

Controllable 3D Face Synthesis with Conditional Generative Occupancy Fields

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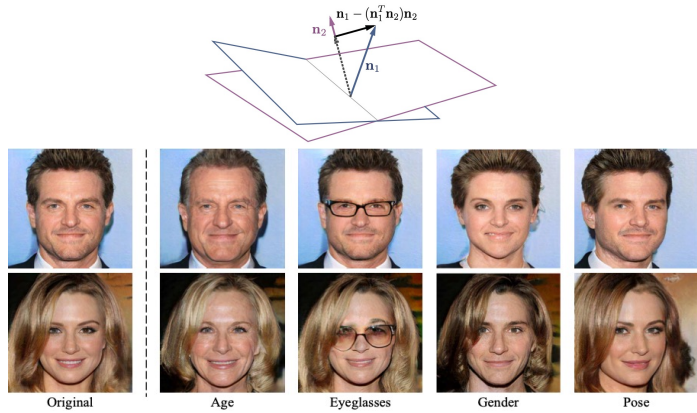
Ning Zhang
SenseTime

Quan Wang
SenseTime

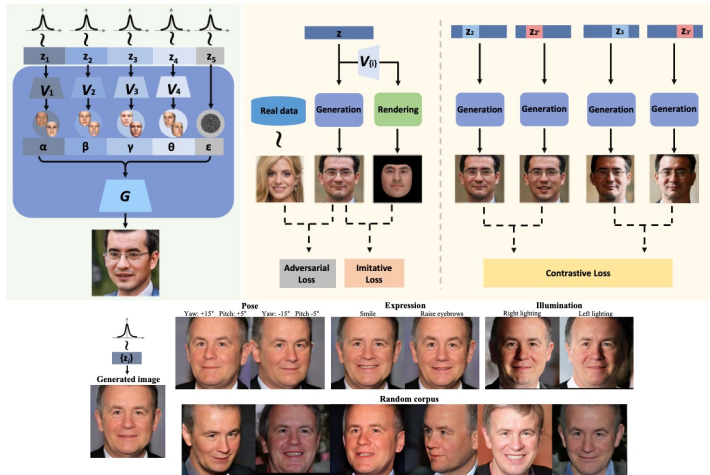
Hongsheng Li
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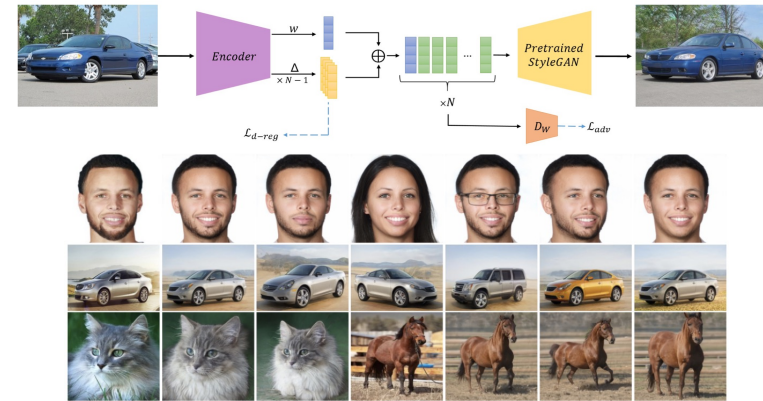
2D Generator Based



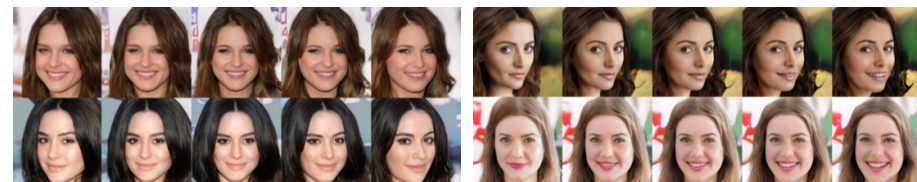
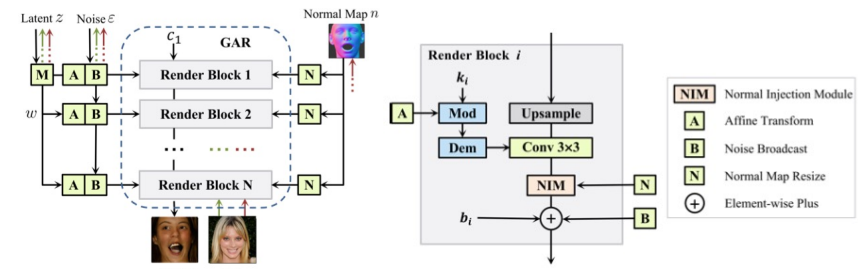
Shen, Yujun, et al. "Interpreting the latent space of gans for semantic face editing." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2020.



Deng, Yu, et al. "Disentangled and controllable face image generation via 3d imitative-contrastive learning." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2020.

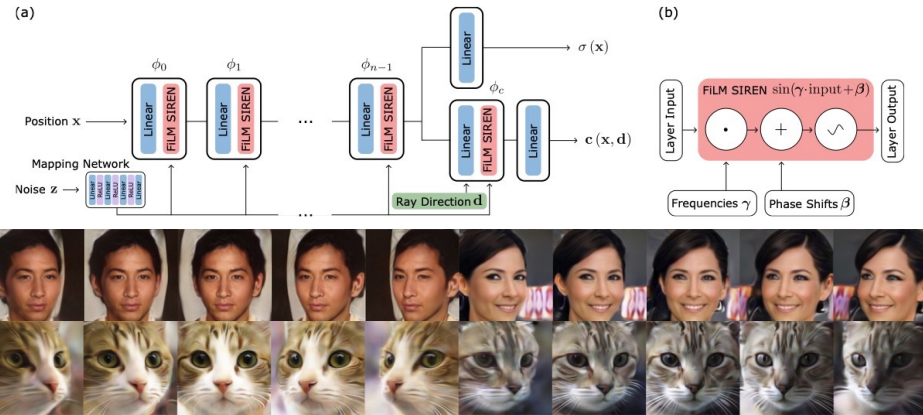


Omer Tov, Yuval Alaluf, Yotam Nitzan, Or Patashnik, and Daniel Cohen-Or. Designing an encoder for stylegan image manipulation. SIGGRAPH, 2021.

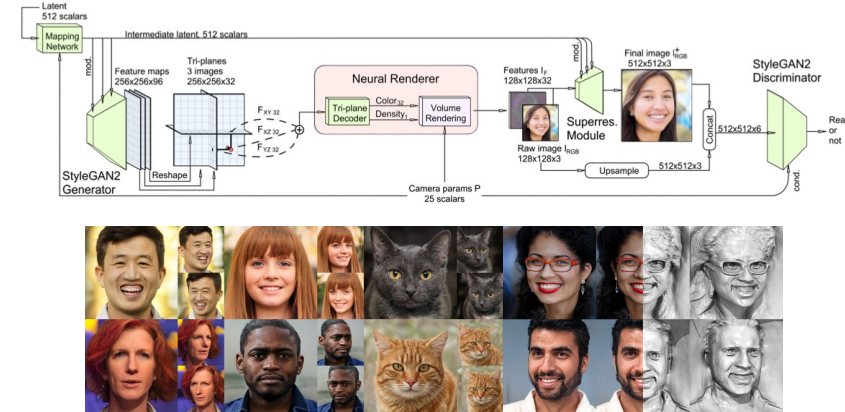


Piao, Jingtian, et al. "Inverting Generative Adversarial Renderer for Face Reconstruction." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021.

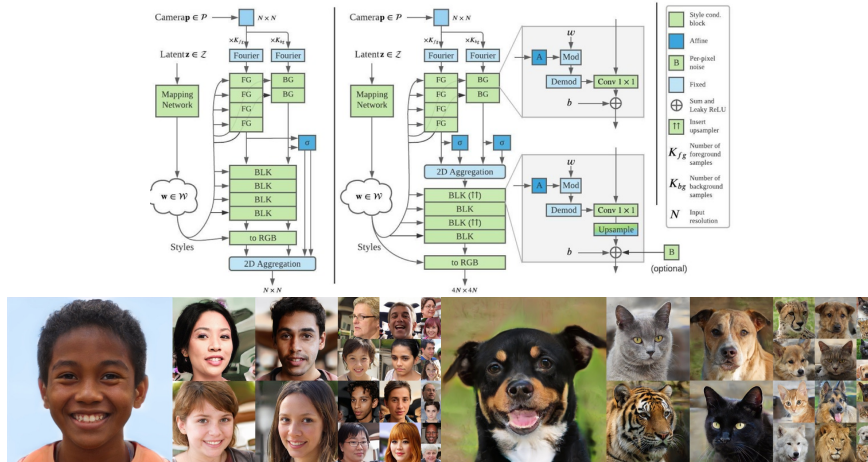
3D Generator



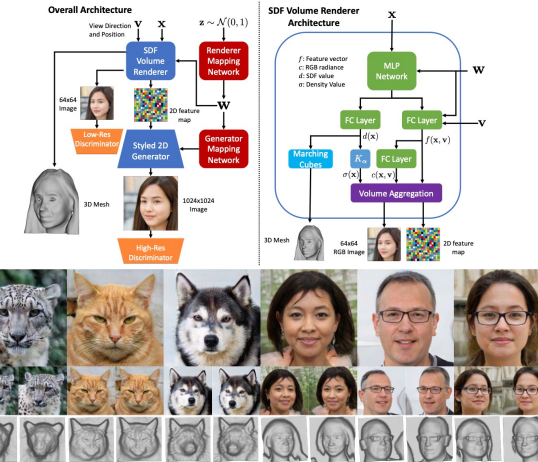
Chan, Eric R., et al. "pi-gan: Periodic implicit generative adversarial networks for 3d-aware image synthesis." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2021.



Chan, Eric R., et al. "Efficient geometry-aware 3D generative adversarial networks." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2022.

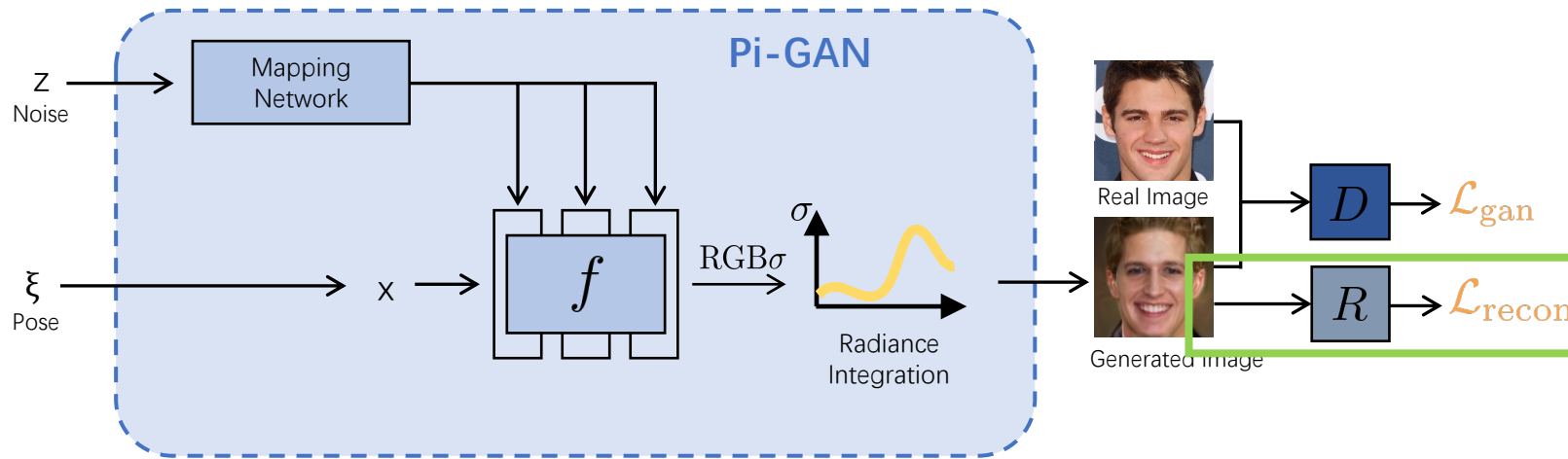


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Conditional Generative Occupancy Fields

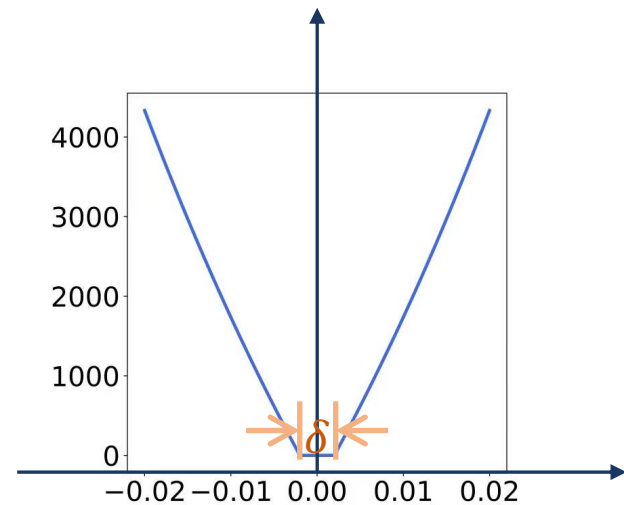
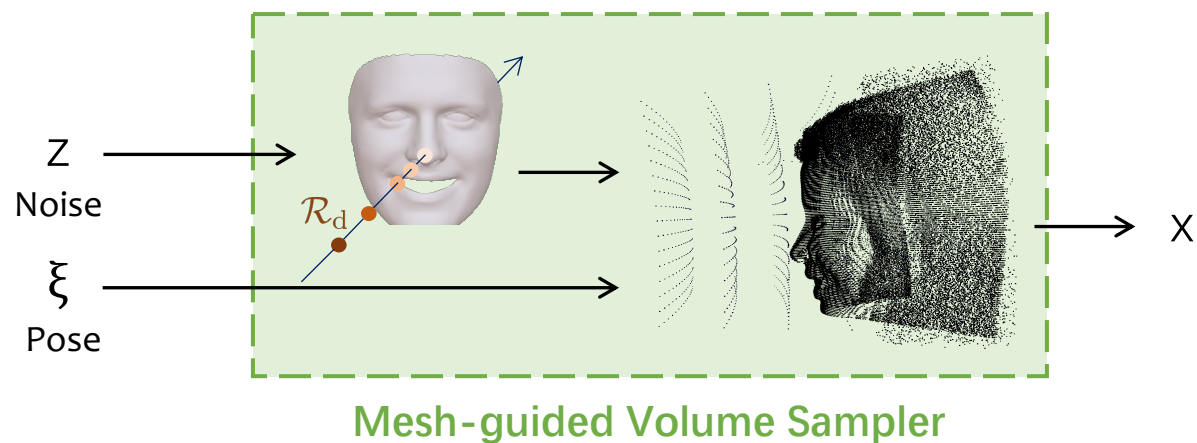


$$\mathcal{L}_{recon} = \|\hat{\mathbf{z}} - \mathbf{z}\|_1, \quad \text{where} \quad \hat{\mathbf{z}} = \tau(R(G(\mathbf{z}, \xi))).$$

Index	Loss	CD ↓	LD ↓	LC ↑	DS_s ↑	DS_e ↑	DS_p ↑	FID (128) ↓
1	\mathcal{L}_{gan}	1.09	5.04	2.04	2.13	2.54	7.16	18.76
2	$+\mathcal{L}_{recon}$	0.87	3.85	26.15	3.56	5.03	11.00	21.97

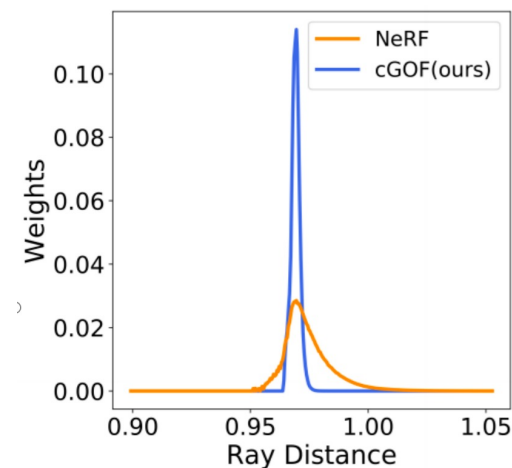
(baseline)

Conditional Generative Occupancy Fields



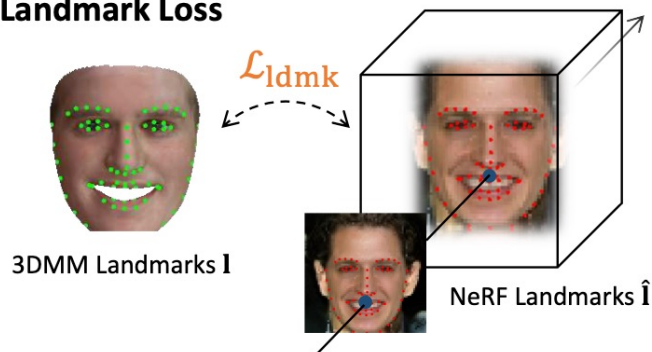
$$R_d = \sum_{i=0}^{N_{vol}} \sigma_i \cdot \underbrace{[\exp(\alpha \cdot \max(d_i - \delta/2, 0)) - 1]}_{\text{Weight Term}}$$

Index	Loss	CD ↓	LD ↓	LC ↑	DS_s ↑	DS_e ↑	DS_p ↑	FID (128) ↓
1	\mathcal{L}_{gan}	1.09	5.04	2.04	2.13	2.54	7.16	18.76
2	+ \mathcal{L}_{recon}	0.87	3.85	26.15	3.56	5.03	11.00	21.97
3	(+ \mathcal{L}_{depth})*	1.65	6.16	0.06	0.93	1.34	1.09	71.67
4	+ MgS	0.29	3.98	27.45	3.55	4.90	9.48	38.91
5	+ \mathcal{R}_d	0.31	3.51	51.74	3.56	5.31	15.94	29.62

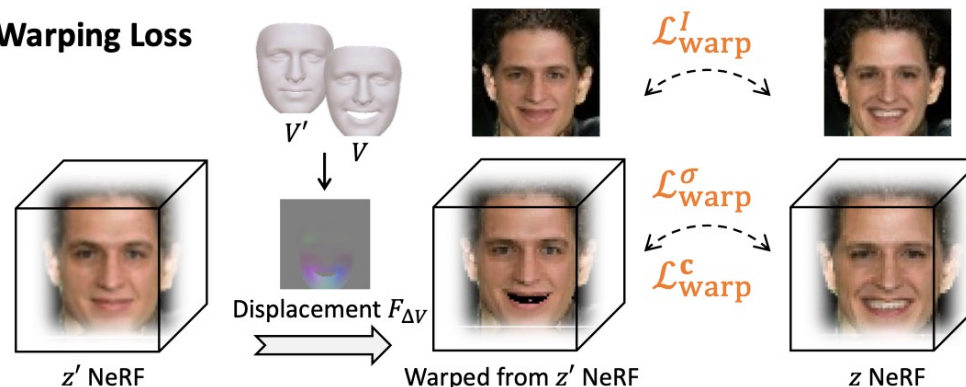


Conditional Generative Occupancy Fields

3D Landmark Loss



Volume Warping Loss

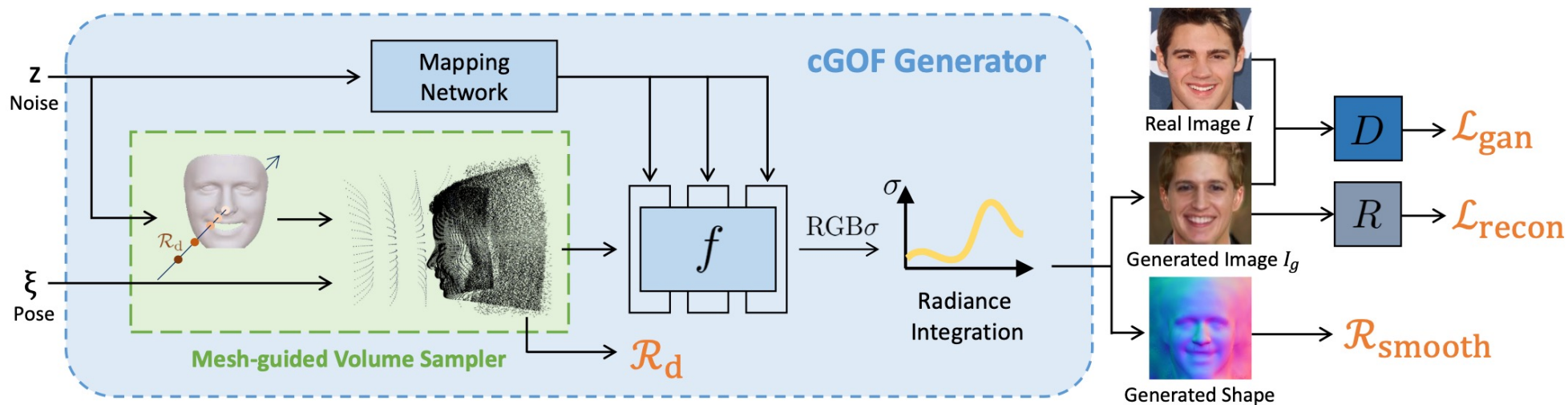


$$\mathcal{L}_{\text{ldmk}} = \sum_{k=1}^{N_k} \|\hat{\mathbf{l}}_k - \mathbf{l}_k\|_1 + \sum_{k=18}^{N_k} \|\hat{\mathbf{l}}'_k - \mathbf{l}_k\|_1.$$

$$\mathcal{L}_{\text{warp}} = \beta_d \cdot \sum_i^{N_{\text{surf}}} \|\sigma'_i - \sigma_i\|_1 + \beta_c \cdot \sum_i^{N_{\text{surf}}} \|\mathbf{c}'_i - \mathbf{c}_i\|_1 + \beta_I \cdot \|\hat{I}_g - I_g\|_1,$$

Index	Loss	CD ↓	LD ↓	LC ↑	DS_s ↑	DS_e ↑	DS_p ↑	FID (128) ↓
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4	+ MgS	0.29	3.98	27.45	3.55	4.90	9.48	38.91
5	+ \mathcal{R}_d	0.31	3.51	51.74	3.56	5.31	15.94	29.62
6	+ $\mathcal{R}_{\text{smooth}}^{\text{norm}}$	0.27	4.72	30.25	3.18	4.43	16.26	31.63
7	+ $\mathcal{L}_{\text{ldmk}}$	0.39	1.86	84.43	16.54	16.65	21.24	56.90
8	+ $\mathcal{L}_{\text{warp}}$	0.26	1.44	89.91	20.47	22.04	22.91	47.18

Conditional Generative Occupancy Fields



$$\mathcal{L} = \lambda_{gan}\mathcal{L}_{gan} + \lambda_{recon}\mathcal{L}_{recon} + \lambda_d\mathcal{R}_d + \lambda_{ldmk}\mathcal{L}_{ldmk} + \lambda_{warp}\mathcal{L}_{warp} + \lambda_{smooth}\mathcal{R}_{smooth}$$

Index	Loss	CD ↓	LD ↓	LC ↑	DS_s ↑	DS_e ↑	DS_p ↑	FID (128) ↓
1	\mathcal{L}_{gan}	1.09	5.04	2.04	2.13	2.54	7.16	18.76
2	+ \mathcal{L}_{recon}	0.87	3.85	26.15	3.56	5.03	11.00	21.97
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8	+ \mathcal{L}_{warp}	0.26	1.44	89.91	20.47	22.04	22.91	47.18
9	+ $\mathcal{R}_{smooth}^{depth}$	0.27	1.26	92.88	23.24	29.13	23.45	26.64

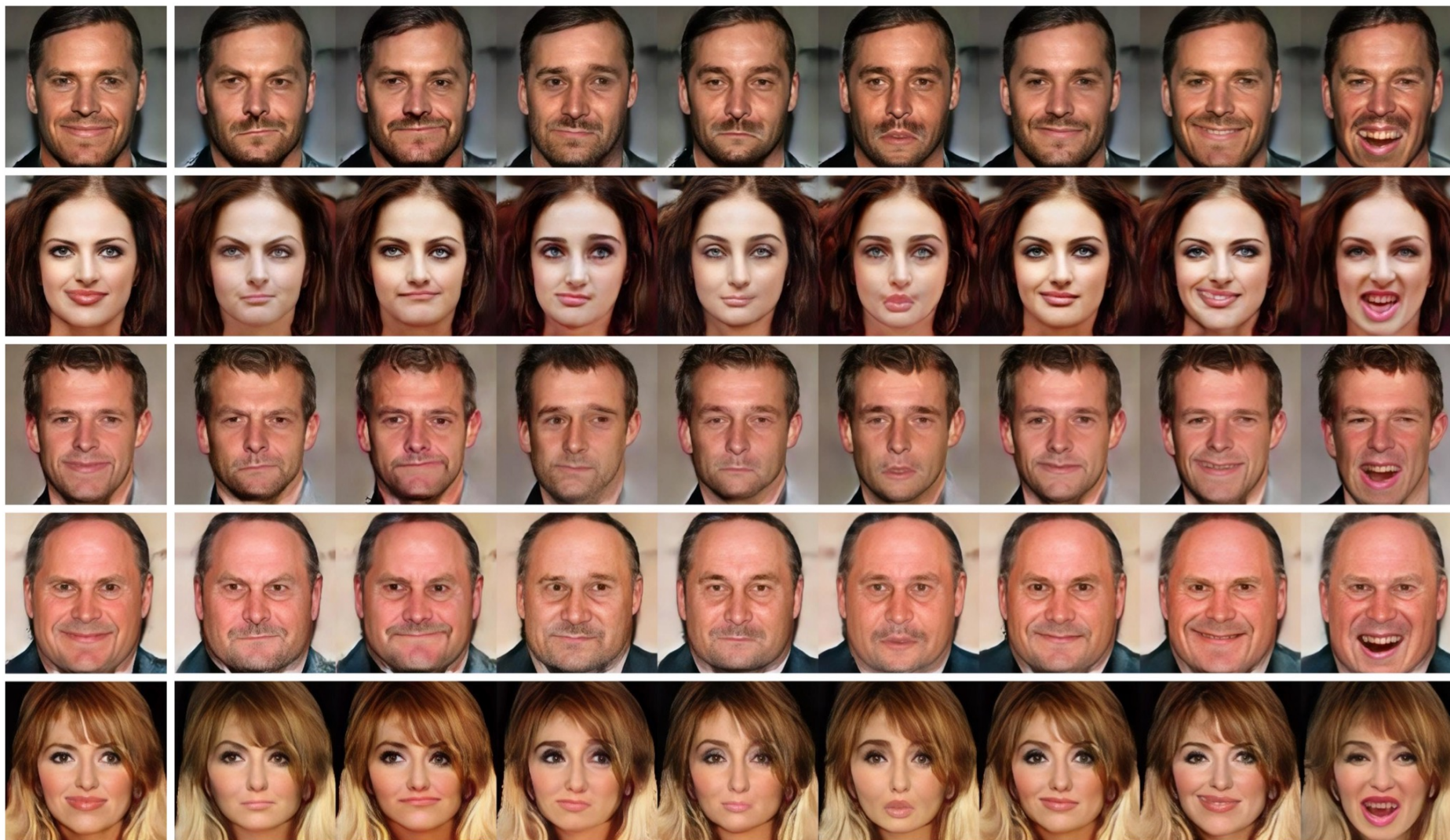
Qualitative Results

Consistent Identity



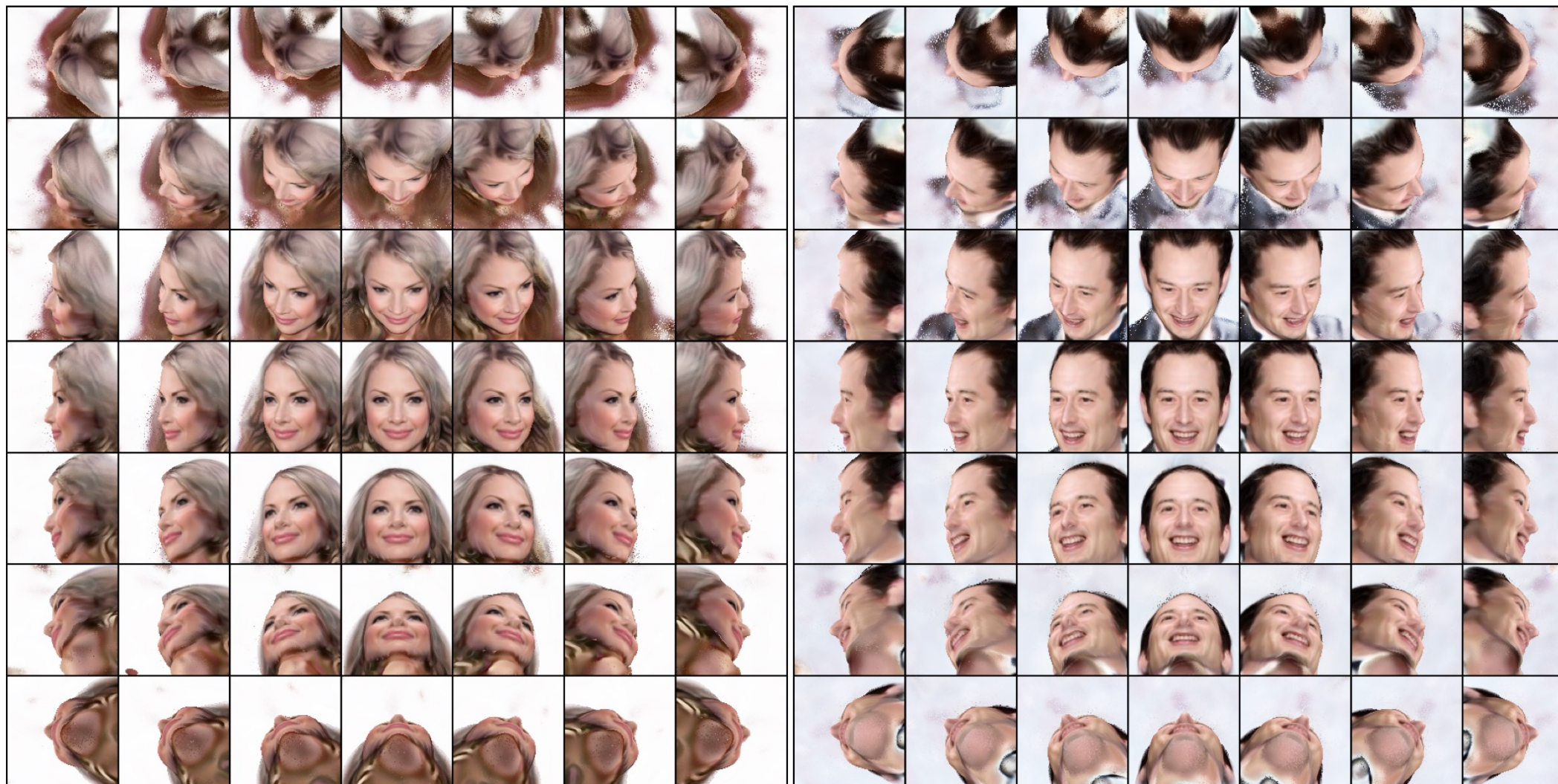
Consistent Expression Control

Qualitative Results



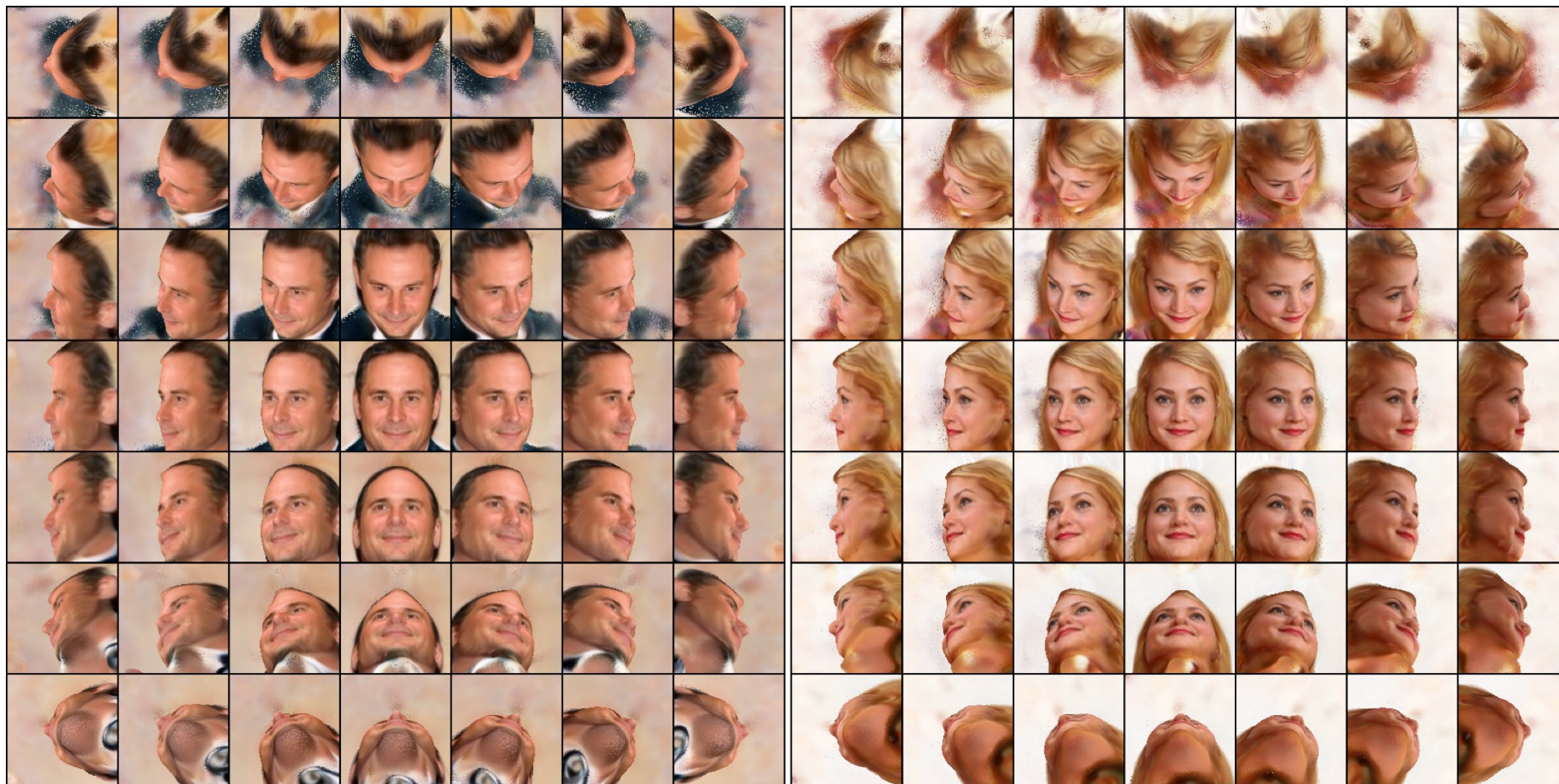
Out-of-distribution Expression Control Results

Qualitative Results



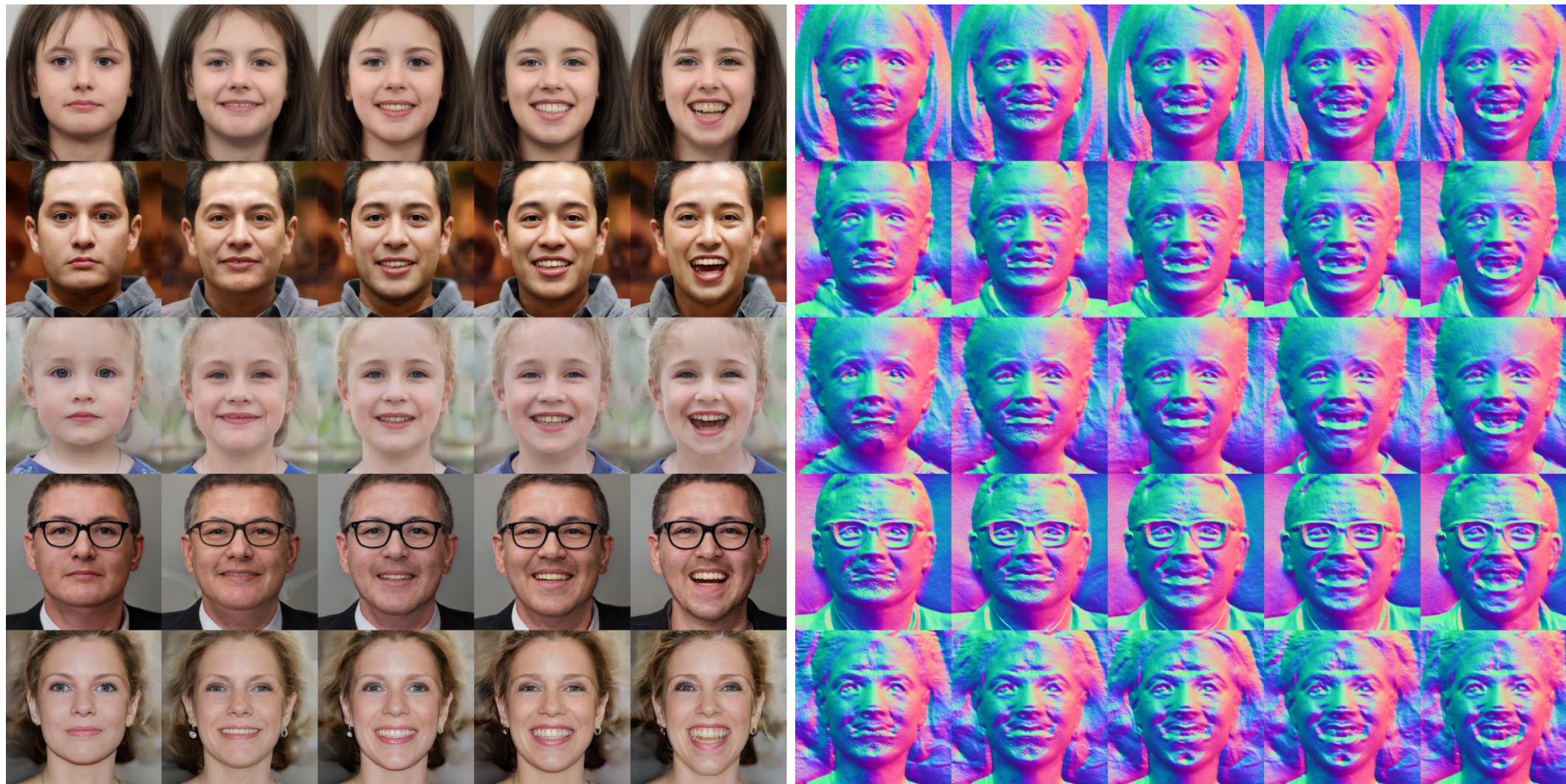
Head Pose Control Results

Qualitative Results



Head Pose Control Results

Extend to EG3D^[1]

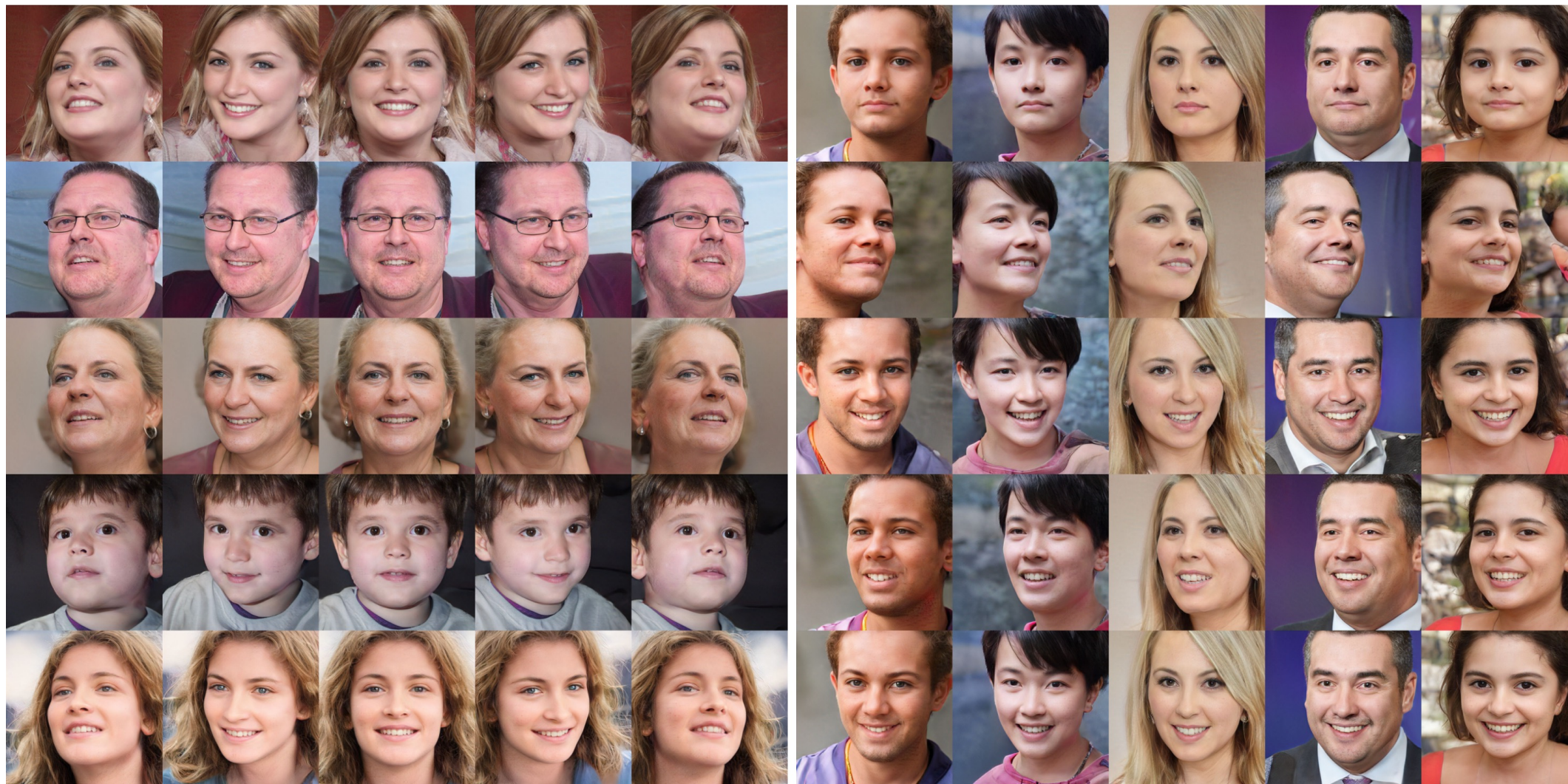


(a) Varying Expressions

(b) Corresponding Normal Maps for (a)

[1] Chan, Eric R., et al. "Efficient geometry-aware 3D generative adversarial networks." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2022.

Extend to EG3D^[1]

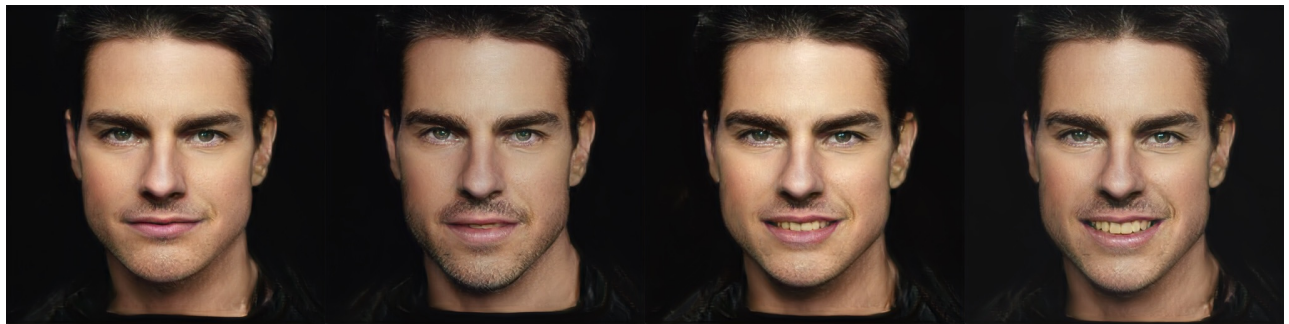
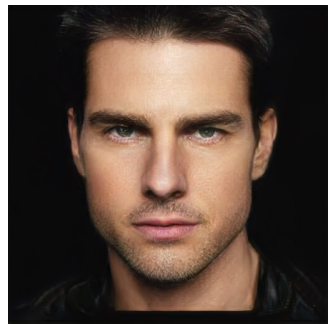
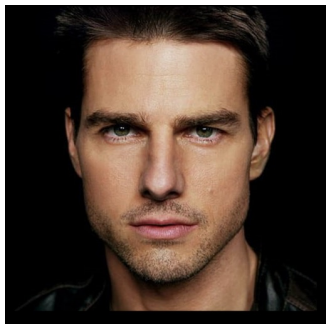


(c) Varying Poses

(d) Varying Identities

[1] Chan, Eric R., et al. "Efficient geometry-aware 3D generative adversarial networks." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2022.

Extend to EG3D^[1]



Input

Inversion

Varying Expression

[1] Chan, Eric R., et al. "Efficient geometry-aware 3D generative adversarial networks." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2022.



Thank You