



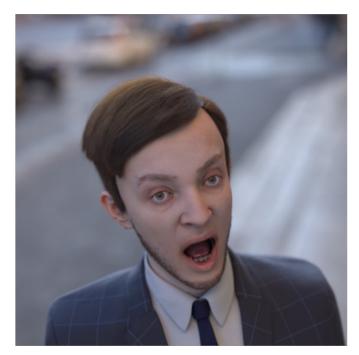
FashionR2R: Texture-preserving Rendered-to-Real Image Translation with Diffusion Models

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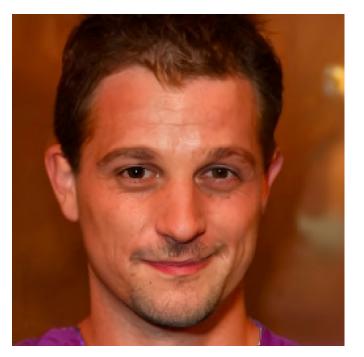
Motivation

- Rendering methods
 - Modeling accuracy
 VS computation efficiency



From FaceSynthetics (ICCV 2021)

- Generative methods
 - Impressive authenticity
 - Poor controllability and editability



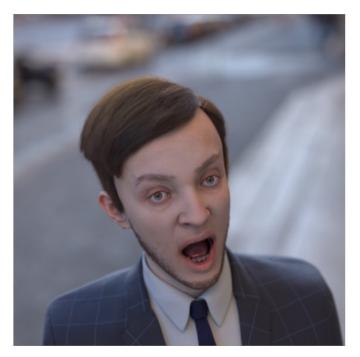
From LDM (CVPR 2022)

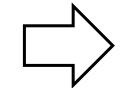


Problem Definition

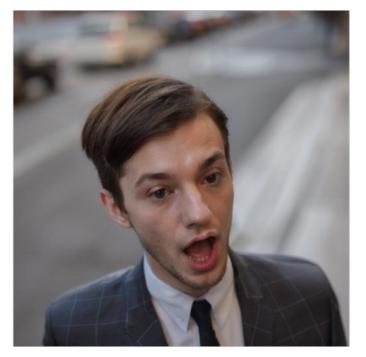
• Rendered-to-Real image translation

Rendered









From FaceSynthetics (ICCV 2021)



Previous Works

• Rendered-to-real image translation

Deep CG2Real (ICCV 2019)





• General image-to-image translation & style transfer

UNSB (ICLR 2024)



VCT (ICCV 2023)



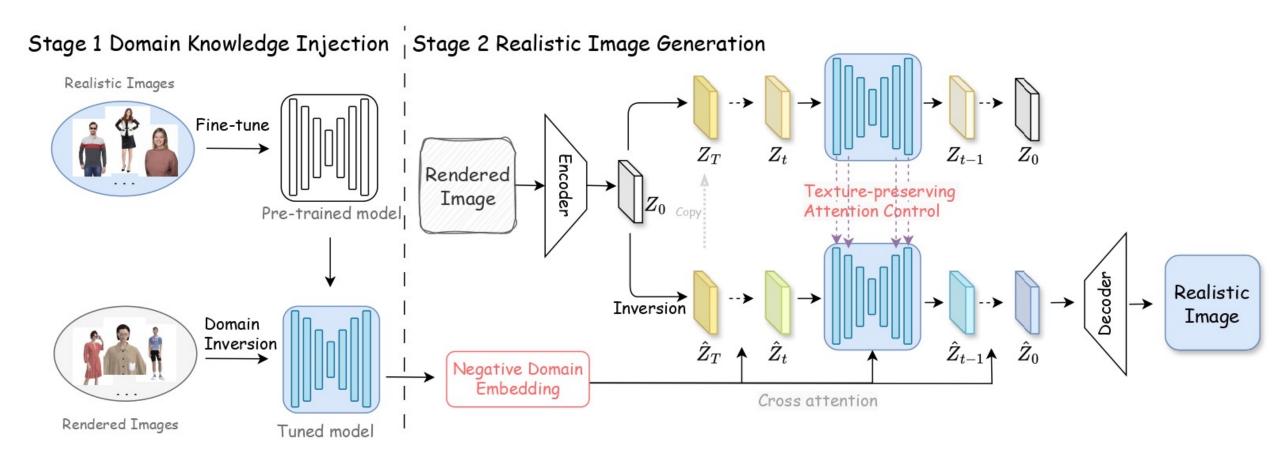


Main Idea

- Leverage generative prior from pretrained T2I diffusion models.
 - Adaptation to realistic image generation under the guidance of distilled rendered prior.
- Exploit decoupled features in the UNet structure.
 - A texture-preserving mechanism by extracting attention features from an inversion pipeline.

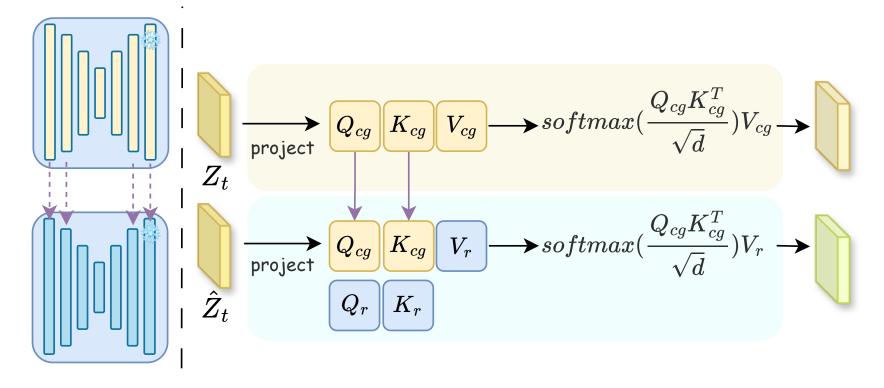


Framework





Texture-preserving Attention Control

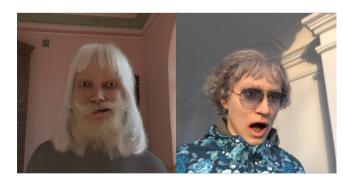


 $\widehat{Q^{t}}, \widehat{K^{t}} = TAC\left(Q_{cg}^{t}, K_{cg}^{t}, Q_{r}^{t}, K_{r}^{t}, t\right) = \begin{cases} Q_{cg}^{t}, K_{cg}^{t} & \text{if } t < \gamma T, f > F \\ Q_{r}^{t}, K_{r}^{t} & \text{otherwise} \end{cases}$



Evaluation

- Datasets
 - Face Synthetics & SynFashion.



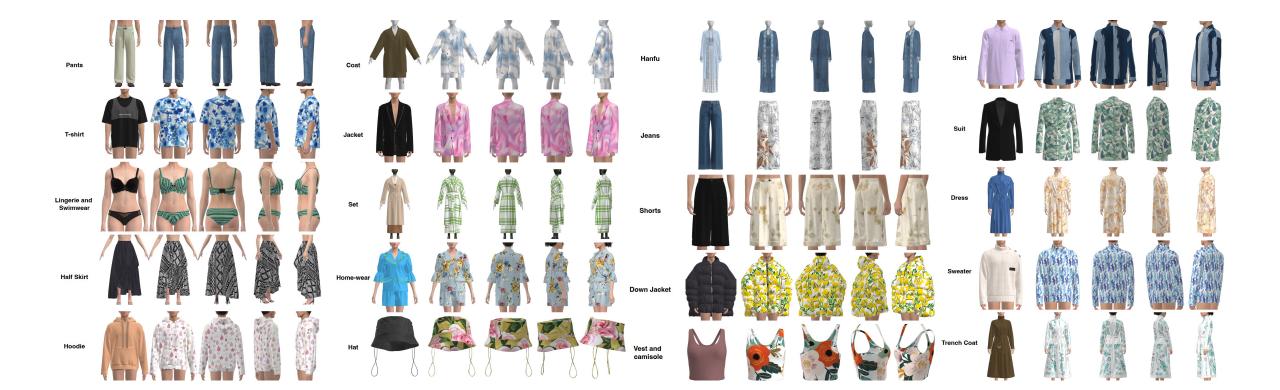


- Metrics
 - KID (to real), LPIPS & SSIM (to rendered).
- User studies
 - Overall realism, image quality and consistency.



SynFashion Dataset

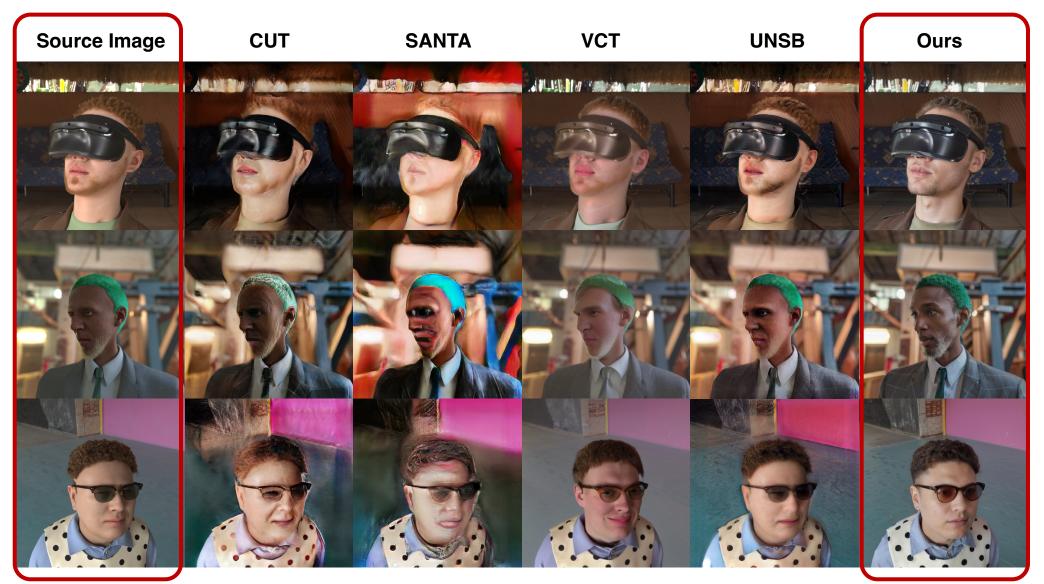
- Collected via Style3D Studio
 - 10k rendered images, 20 categories, 375 3D projects, 500 textures







Qualitative Results – Face Synthetics





Qualitative Results – SynFashion





Quantitative Results

• Quantitative comparisons

Dataset	Face Synthetics			SynFashion		
	KID↓(std)	LPIPS↓(std)	SSIM [†] (std)	KID↓(std)	LPIPS↓(std)	SSIM†(std)
CUT [10]	80.553 (2.447)	0.365 (0.073)	0.664 (0.079)	59.238 (1.599)	0.170 (0.060)	0.847 (0.067)
SANTA [11]	90.390 (2.929)	0.387 (0.079)	0.618 (0.104)	61.636 (1.628)	0.294 (0.067)	0.741 (0.082)
VCT [13]	74.445 (2.273)	0.096 (0.027)	0.807 (0.072)	59.489 (1.499)	0.178 (0.058)	0.807 (0.085)
UNSB [12]	76.389 (2.465)	0.229 (0.069)	<u>0.818</u> (0.070)	59.496 (1.453)	<u>0.130</u> (0.040)	0.891 (0.054)
Ours	73.871 (1.973)	<u>0.121</u> (0.035)	0.831 (0.068)	54.720 (1.362)	0.067 (0.025)	<u>0.881</u> (0.055)

• User studies - percentage of votes each method are preferred to ours

Dataset	F	ace Synthetics		SynFashion			
	Overall Realism	Image Quality	Consistency	Overall Realism	Image Quality	Consistency	
CUT	0.529%	0.529%	13.175%	8.994%	6.878%	16.931%	
SANTA	0.922%	1.383%	12.304%	3.333%	5.238%	11.571%	
VCT	5.952%	14.286%	20.714%	2.041%	6.122%	18.367%	
UNSB	4.511%	6.767%	21.278%	9.821%	9.821%	26.607%	



Ablation Studies

• Visual examples



• Numerical results

Dataset	Face Synthetics			SynFashion			
	KID↓(std)	LPIPS↓(std)	SSIM [†] (std)	KID↓(std)	LPIPS↓(std)	SSIM [†] (std)	
w/o source DKI	77.376 (2.063)	0.107 (0.029)	0.857 (0.059)	58.520 (1.902)	0.059 (0.019)	0.903 (0.065)	
w/o target DKI	78.927 (2.134)	0.114 (0.031)	0.845 (0.063)	60.186 (1.623)	0.064 (0.022)	0.897 (0.056)	
w/o TAC	69.349 (1.485)	0.253 (0.070)	0.720 (0.085)	51.392 (1.083)	0.183 (0.047)	0.794 (0.074)	
Ours	73.831 (1.973)	0.121 (0.035)	0.831 (0.068)	54.720 (1.362)	0.067 (0.025)	0.881 (0.055)	



Conclusion

- A novel framework for rendered-to-real fashion image translation.
 - Generative prior from pretrained diffusion models.
- Two-stage: Domain Knowledge Injection and Realistic Image Generation.
 - DKI: positive domain finetuning & negative domain embedding.
 - RIG: texture-preserving attention control.
- A high-quality rendered fashion image dataset: SynFashion.