# Supplement to "From Continuity to Editability: Inverting GANs with Consecutive Images"

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## 1. Supplemental Results

To further demonstrate our method is not restricted with the linear-based editing, we synthesize a new dataset under the nonlinear constraints by StyleFlow [1]. It consists of 1,000 sequences resulting in 5,000 images, with different semantic changes, such as pose, illumination, expression, eyeglasses, gender, and age. We conduct an inversion experiment on it and the results are shown in the Tab. 1, Fig. 1. Our method can obtain an accurate reconstruction on this nonlinear dataset. Besides, we also conduct nonlinear semantic editing task using the nonlinear StyleFlow [1], as shown in the right parts of Tab. 1 and Fig. 2. Our results are more similar with the GT (see the hair color of "*age+*" in the right-bottom corner of Fig. 2). These results prove that our method is not constrained by linear-editing assumption. That because our method is an *optimization-based* GAN inversion method that does not rely on any attribute constraint for the input images, and the optimization is image-specific *without training* a general network.

We also give more qualitative comparison on image reconstitution on RAVDESS-12 Dataset and the linear-based Synthesized Dataset in Fig. 3. We can see that our method can reconstruct the most faithful appearances by optimization latent code in the $\mathcal{W}+$ space. Involving the $\mathcal{N}$ space largely improves reconstruction quality and Ours++ can reconstruct the correct colors.

The qualitative comparison on image editing task on Synthesized dataset can be seen in Fig. 4. Our edited results are more similar with the ground truths and show the pleasure appearances, which indicates that our inverted latent codes are close enough with the GT codes.

## References

[1] Rameen Abdal, Peihao Zhu, Niloy J Mitra, and Peter Wonka. Styleflow: Attribute-conditioned exploration of stylegan-generated images using conditional continuous normalizing flows. *ACM TOG*, 40(3):1–21, 2021. 1

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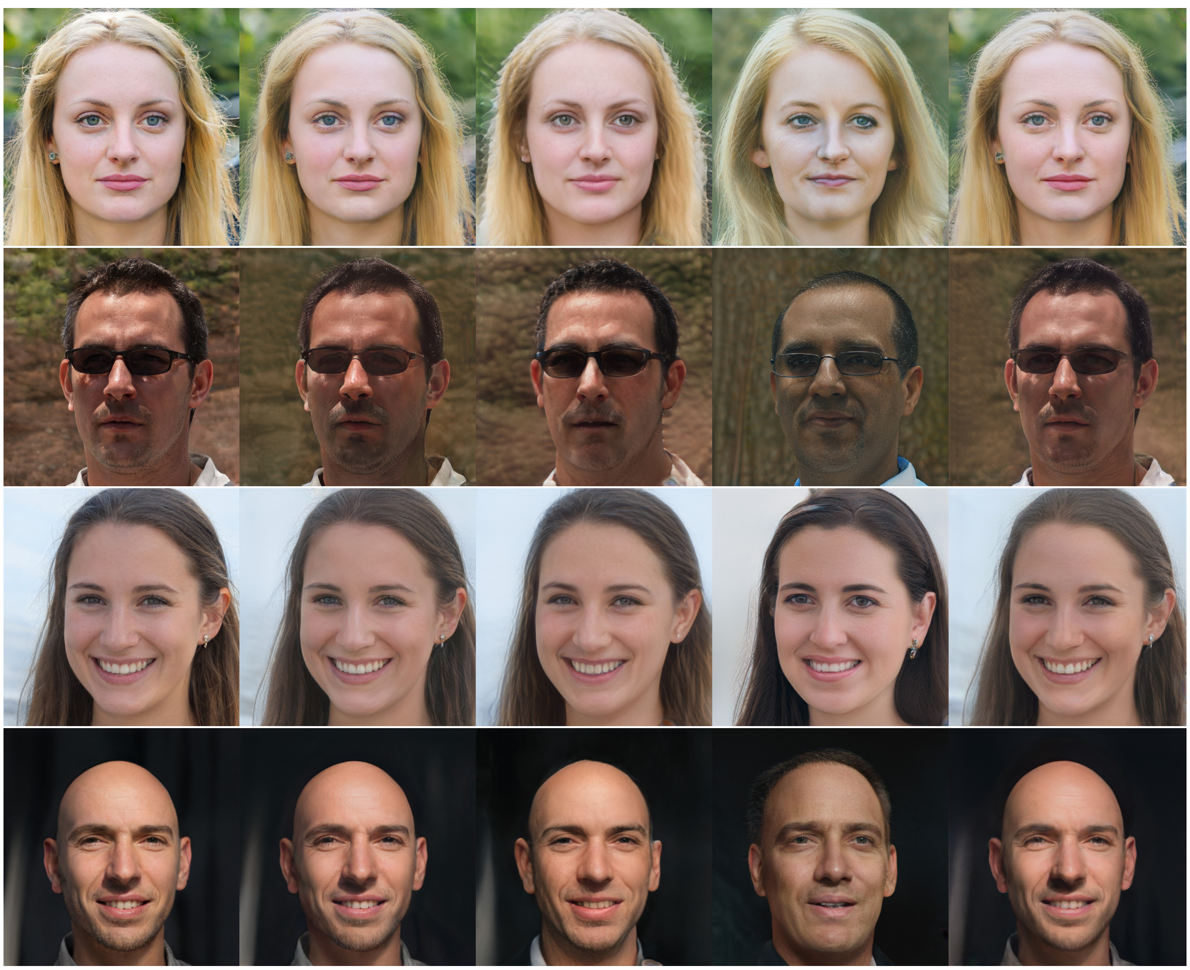
Table 1: Quantitative evaluations on image reconstruction and semantic editing tasks on the nonlinear dataset.

| Metrics \ Methods | Image Reconstruction | | | | Nonlinear Semantic Edit | | | |
|---|---|---|---|---|---|---|---|---|
| | I2S | pSp | InD | Ours | I2S | pSp | InD | Ours |
| NIQE ↓ | 3.632 | 3.439 | 3.254 | **2.997** | 3.940 | 3.974 | 3.703 | **3.476** |
| FID ↓ | 40.098 | 62.932 | 77.692 | **33.692** | 48.032 | 64.224 | 51.607 | **37.039** |
| LPIPS ↓ | 0.252 | 0.323 | 0.414 | **0.238** | 0.489 | 0.522 | 0.471 | **0.403** |
| MSE↓(×e-3) | 30.767 | 79.878 | 83.294 | **25.192** | 87.361 | 118.285 | 99.623 | **69.449** |

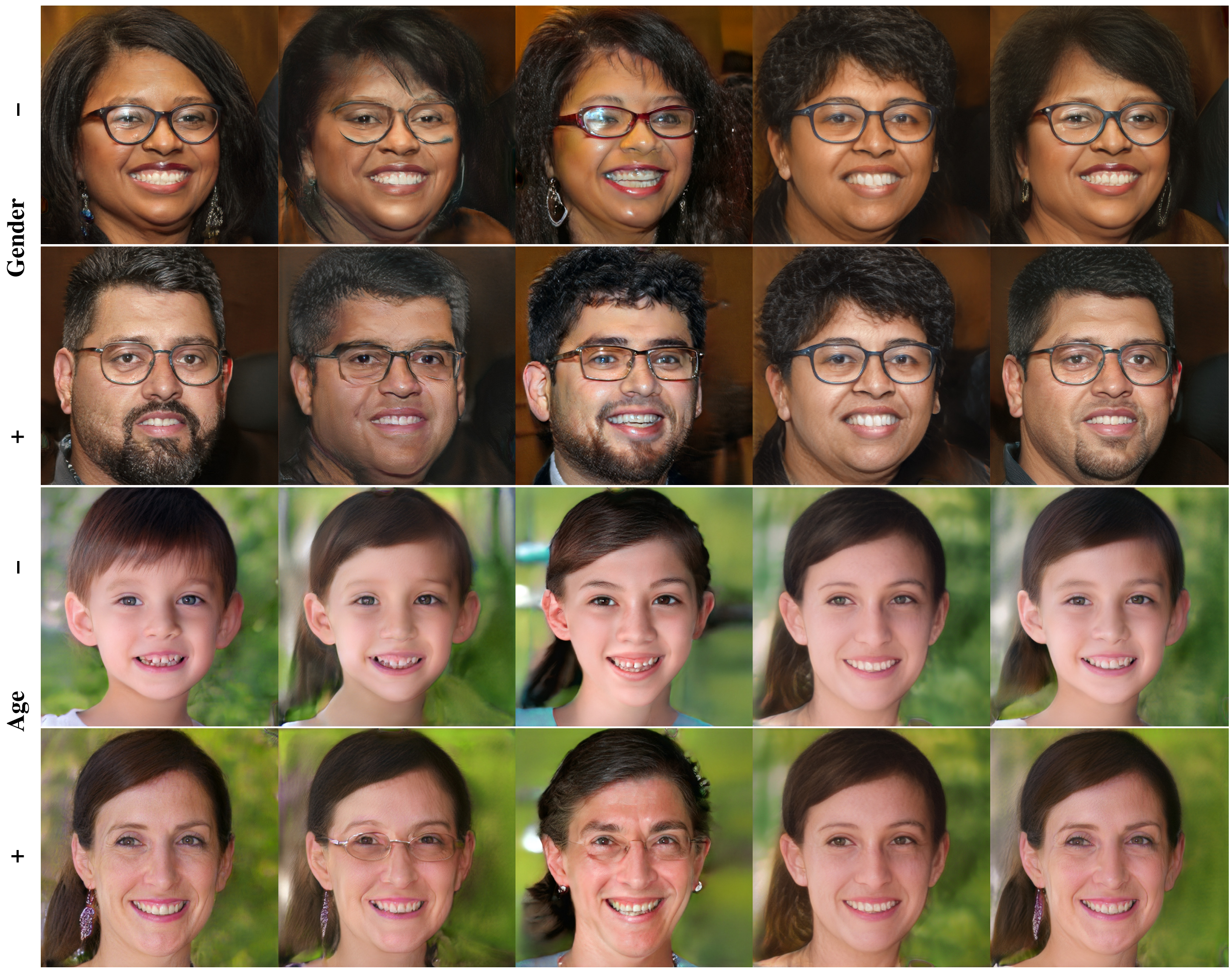


(a) Original (b) I2S (c) pSp (d) InD (e) Ours

Figure 1: Qualitative comparison on image reconstruction on the nonlinear dataset.


Figure 2: Qualitative comparison on semantic edit on the nonlinear dataset.


Figure 3: Qualitative comparison on image reconstruction.




(a) GT (b) I2S (c) Ind (d) pSp (e) Ours

Figure 4: Qualitative comparison on semantic editing.