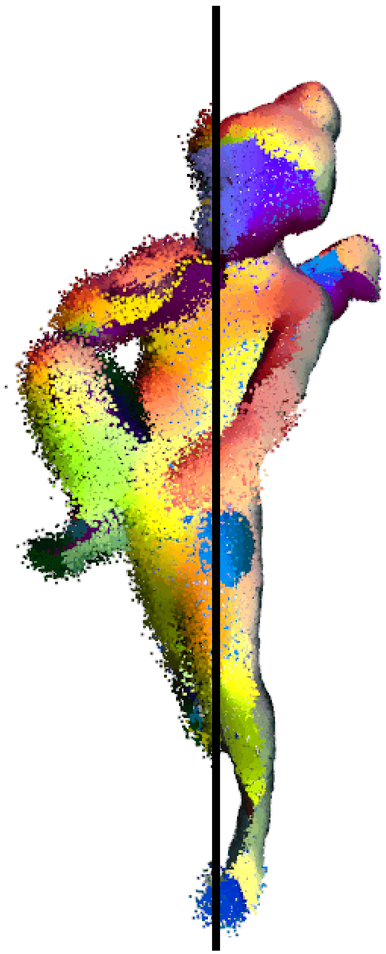

PCPNet Dataset
Star_sharp
Ours
PCA+MST
PCA+ODP
PCA+QPBO
Normal
(RGB)
180
0
Oriented
Normal RMSE
Surface
Reconstruction

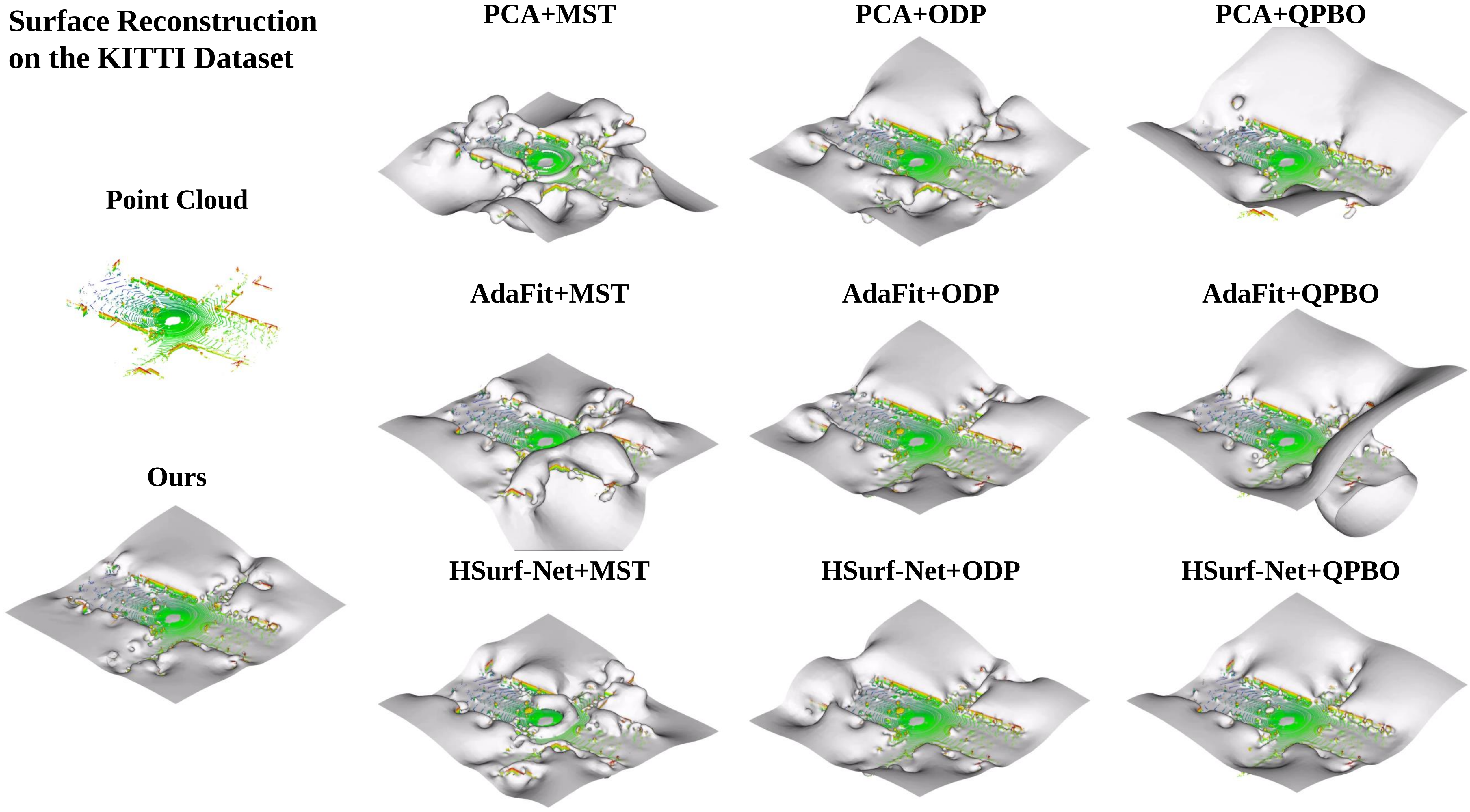

PCPNet Dataset
Star_sharp
Ours
AdaFit+MST
AdaFit+ODP
AdaFit+QPBO
Normal
(RGB)
Oriented
Normal RMSE
180
0
Surface
Reconstruction


PCPNet Dataset
Star_sharp
Ours
HSurf-Net+MST
HSurf-Net+ODP
HSurf-Net+QPBO
Normal
(RGB)
Oriented
Normal RMSE
180
0
Surface
Reconstruction

3 Application: Point Cloud Denoising






Surface Reconstruction on the KITTI Dataset
Point Cloud
Ours
PCA+MST
PCA+ODP
PCA+QPBO
AdaFit+MST
AdaFit+ODP
AdaFit+QPBO
HSurf-Net+MST
HSurf-Net+ODP
HSurf-Net+QPBO

4 Summary

- In summary, our contributions include:
  (a) We introduce a new technique to represent point cloud geometric properties as signed hyper surfaces in a high-dimensional feature space.
  (b) We show that the signed hyper surfaces can be used to estimate normals with consistent orientations directly from point clouds, rather than through a two-stage paradigm.
  (c) We experimentally demonstrate that our method is able to estimate normals with high accuracy and achieves the state-of-the-art results in both unoriented and oriented normal estimation.

Thanks for your attention!

https://leoqli.github.io/SHS-Net/