

# PMNI: Pose-free Multi-view Normal Integration for Reflective and Textureless Surface Reconstruction

For more information, please visit:

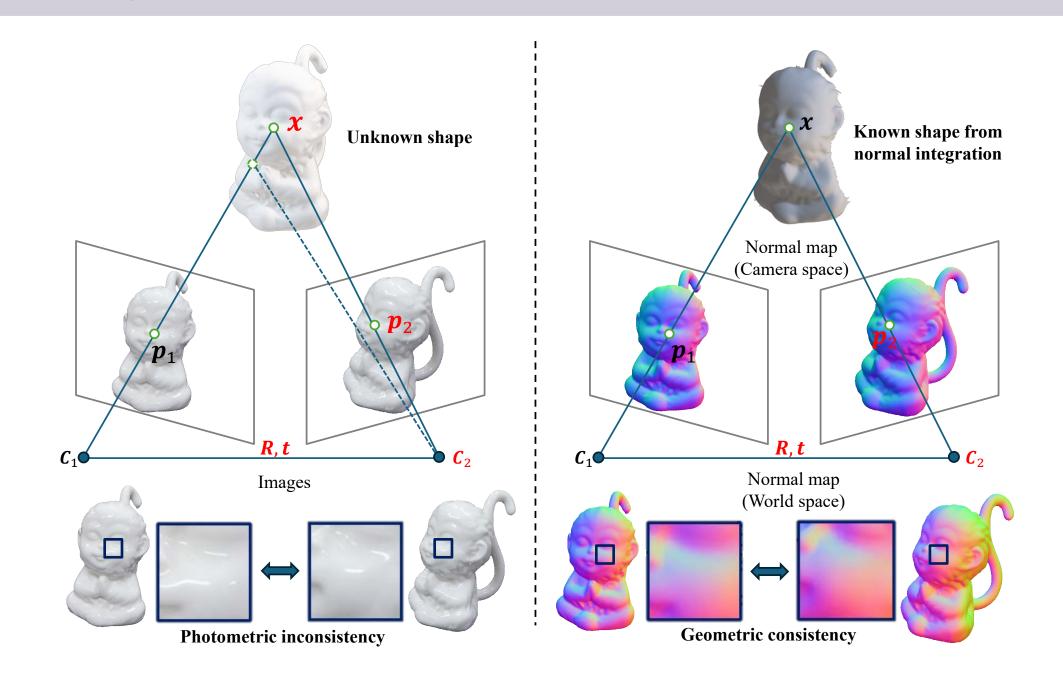
https://pmz-enterprise.github.io/PMNI/



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# **Problem definition** Input: Multi-light Multi-view Images Output: Shape & Pose

#### **Motivation & Contribution**



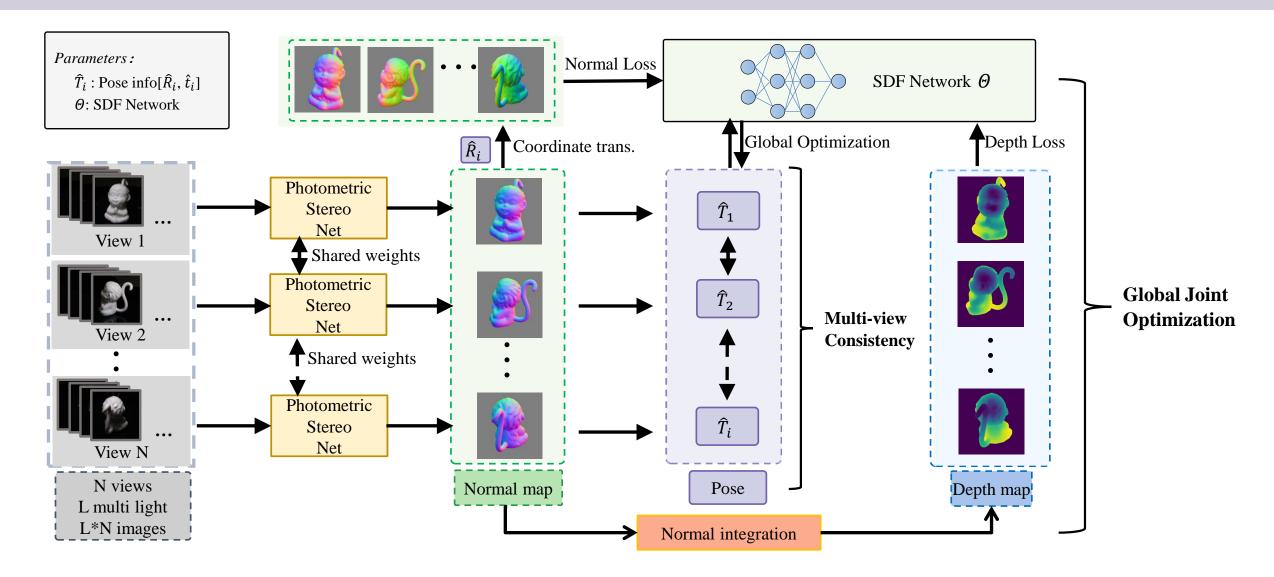
#### **Motivation:**

- Reflective and textureless surfaces remain challenging for 3D reconstruction without precise camera pose calibration, as RGB feature extraction and matching fails due to photometric inconsistency.
- Existing methods often require calibration boards, limiting their use in casual-capture setups.
- Surface normal maps maintain geometric consistency, offering a robust alternative to RGB images for shape and pose estimation.

#### **Contribution:**

- PMNI is the first method achieving high-quality reflective surface reconstruction without camera pose calibration
- By leveraging multi-view surface normal maps from photometric stereo, PMNI can jointly optimize both the surface shape and camera poses.

#### Method



World-to-camera surface normal loss:  $\mathcal{L}_{normal} = \sum_{i=1}^{N} \sum_{\mathbf{p}} |\mathbf{R}_i \mathbf{n}_i^w(\mathbf{p}) - \mathbf{n}_i^c(\mathbf{p})|_2^2$ 

Normal integration loss:  $\mathcal{L}_{ni} = \sum_{i=1}^{N} |\mathbf{z}_{i}^{r} - \alpha_{i}\mathbf{z}_{i}^{ni}|$ 

Multi-view normal consistency loss:  $\mathcal{L}_c = \sum_{i=1}^{N-1} \gamma_i(\mathbf{x}) \| \bar{\mathbf{R}} \bar{\mathbf{n}}^c(\mathbf{p}) - \mathbf{R}_i \mathbf{n}_i^c(\pi_i(\mathbf{x})) \|_2^2$ 

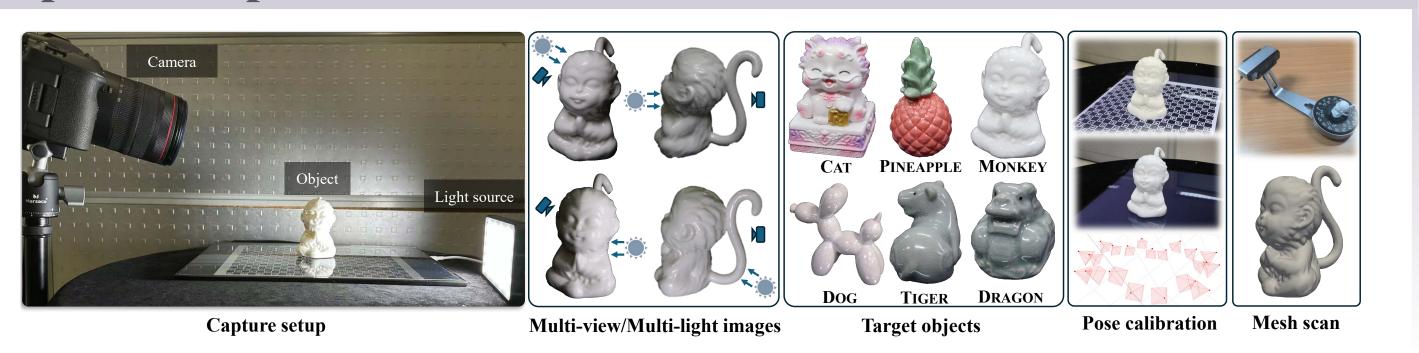
Mask loss:  $\mathcal{L}_{mask} = \sum_{i}^{N} \sum_{\mathbf{p}} BCE(\hat{o}_{i}(\mathbf{p}), o_{i}(\mathbf{p}))$ 

Eikonal loss:  $\mathcal{L}_{eikonal} = \sum_{\mathbf{x}} (\|\nabla f(\mathbf{x})\|_2 - 1)^2$ 

Joint optimization of pose and shape:

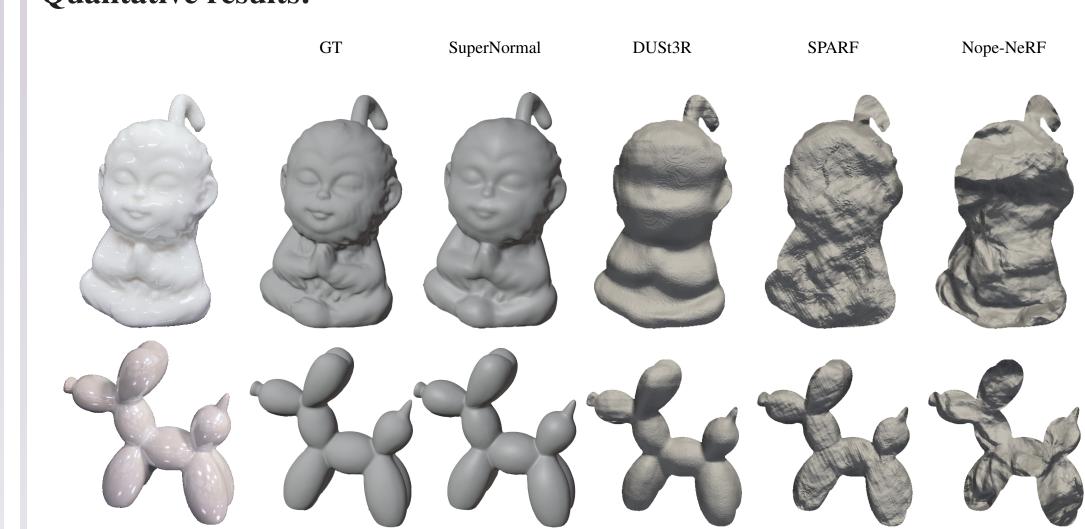
$$\mathcal{L} = \lambda_0 \mathcal{L}_{normal} + \lambda_1 \mathcal{L}_{ni} + \lambda_2 \mathcal{L}_c + \lambda_3 \mathcal{L}_{eikonal} + \lambda_4 \mathcal{L}_{mask}$$

## Capture setup & Dataset



## **Experimental results**

#### **Qualitative results:**



Calib. pose	Init. pose	DUSt3R	SPARF	Nope-NeRF	CF-3DGS	Ours

### **Quantitative results:**

Method	$RPEr (^{\circ}) \downarrow$						RPEt ↓					Relative Depth Error ↓							
	Monkey	Cat	Pineapple	Dog	Dragon	Tiger	Avg Monkey	Cat	Pineapple	Dog	Dragon	Tiger	Avg Monkey	Cat	Pineapple	Dog	Dragon	Tiger	Avg
DUSt3R	3.175	2.049	2.640	2.216	2.602	4.839	<u>2.920</u> <u>0.329</u>	0.199	0.247	0.490	0.224	0.335	0.304 <u>0.062</u>	0.056	0.046	0.147	0.046	0.075	0.072
Nope-NeRF	9.371	8.472	7.513	8.674	8.467	8.282	8.463 0.695	0.596	0.610	0.774	0.654	0.637	0.661 0.276	0.191	0.305	0.489	0.231	0.176	0.278
SPARF	7.233	6.395	3.485	3.620	0.731	<u>0.695</u>	3.693 0.375	0.203	<u>0.146</u>	0.261	<u>0.041</u>	0.058	<u>0.181</u> 0.099	<u>0.055</u>	0.038	<u>0.131</u>	<u>0.029</u>	<u>0.050</u>	0.067
CF-3DGS	16.867	16.664	17.276	14.789	15.625	16.659	16.313 0.947	0.796	1.092	0.878	0.998	1.124	0.972 0.363	0.360	0.475	0.488	0.477	0.502	0.444
Ours	0.230	0.356	0.258	0.258	0.439	0.582	0.354 0.015	0.020	0.016	0.019	0.027	0.035	0.022 0.011	0.017	0.008	0.010	0.011	0.026	0.014

#### Reference:

- [1] SuperNormal [Xu Cao et al., CVPR24]
- [2] SDM-UniPS [Ikehata et al., CVPR23]
- [3] SPARF [Prune Truong et al., CVPR23
- [4] CF-3DGS [Yang Fu et al., CVPR24]
- [6] DUSt3R [Shuzhe Wang et al., CVPR24]

#### **Bring-home Message**

- We propose PMNI, the first pose-free method for high-quality 3D reconstruction of reflective surfaces using multi-view surface normal maps.
- By jointly optimizing shape and camera poses, our method achieves state-of-art performance without precise calibration.