A Trilateral Weighted Sparse Coding Scheme for Real-World Image Denoising

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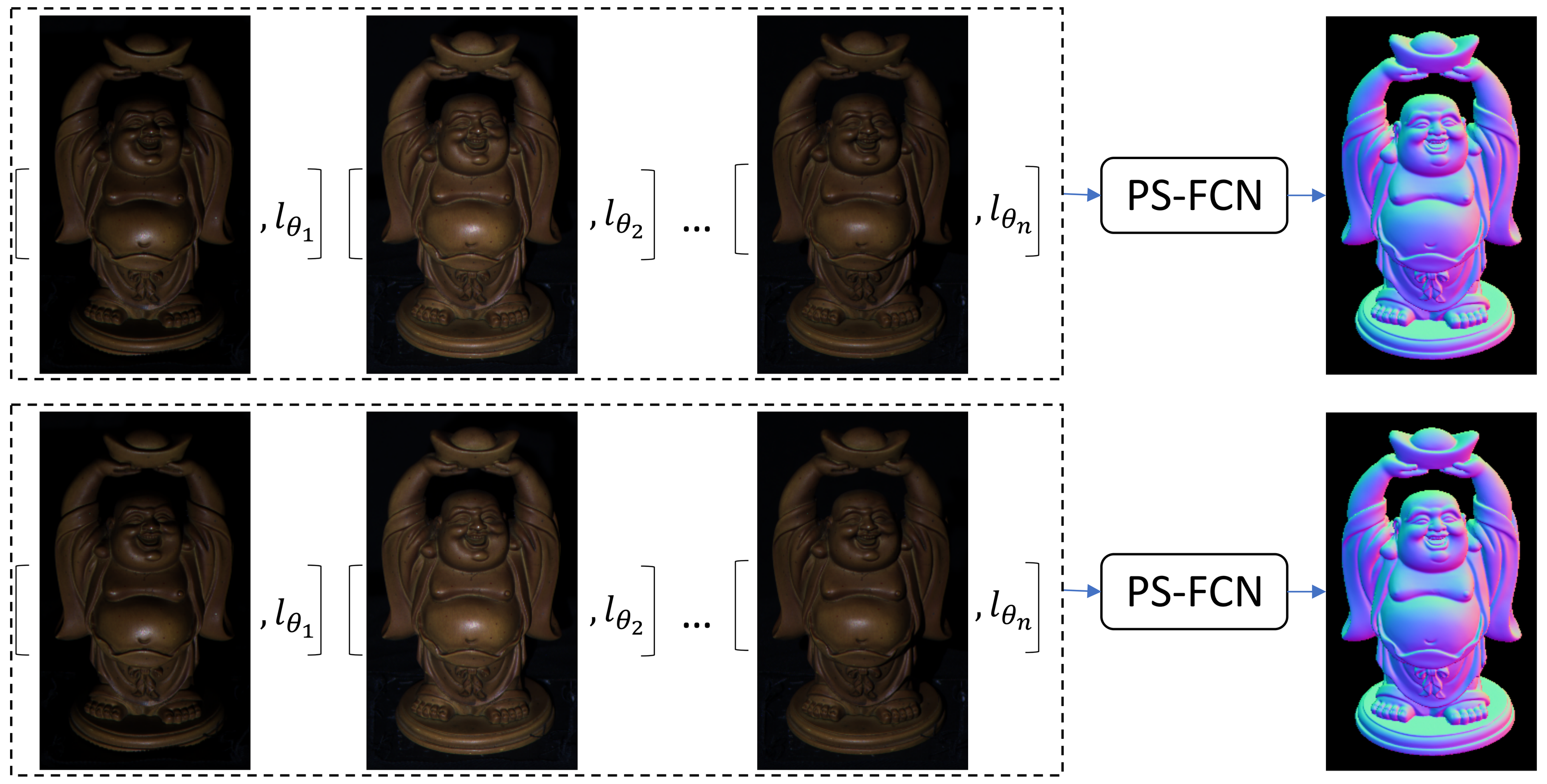
Problem Definition and Contribution

Goal: Estimating the latent clean image from the input real-world noisy image.

Key Motivations and Contributions:

- Realistic noise show the channel-wise statistics and locally signal dependent property;
- Propose a trilateral weighted sparse coding (TWSC) scheme for real-world image denoising;
- TWSC achieves much better performance than state-of-the-art denoising methods.



Formulation

Assumption: Orthographic projection and directional lights.

Image Formation Equation: Given q color images of an object with p pixels captured under different light directions, a normal matrix $\mathbf{N}_{3\times p}$, a light direction matrix $\mathbf{L}_{3\times q}$, and an observation matrix $\mathbf{I}_{3\times p\times q}$ can be constructed. Denoting the BRDFs for all observations as $\mathbf{\Theta}_{3\times p\times q}$, the image formation equation can be written as

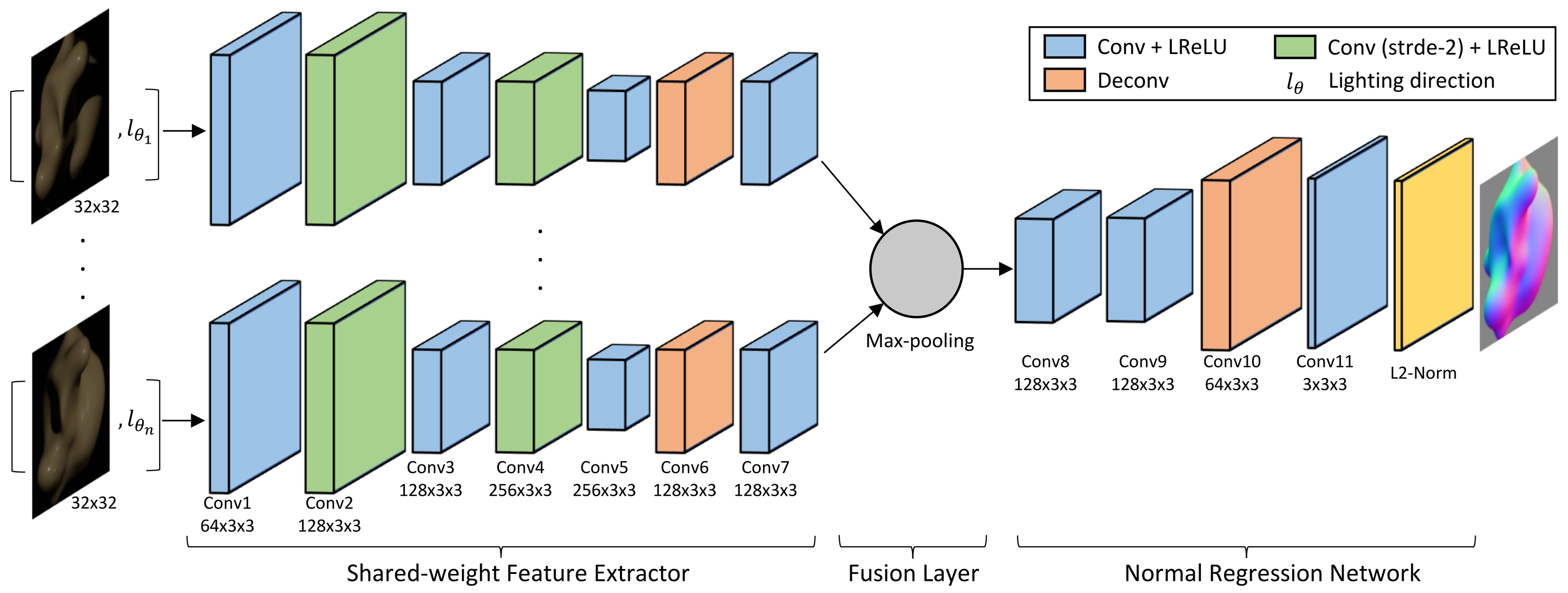
$$\mathbf{I} = \mathbf{\Theta} \circ \mathrm{repmat}(\mathbf{N}^\top \mathbf{L}, 3), \tag{1}$$

where $\circ$ represents element-wise multiplication, and $\mathrm{repmat}(\mathbf{X}, 3)$ repeats the matrix $\mathbf{X}$ three times along the first dimension.

Main Idea: Our method directly learns the mapping from $(\mathbf{I}, \mathbf{L})$ to $\mathbf{N}$ without explicitly modeling $\mathbf{\Theta}$.

Method

Network Architecture: PS-FCN consists of three components, namely a shared-weight feature extractor, a fusion layer, and a normal regression network.

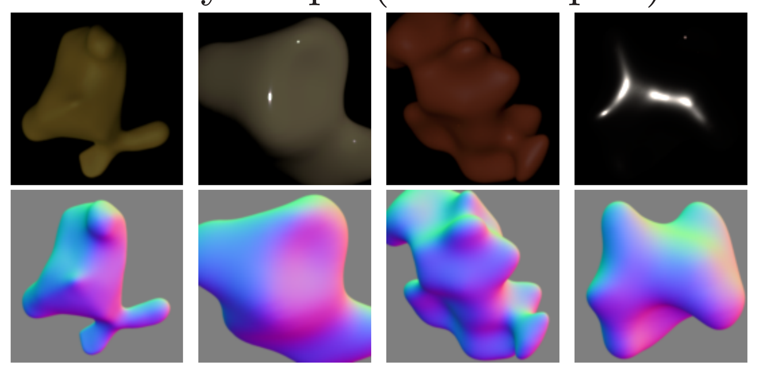


Loss function:

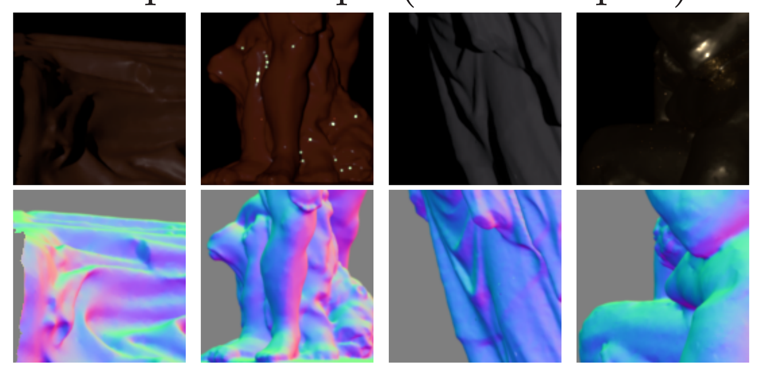
Experiments & Results

Synthetic Datasets for Training:

Blobby shape (26K samples).



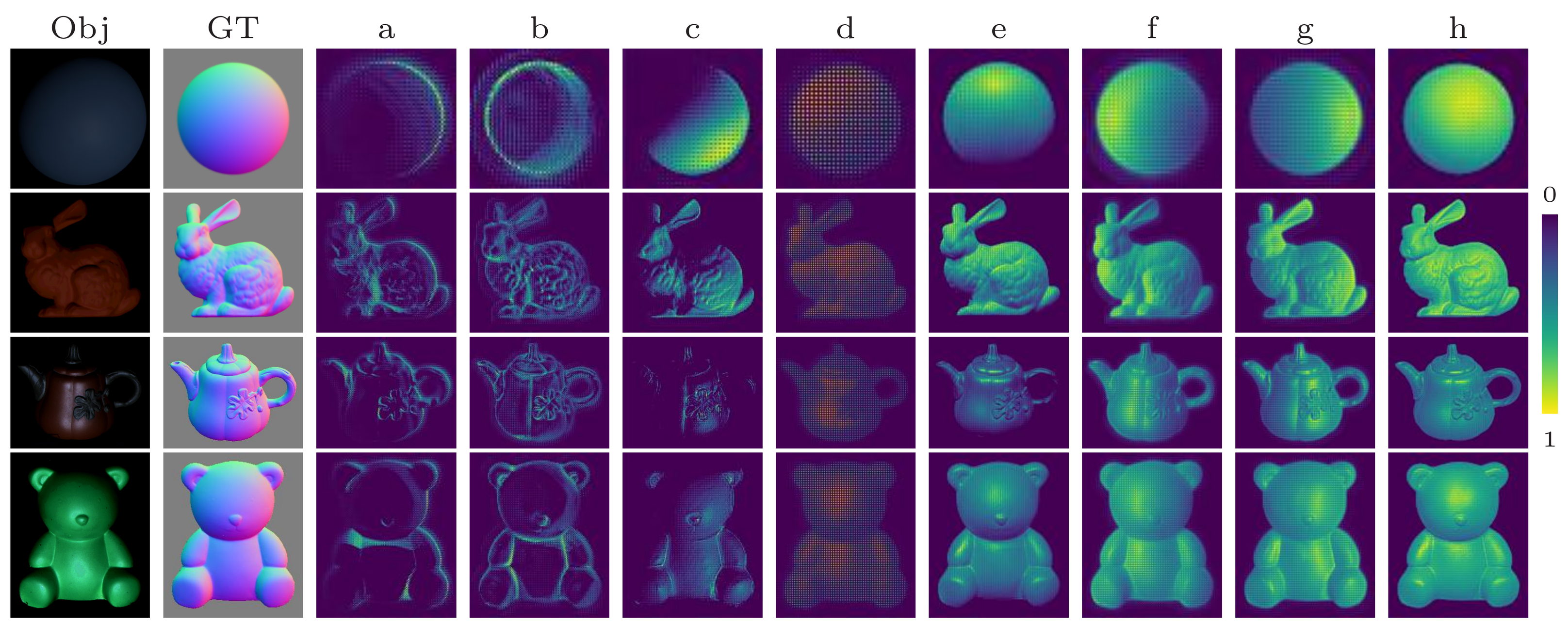
Sculpture shape (59K samples).



Quantitative Results on DiLiGenT Main Dataset:

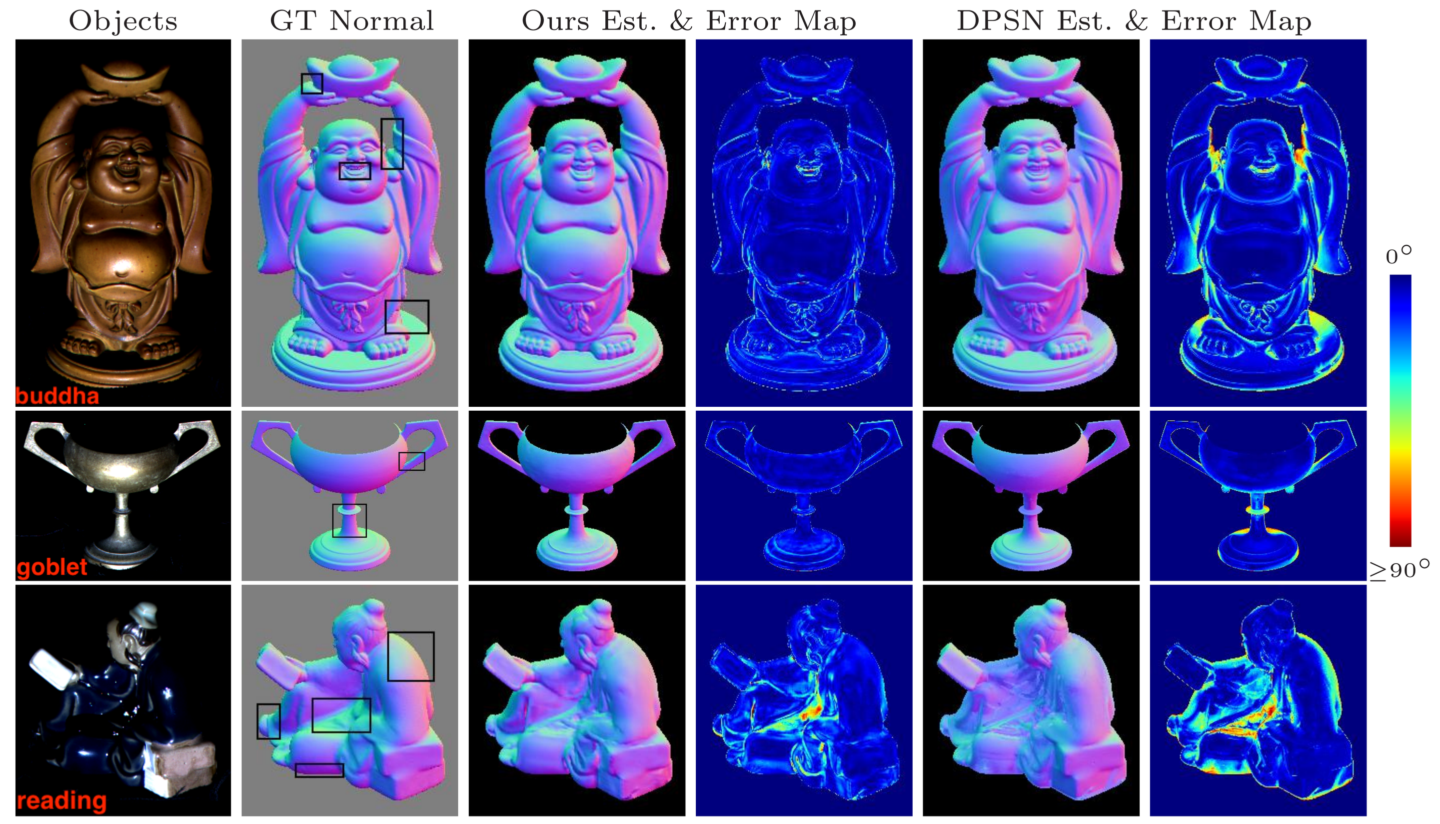
Method	ball	cat	pot1	bear	pot2	buddha	goblet	reading	cow	harvest	Avg.
L2	4.10	8.41	8.89	8.39	14.65	14.92	18.50	19.80	25.60	30.62	15.39
AZ08	2.71	6.53	7.23	**5.96**	11.03	12.54	13.93	14.17	21.48	30.50	12.61
WG10	2.06	6.73	7.18	6.50	13.12	10.91	15.70	15.39	25.89	30.01	13.35
IA14	3.34	6.74	6.64	7.11	8.77	10.47	9.71	14.19	13.05	25.95	10.60
ST14	**1.74**	**6.12**	**6.51**	6.12	8.78	10.60	10.09	13.63	13.93	25.44	10.30
DPSN	2.02	6.54	7.05	6.31	7.86	12.68	11.28	15.51	8.01	16.86	9.41
PS-FCN (B+S+32, 16)	3.31	7.64	8.14	7.47	8.22	8.76	9.81	14.09	8.78	17.48	9.37
PS-FCN (B+S+32, 96)	2.82	6.16	7.13	7.55	**7.25**	**7.91**	**8.60**	**13.33**	**7.33**	**15.85**	**8.39**

Feature Visualization:

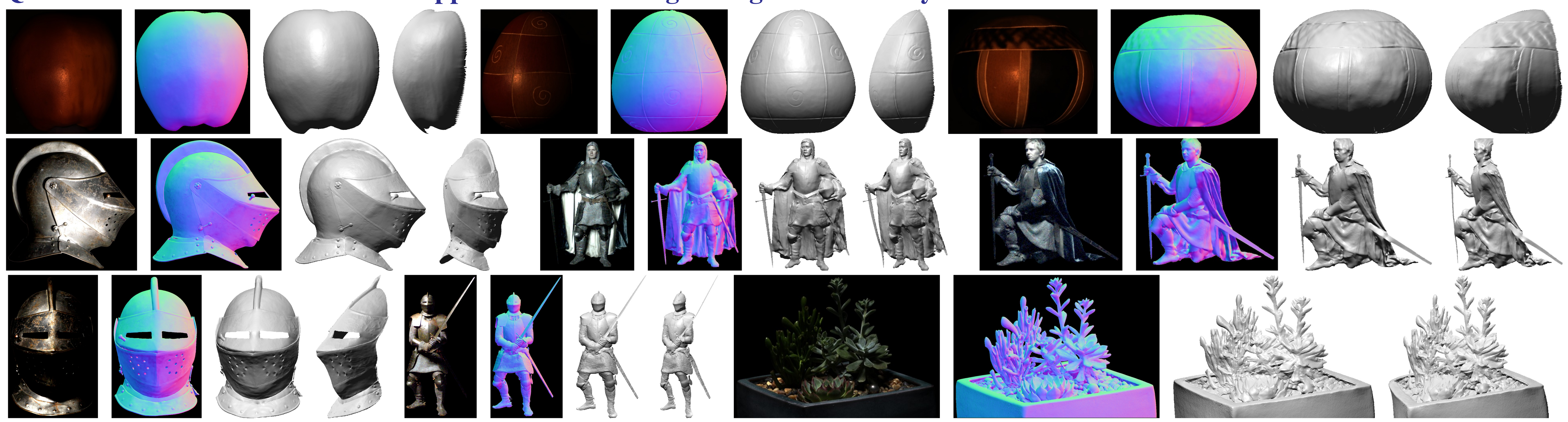


- Different regions with similar normal directions are fired in different channels. Each channel can therefore be interpreted as the probability of the normal belonging to a certain direction.

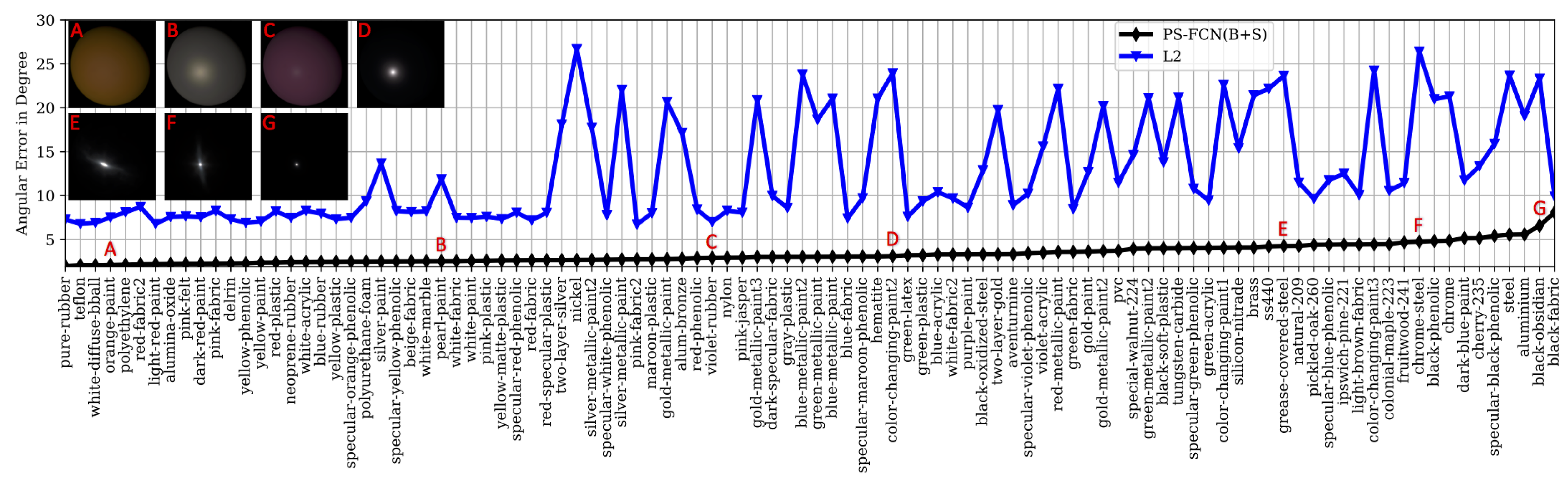
Qualitative Results on DiLiGenT Main Dataset:



Qualitative Results on the Gourd&Apple Dataset and Light Stage Data Gallery:



Quantitative Results on Spheres Rendered with 100 Different Materials:



Quantitative Results of Uncalibrated PS-FCN on DiLiGenT Main Dataset:

Method	ball	cat	pot1	bear	pot2	buddha	goblet	reading	cow	harvest	Avg.
AM07	7.27	31.45	18.37	16.81	49.16	32.81	46.54	53.65	54.72	61.70	37.25
SM10	8.90	19.84	16.68	11.98	50.68	15.54	48.79	26.93	22.73	73.86	29.59
WT13	**4.39**	36.55	**9.39**	**6.42**	14.52	**13.19**	20.57	58.96	19.75	55.51	23.93
PF14	4.77	**9.54**	9.51	9.07	15.90	14.92	29.93	24.18	19.53	29.21	16.66
LC18	9.30	12.60	12.40	10.90	15.70	19.00	**18.30**	**22.30**	15.00	28.00	16.30
UPS-FCN	6.62	14.68	13.98	11.23	**14.19**	15.87	20.72	23.26	**11.91**	**27.79**	**16.02**

Project Webpage:

Code & Dataset & Model