Cross-modal Learning for Image-Guided Point Cloud Shape Completion - Supplementary material

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1 Resource Usage Comparison

Methods	#Params (M)	Inference Time (ms)		
PCN [2]	6.86	2.7		
VRC-Net [1]	17.47	183.3		
ViPC [3]	11.48	62.9		
XMFnet	10.04	16.2		

Table 1: Computational Comparison

We evaluated the resource usage by PNC [2], VRC-Net [1], ViPC [3] and our XMFnet. The results are reported in Table 1, our model has a lower number of parameters and it is faster in inference with respect to the state of the art ViPC and VRC-Net. This is due to the good parameters' exploitation of our architecture and the fact that differently from ViPC we do not reconstruct a coarse point cloud from the image, avoiding unnecessary computational overhead.

2 Standard Deviation of Evaluation

Table 2: Mean Chamfer Distance per point ($\times 10^{-3}$). ShapeNet-ViPC dataset. Standard deviation for each category. XFMnet.

	Airplane	Cabinet	Car	Chair	Lamp	Sofa	Table	Watercraft
CD std	0.572 ± 0.037	1.980 ± 0.066	1.754 ± 0.075	1.403 ± 0.064	1.810 ± 0.138	1.702 ± 0.078	1.386 ± 0.055	$\begin{array}{c} 0.945 \\ \pm 0.042 \end{array}$

The value of standard deviation for each category are reported in Table 5. Lamp category is the one with higher variability and is also the one with the lowest F-Score.

^{*}Code of the project: https://github.com/diegovalsesia/XMFnet

³⁶th Conference on Neural Information Processing Systems (NeurIPS 2022).

3 Completion results as function of input view

We show how different input views affect the completion in Figure 1. We generated several completion starting from the same partial input point cloud and different input views. It can be noticed that views that contain more information about the missing regions provide better completion results.



Figure 1: Completion Results with respect to different input views.

4 Failure Cases

We show some difficult samples where our model struggles to reconstruct one particular challenging class is the lamp category. Figure 2 shows difficult samples for the supervised setting, while Figure 3 for the self-supervised one.



Figure 2: Qualitative visualization of difficult samples for the supervised setting.



Figure 3: Qualitative visualization of difficult samples for the self-supervised setting.

References

- [1] L. Pan, X. Chen, Z. Cai, J. Zhang, H. Zhao, S. Yi, and Z. Liu. Variational relational point completion network. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8524–8533, 2021.
- [2] W. Yuan, T. Khot, D. Held, C. Mertz, and M. Hebert. PCN: Point completion network. In 2018 *International Conference on 3D Vision (3DV)*, pages 728–737. IEEE, 2018.
- [3] X. Zhang, Y. Feng, S. Li, C. Zou, H. Wan, X. Zhao, Y. Guo, and Y. Gao. View-guided point cloud completion. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 15890–15899, 2021.