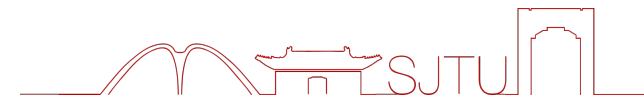




上海交通大学  
SHANGHAI JIAO TONG UNIVERSITY



# Monocular Identity-Conditioned Facial Reflectance Reconstruction

**CVPR 2024**

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**Shanghai Jiao Tong University**

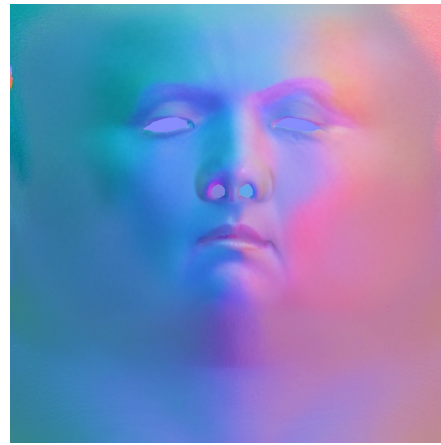
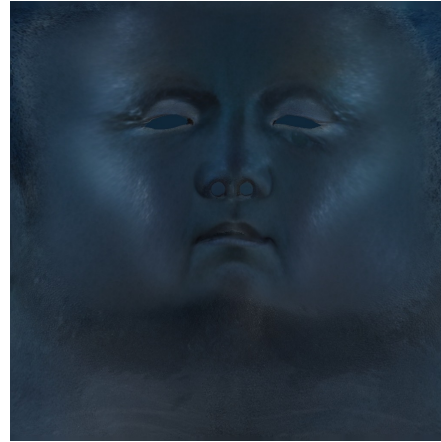
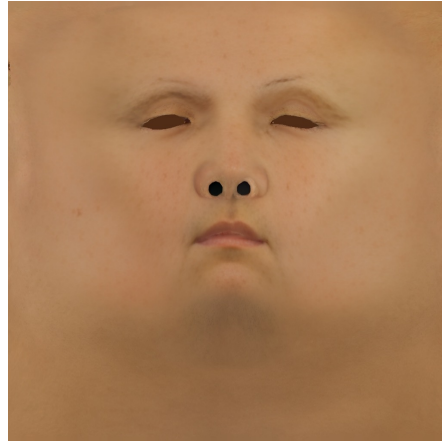
饮水思源 · 爱国荣校

# Overview | ID2Reflectance





# Overview | ID2Reflectance

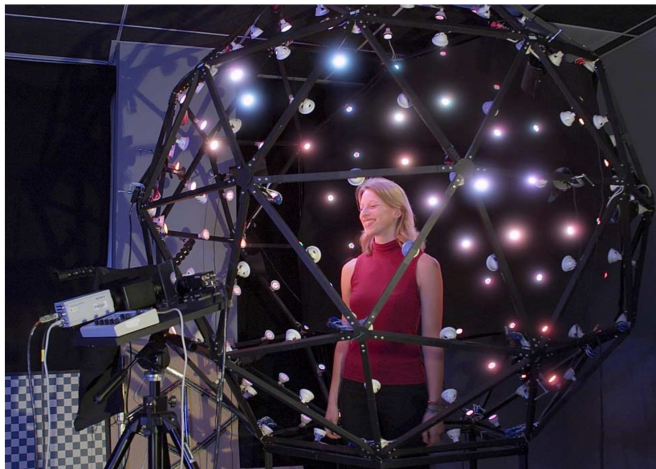




# Industrial pipeline | Capture System



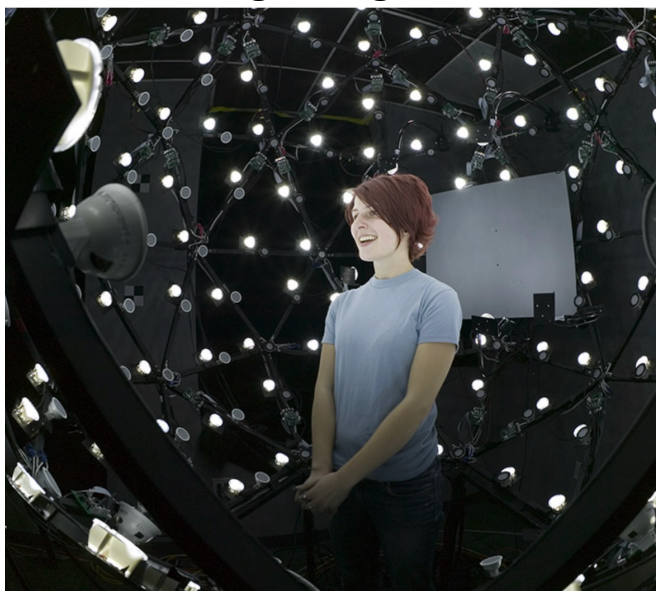
Lightstage 1



Lightstage 3



Lightstage 2



Lightstage 5



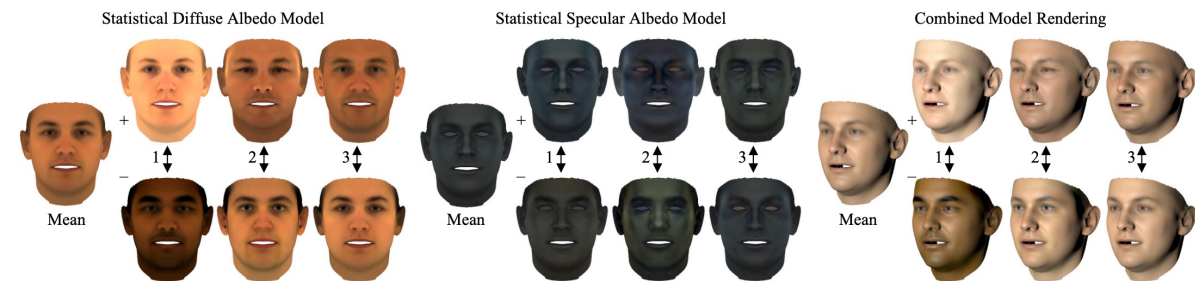
Our LightStage System

**Complicated and High Cost**

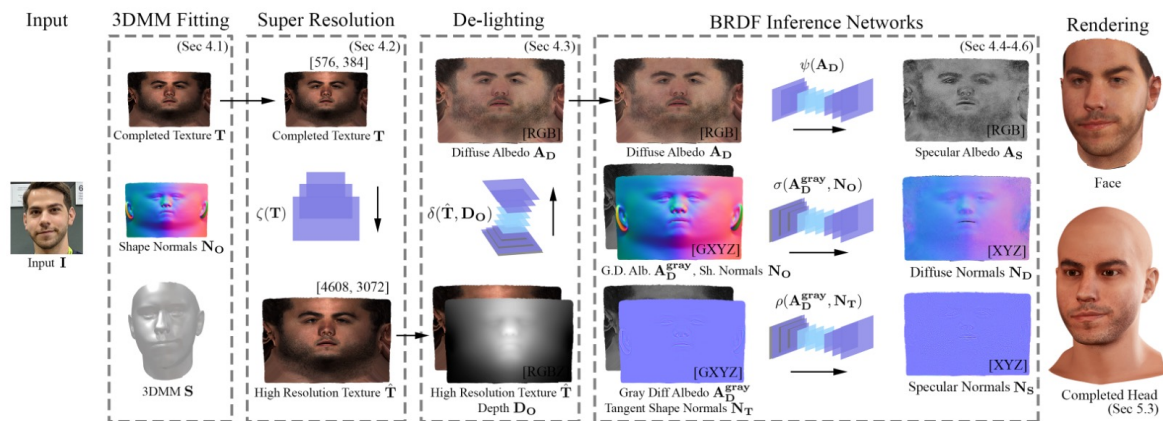




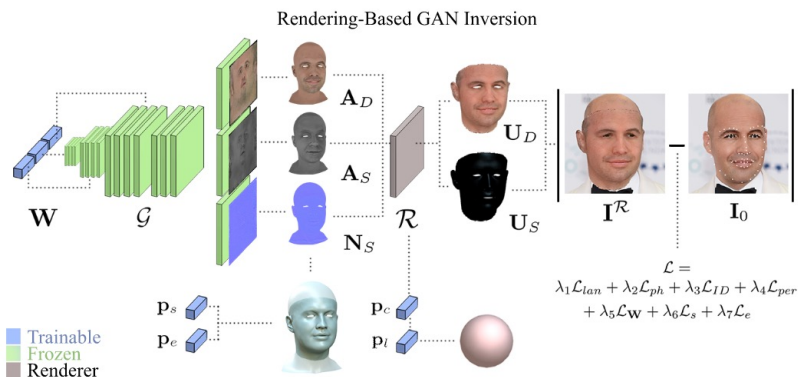
# Related Works



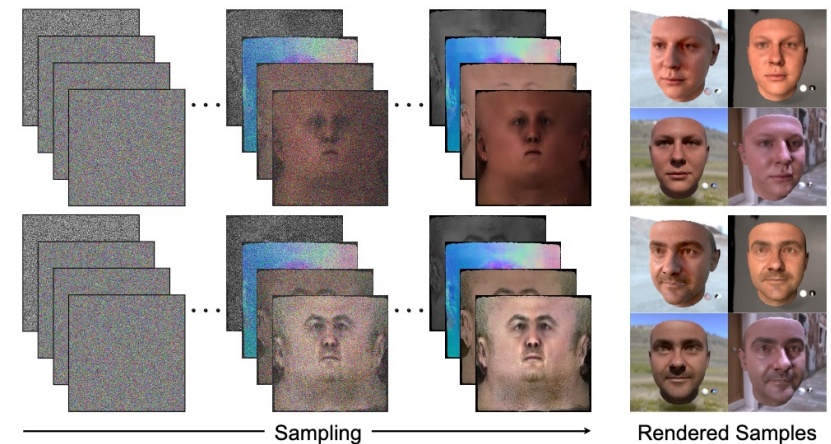
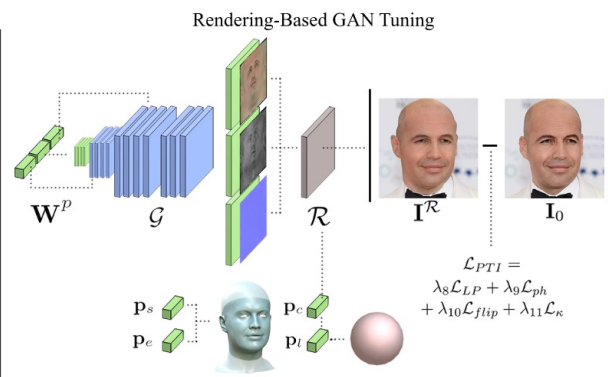
Facial Albedo Morphable, Smith et al. CVPR 2020



AvatarMe, Lattas et al. CVPR 2020



FitMe, Lattas et al. CVPR 2023



Relightify, Papantoniou et al. ICCV 2023



# Challenge



NEW

## 10 x HD head scan Pack 7

£3,426.00

- Model: 10 x HD Head Scan Pack 07
- SKU: 10XHDSP07

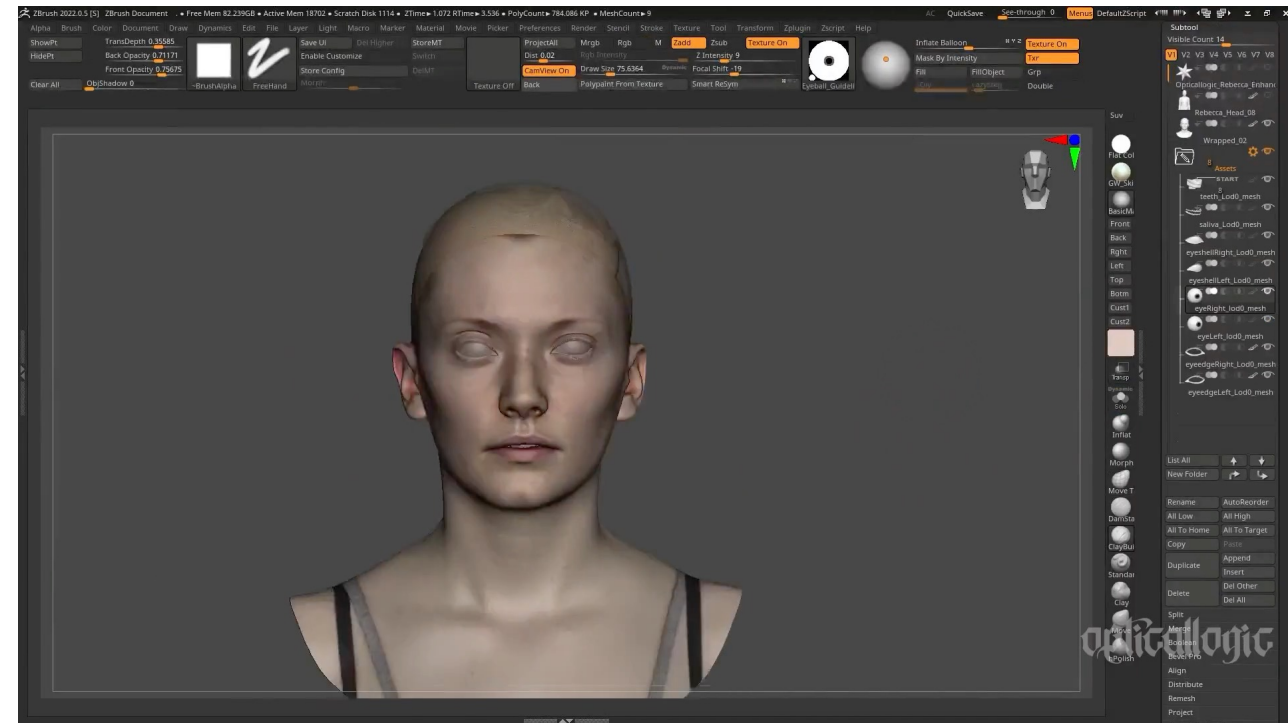
### Select Licence \*

- Personal Single User Licence
- Business R&D Licence (+£1,034.00)
- Business Commercial Single Project Licence (+£1,943.00)

ADD TO CART

**Limited** high-quality reflectance data available for **purchase**

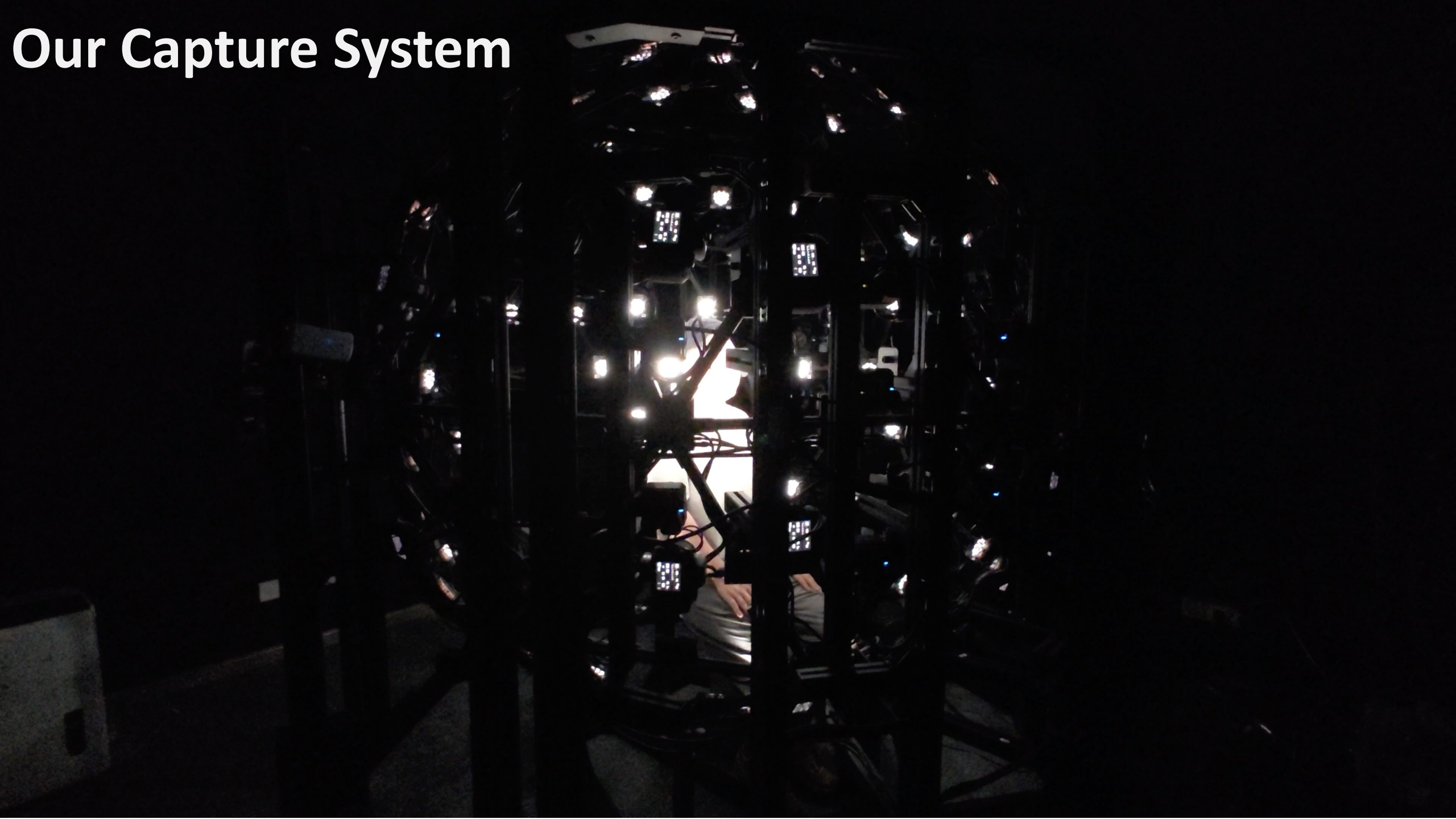
## High **post-processing** costs





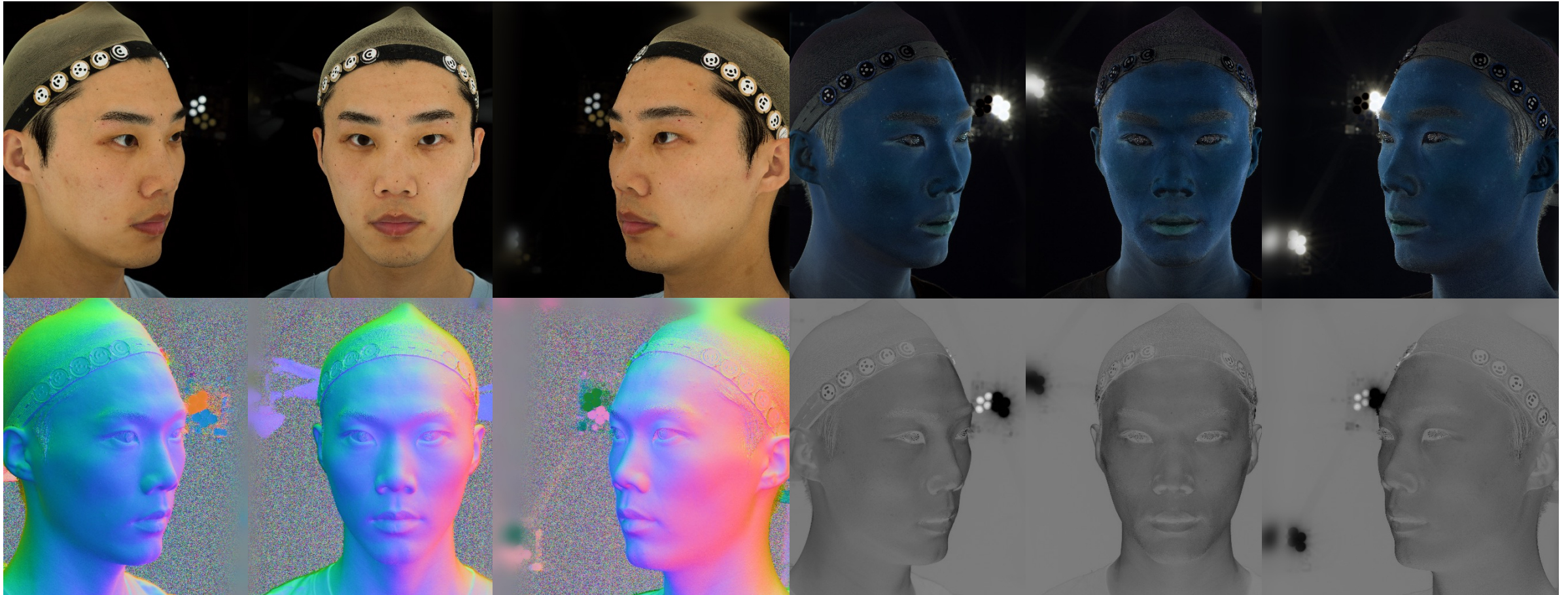
How to achieve **facial reflectance reconstruction**  
for a single image with **limited captured raw data?**

# Our Capture System

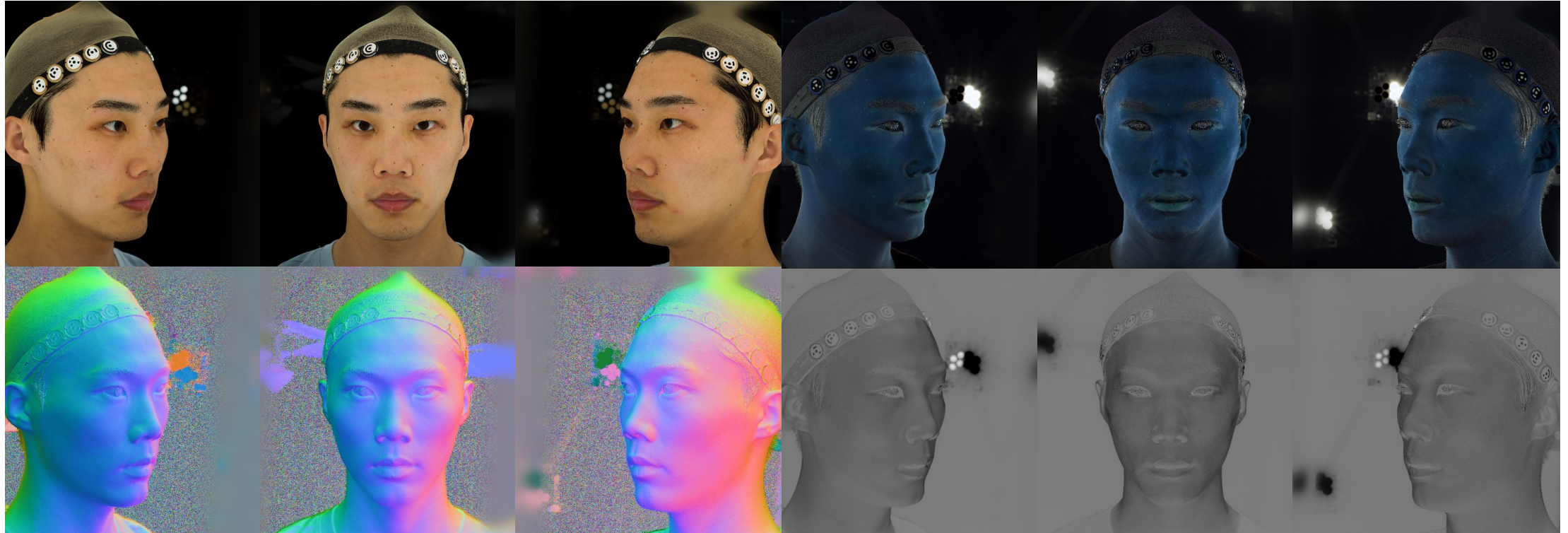




# Motivation



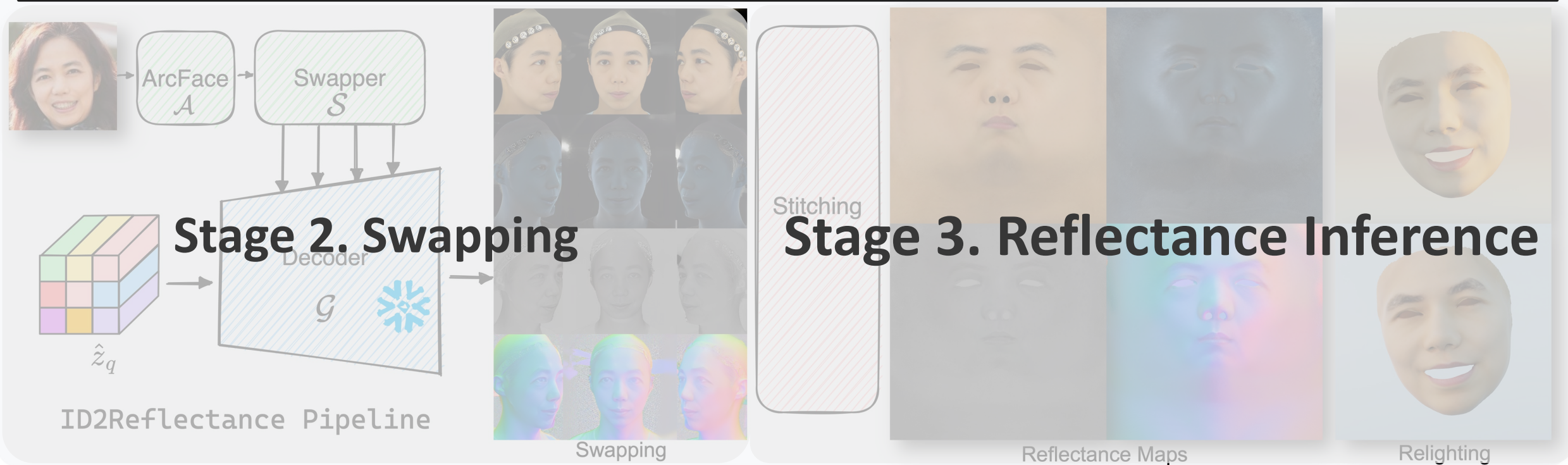
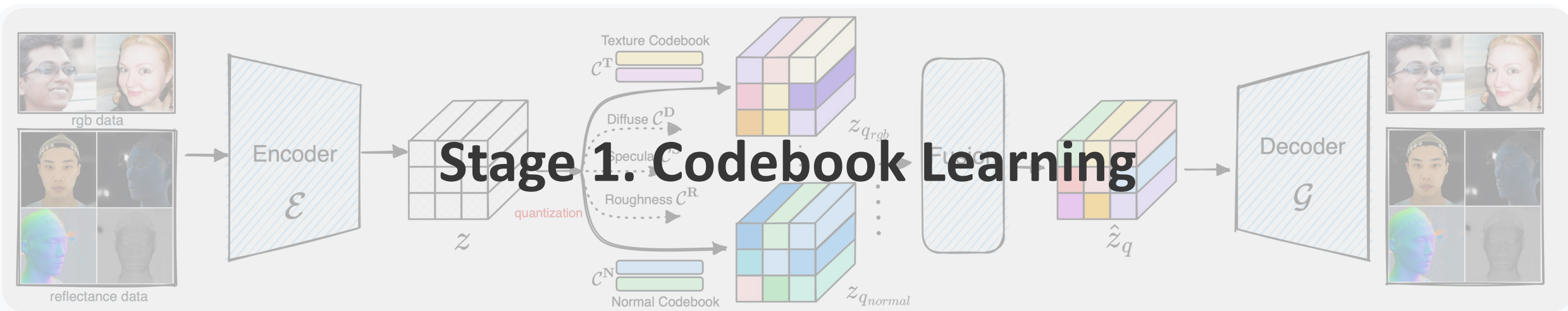




Insight: Model the **facial structure** (lots of RGB data) and the **appearance** (limited reflectance data) separately.



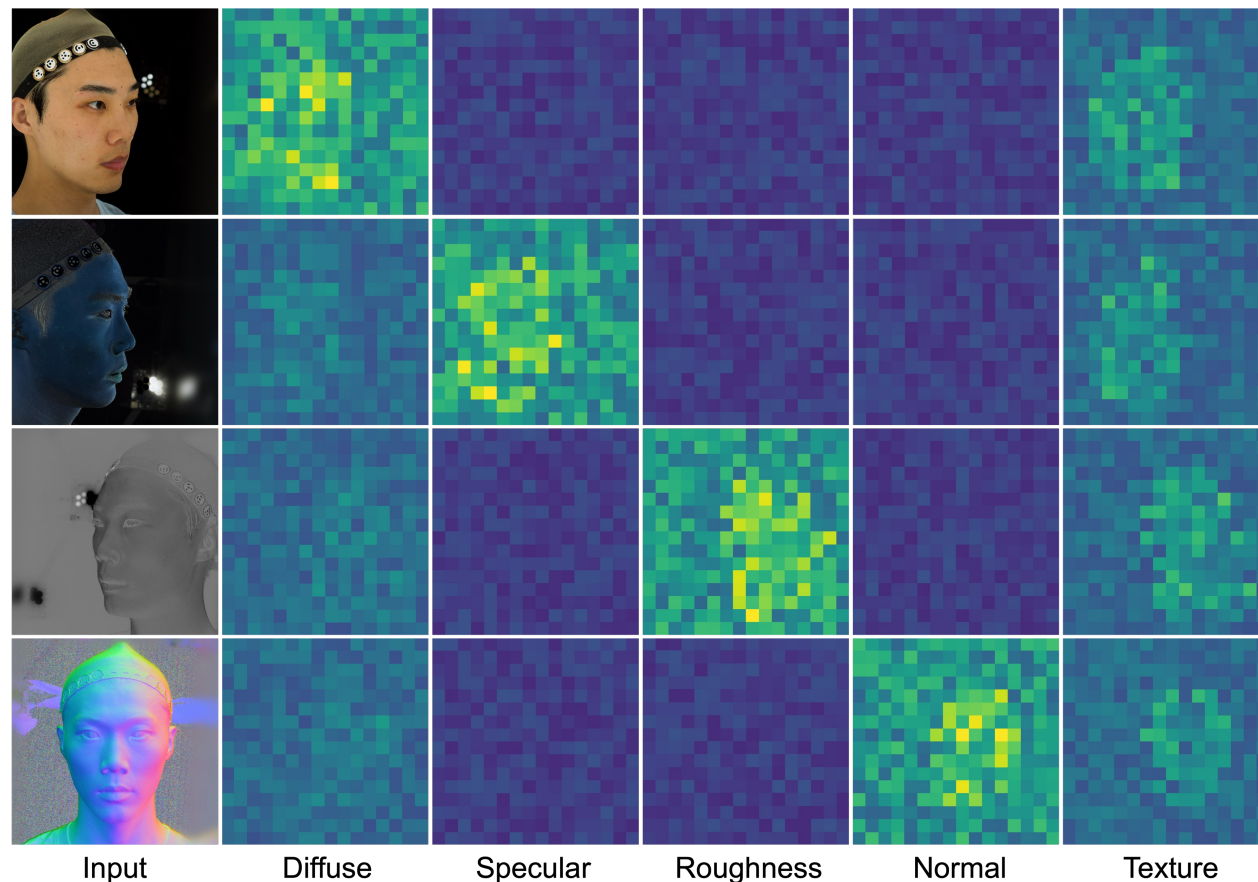
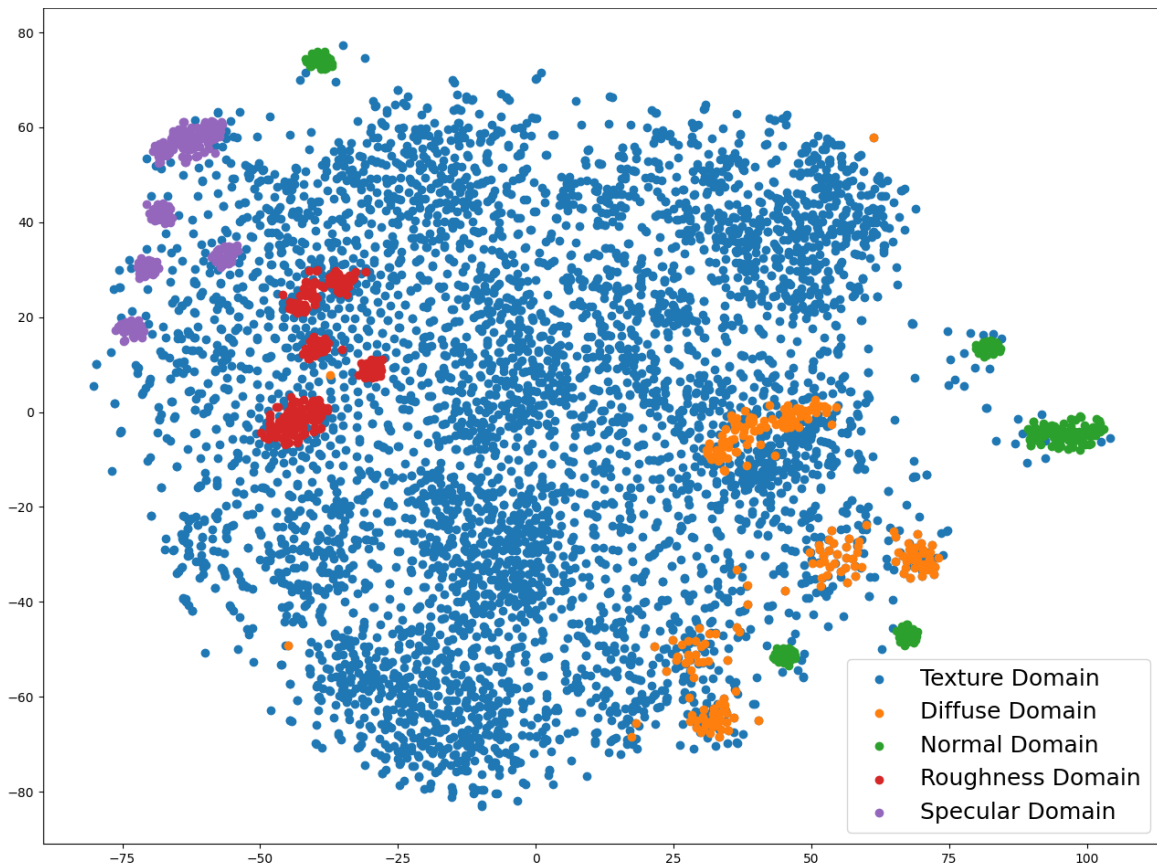
# Method | Pipeline



# Method | Codebook Learning



- **Stage 1:** Train a shared codebook by high quality facial RGB and reflectance data.
- **Stage 2:** Train a multi-domain codebook to further improve facial reflectance reconstruction.



t-SNE distribution of latent feature  $z_q$  for reflectance data and RGB data.

Visualization of codebook fusion weights.

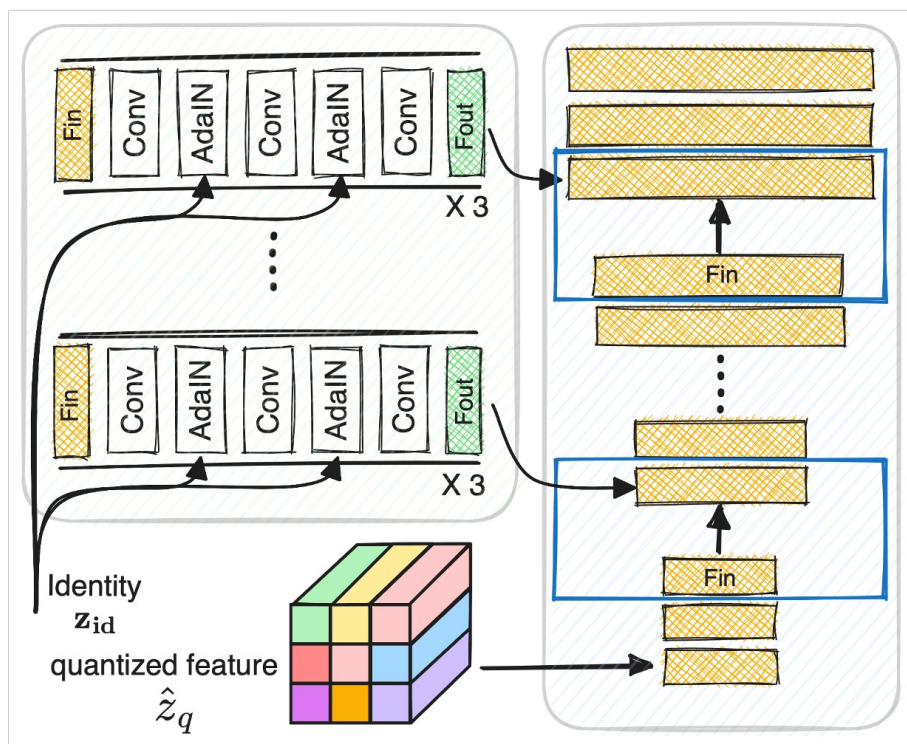




# Method | Identity Swapping



- **Codebook-based identity swapping:** Once identity injection module trained on RGB data, which can be automatically migrated to the facial reflectance domain.



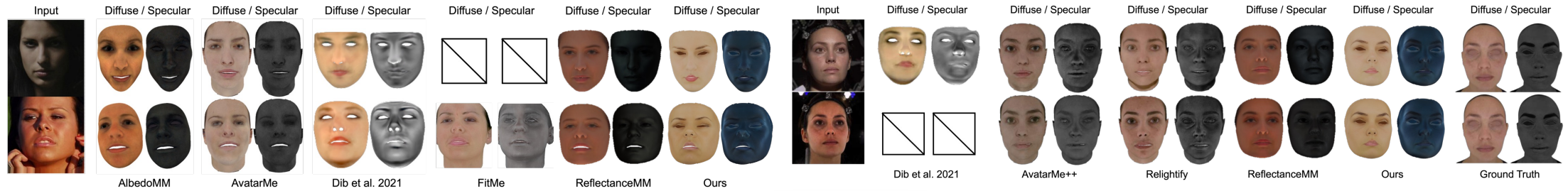
Detailed architecture of our swapper module.

Comparison of swapper module under different configurations. F16 means that the source identity is injected from an upsample layer with a feature size of 16x16.

Configuration	ID-Retrieval $\uparrow$	pose $\downarrow$
F16	N/A	N/A
F16 + F32	0.894	0.0143
F16 + F32 + F64	0.941	0.0132
F16 + F32 + F64 + F128 + F256	0.933	<b>0.0128</b>
F16 + F32 + F64 + F128 (Ours)	<b>0.965</b>	0.0129



# Experiments | Facial Reflectance Reconstruction



Input / Relighting

Swapping

Reflectance Maps

Input / Relighting

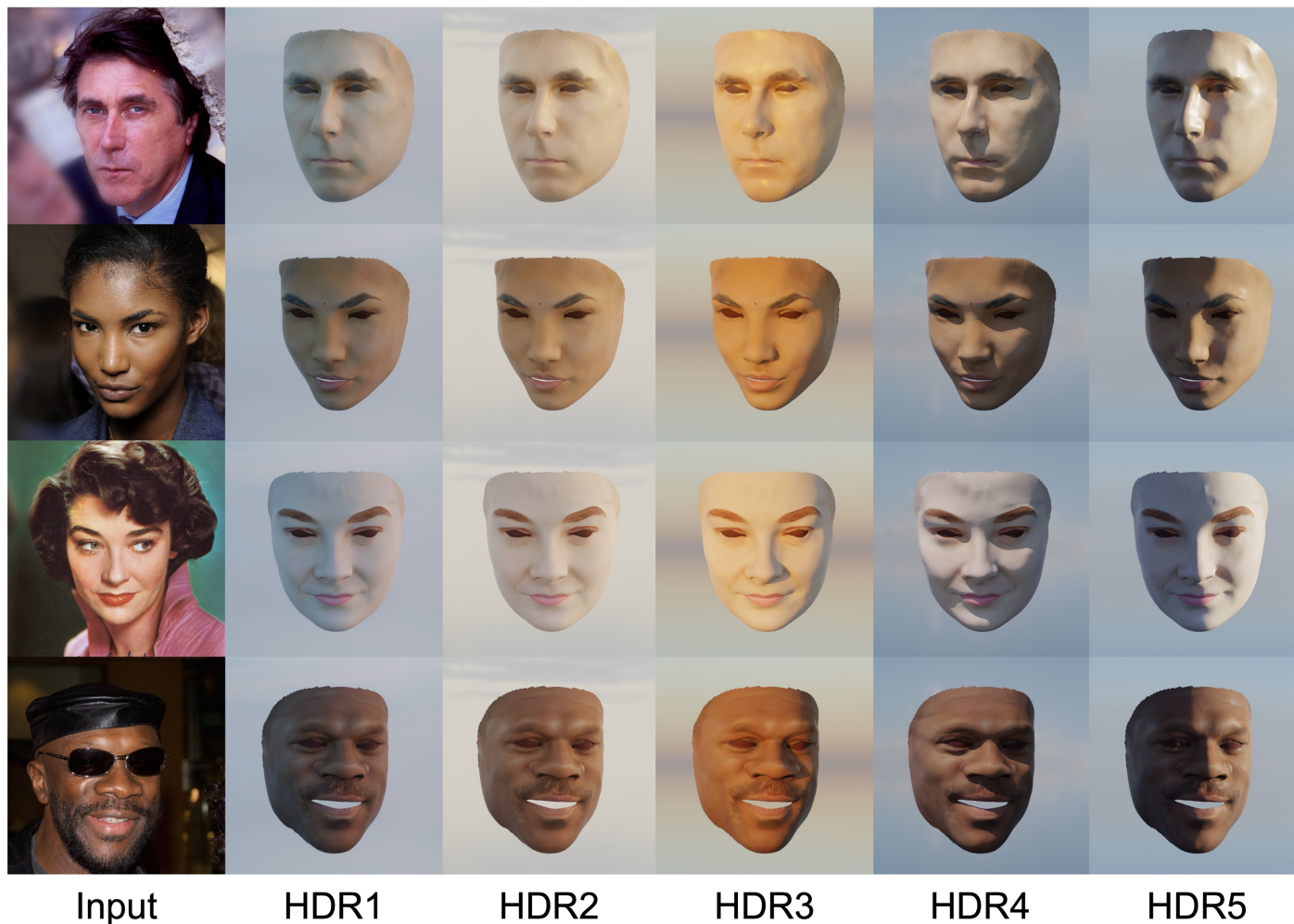
Swapping

Reflectance Maps





# Experiments | Albedo Reconstruction & Relighting



Comparisons of our method with previous methods on albedo estimation

Methods	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	ID $\uparrow$
TRUST [17]	21.63	0.852	0.2014	0.478
ID2Albedo [54]	23.72	0.884	0.1549	0.532
Ours	<b>28.47</b>	<b>0.923</b>	<b>0.1248</b>	<b>0.735</b>



# Experiments | Relighting results via hard inputs



Input

HDR1

HDR2

HDR3

HDR4

HDR5

HDR6

HDR7

HDR8

HDR9

HDR10





# Ablation Studies | Reflectance Codebooks



Comparison to state-of-the-arts on the FAIR benchmark

Method	Avg. ITA ↓	Bias ↓	Score ↓	MAE ↓	ITA per skin type ↓					
					I	II	III	IV	V	VI
Deep3D [13]	22.57	24.44	47.02	27.98	<b>8.92</b>	<b>9.08</b>	8.15	10.90	28.48	69.90
GANFIT [20]	62.29	31.81	94.11	63.31	94.80	87.83	76.25	65.05	38.24	11.59
MGCNet [57]	21.41	17.58	38.99	25.17	19.98	12.76	8.53	<b>9.21</b>	22.66	55.34
DECA [18]	28.74	29.24	57.98	38.17	9.34	11.66	11.58	16.69	39.10	84.06
INORig [2]	27.68	28.18	55.86	33.20	23.25	11.88	<b>4.86</b>	9.75	35.78	80.54
CEST [68]	35.18	12.14	47.32	29.92	50.98	38.77	29.22	23.62	21.92	46.57
TRUST [17]	13.87	<b>2.79</b>	<b>16.67</b>	<b>18.41</b>	11.90	11.87	11.20	13.92	<b>16.15</b>	18.21
ID2Albedo [54]	<b>12.07</b>	4.91	16.98	23.33	18.30	9.13	5.83	9.46	19.09	<b>10.59</b>
Ours	14.21	4.22	18.43	22.02	12.91	13.11	9.68	10.22	17.72	21.63

Comparison of ID2Reflectance framework under different training data.

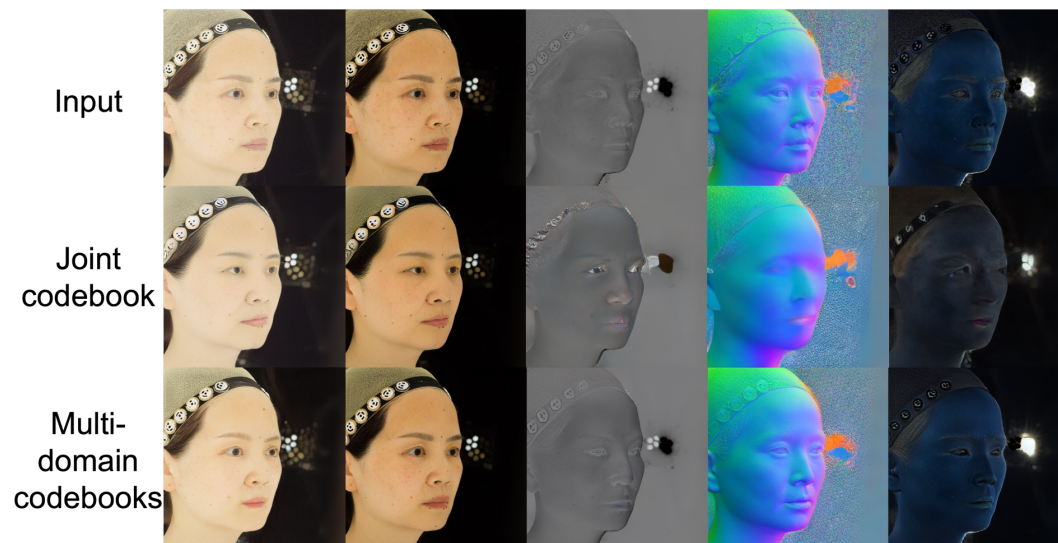
Numbers	Diffuse	Specular	Roughness	Normal
30 subjects	25.09	24.12	24.78	23.55
60 subjects	28.63	27.58	28.22	27.05
90 subjects	30.54	29.84	30.41	29.22
115 subjects	31.62	30.96	31.59	30.32

Comparison of ID2Reflectance framework under different configurations.

(1) joint codebook v.s. multi-domain codebooks for reflectance reconstruction, and (2) fixed swapping template v.s. closest swapping template for identity-conditioned reflectance prediction.

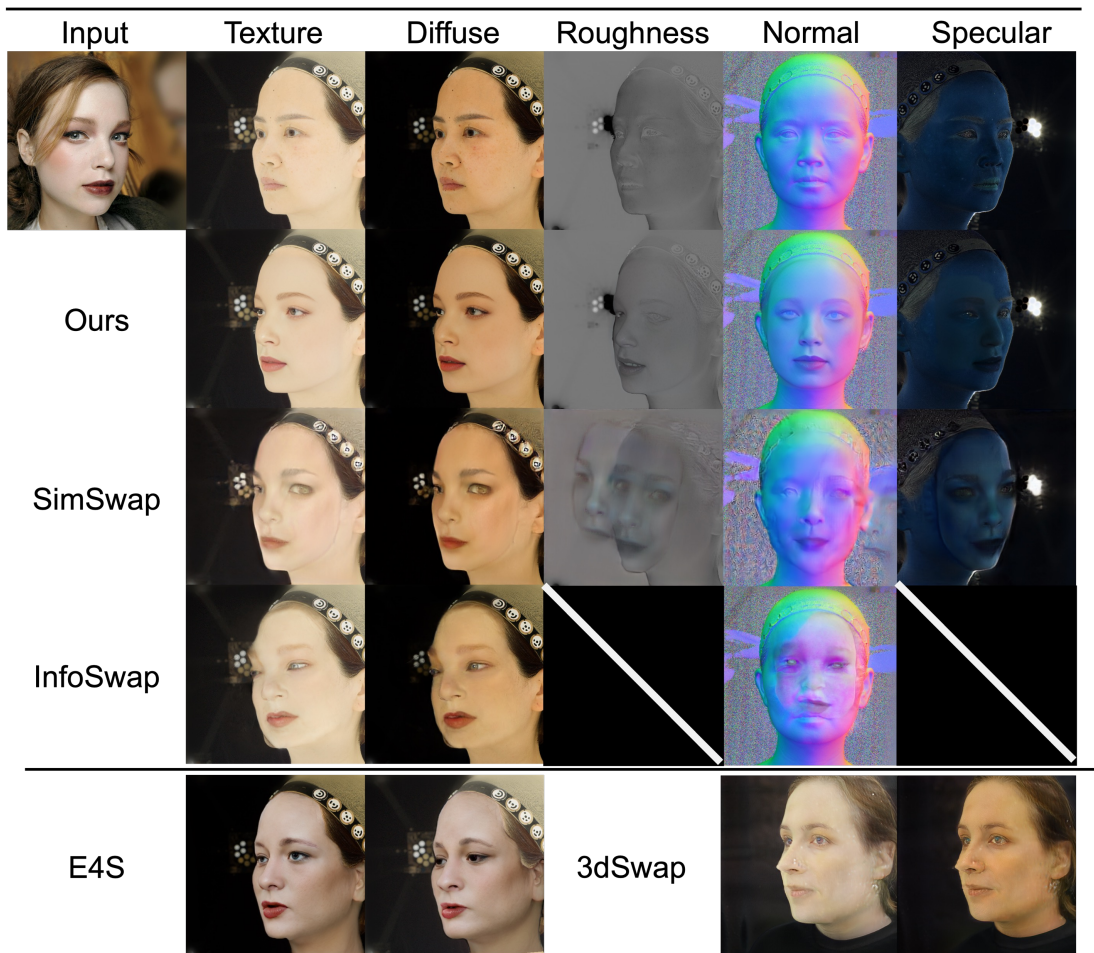
Configs	Diffuse	Specular	Roughness	Normal
Joint codebook	24.87	20.95	21.31	20.56
Multi-domain codebooks	31.62	30.96	31.59	30.32
Fixed Template	25.26	26.44	29.56	25.77
Closest Template	28.47	26.68	30.32	26.83

Reconstruction comparison of using joint and multi-domain codebooks. Inputs are the same faces from PBR domains.

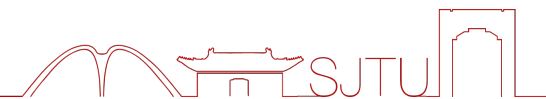




# Ablation Studies | Face Swapping



Cross-domain swapping comparison with other methods.







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人工智能研究院

Artificial Intelligence Institute

Thank you

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