







Preview

- Current approaches only learn to swap 2D facial images:
 - Exist undesirable artifacts
 - Transfer less accurate geometric facial features
- We swap face in a 3D-aware manner!



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What is Face Swapping?



Source Image



Target Image



Swapped Face





Motivation

- Existing face swapping approaches
 - 3D-based methods
 - GAN-based methods / GAN-inversion-based methods
- Problems of existing approaches



3D-based Method



GAN-based Method





Challenges

- Challenges of 3D-aware face swapping task:
 - How to infer both geometry and texture prior from single-view 2D images?
 - How to leverage such inferred prior to swap face in a 3D-aware manner?



Source

Target View

Intermediate Views

Source View

Geometry





Infer 3D Prior

- How to infer both geometry and texture prior from single-view 2D images?
 - Solution: Introduce a 3D GAN inversion framework to project 2D inputs into 3D latent space.
- Difference between 2D/3D GAN inversion
 - For 2D GAN inversion
 - Formulation

 $w^* = \underset{w}{\operatorname{arg\,min}} \mathcal{L}(G(w), x)$

- Information of camera pose is embedded in the latent space
- For 3D GAN inversion
 - Formulation

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \mathcal{L}(G(\boldsymbol{w}, \boldsymbol{p}), \boldsymbol{x})$$

· Information of camera pose is disentangled from the latent space





Infer 3D Prior

• Pseudo-multi-view train strategy



 $\min_{\theta} \{ \mathcal{L}(x, x') + \eta \mathcal{L}(x, \hat{x}') + \mathcal{L}(w_x, w_{\hat{x}}) \}$



Latent Code Manipulation

- How to leverage such inferred prior to swap face in a 3D-aware manner?
 - Solution: Design a face swapping algorithm based on the 3D latent codes and directly synthesize the swapped faces with the 3D-aware generator.







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$$w_{fs}^{(i)} = \begin{cases} \rho^{(i)} \times w_t^{(i)} + (1 - \rho^{(i)}) \times w_s^{(i)} & i \in [5, 9] \\ w_t^{(i)} & otherwise \end{cases}$$





Joint Pivot Tuning

- How to bridge the gap between 2D image generating and 3D rendering?
 - Solution: Implement a "joint" pivot tuning¹ considering both reconstruction quality and face swapping performance.

 $\min_{\theta^*} \{ \mathcal{L}(x_{s/t}, \mathcal{G}_{\theta^*}(w_{s/t}, d_{s/t})) + \mathcal{L}(x_t \cdot M_f, \mathcal{G}_{\theta^*}(w_{fs}, d_t) \cdot M_f) \},\$

• Finally, we can synthesize the swapped face *y* in any direction *d* by:

 $y = \mathcal{G}_{\theta^*}(w_{fs}, d)$

1. D. Roich, R. Mokady, A. Bermano, and D. Cohen-Or. "Pivotal tuning for latent-based editing of real images." TOG, pages 1-13, 2022.





Experiments on CelebA-HD Dataset

- CelebA-HD¹ is a large-scale high-quality face attributes dataset.
- Robustness of 3dSwap is validated under several challenging settings:



3dSwap

Source

1. T. Karras, T. Aila, S. Laine and J. Lehtinen. "Progressive growing of GANs for improved guality, stability, and variation." In ICLR, 2018.



Comparison with 2D Approaches







Multi-view Results on CelebA-HD







Conclusion

- We propose the first 3D-aware face swapping framework, where:
 - Infer both geometry and texture facial prior from a single-view image with 3D GAN inversion
 - Design an unique latent code manipulation algorithm for face swapping
 - Bridge the image quality between 2D generating and 3D rendering with a joint pivot tuning







Thanks!

