FPGAN-Control: A Controllable Fingerprint Generator for Training with Synthetic Data —Supplementary—

1. Additional FPGAN-Control generation results

Figures 1, 2, 3, and 4 show additional results for images generated by FPGAN-Control models trained with different values of w_{app} ($0, 1, 5$ and 20 respectively). Each column corresponds to images generated with the same ID latent and each row corresponds to images generated with the same appearance latent. As expected, for $w_{app} = 0$ the image appearance (of each identity) is hardly changing between rows, while as w_{app} increases, fingerprints with the same identity exhibit larger appearance variety. In addition, the figures demonstrate the improvement in appearance control with the increase of w_{app}. This is evident when examining Figure 4 ($w_{app} = 20$), where all images in the same row have very similar appearance.

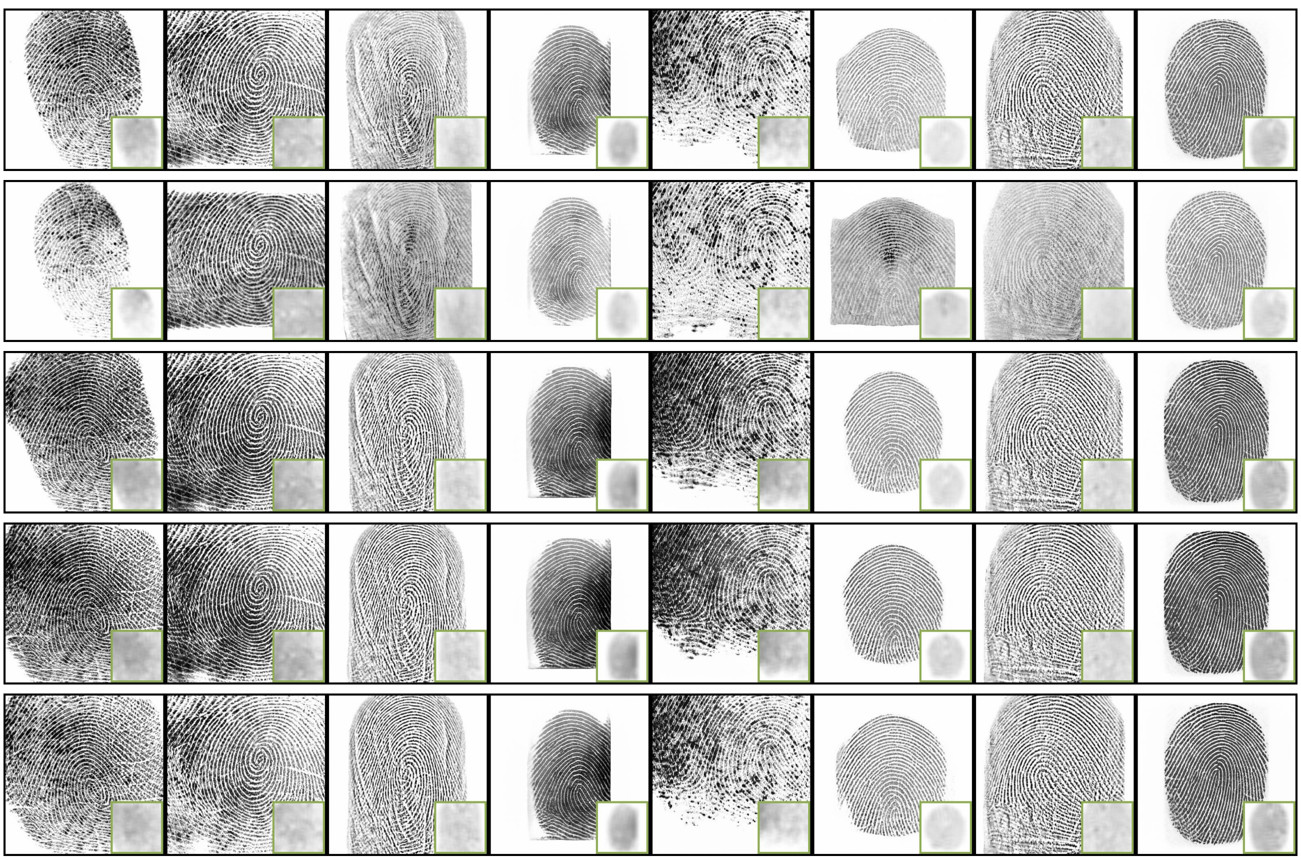

Figure 1. **Generation results of FPGAN-Control trained using $w_{app} = 0$.**

Table 1 shows the FID scores [1] of the FPGAN-Control models used in the paper.

Figure 2. **Generation results of FPGAN-Control trained using $w_{app} = 1$.**

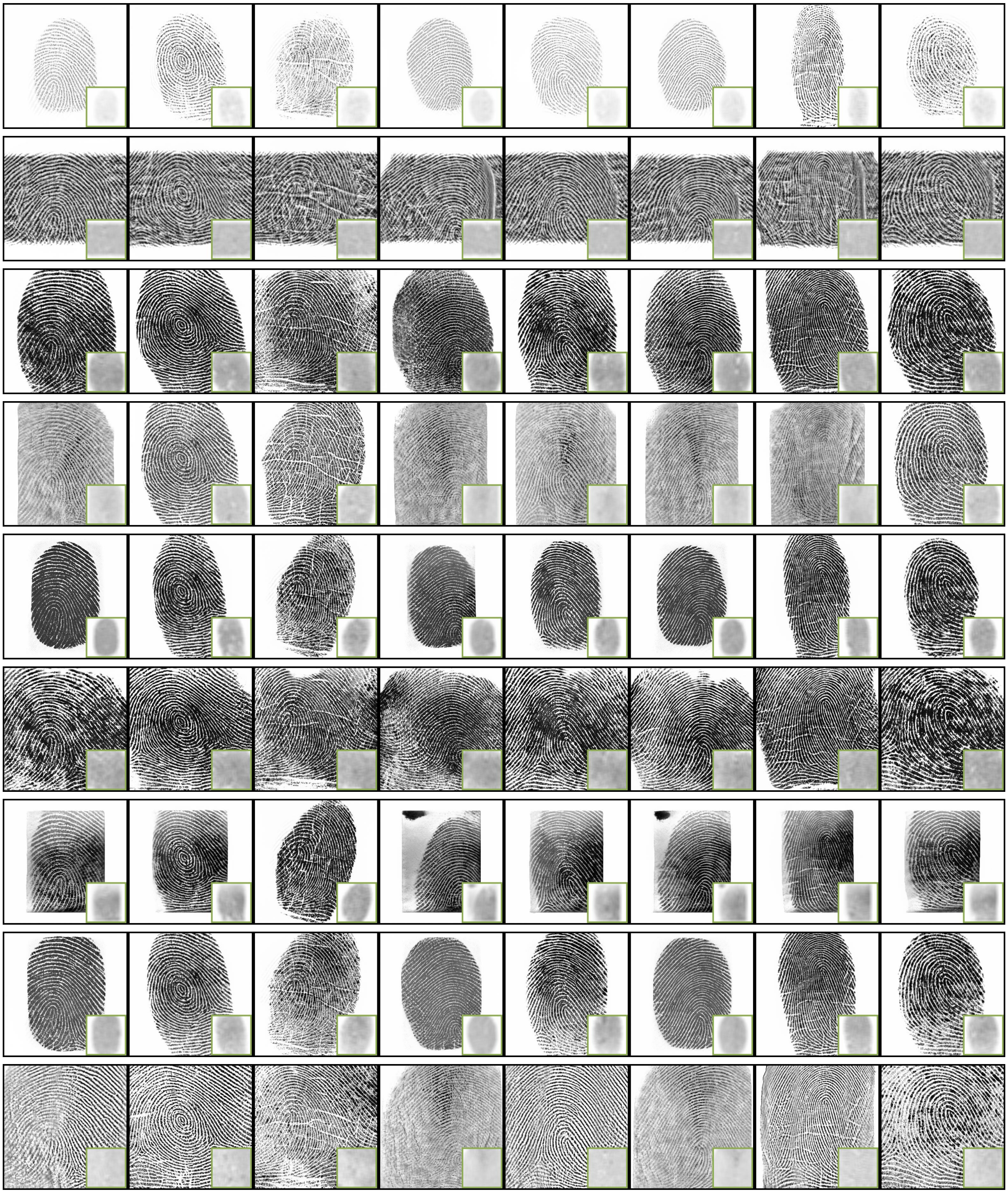

Figure 3. **Generation results of FPGAN-Control trained using $w_{app} = 5$.**

Figure 4. **Generation results of FPGAN-Control trained using $w_{app} = 20$.**

w_{app}	0	0.25	0.5	1	5	20
FID↓	4.74	4.72	5.56	4.73	5.04	5.61

Table 1. **FID scores of FPGAN-Control models trained with different w_{app} values.**

2. Additional training with synthetic data results

Training dataset	**Res18**	**Res34**	**Res50**	**Res101**	**Mob-050**	**Mob-100**	**Eff-s**
Real data	90.54	89.72	92.00	93.69	93.74	94.22	93.69
StyleGAN2	12.57	5.46	5.86	4.07	38.16	19.36	16.18
PrintsGAN	61.30	56.30	62.17	67.20	69.88	76.58	68.05
FPGC-0	80.23	75.17	80.39	88.57	88.55	89.75	80.01
FPGC-0.25	80.42	78.27	81.48	90.29	87.68	88.78	80.39
FPGC-0.5	81.37	79.14	82.88	89.38	87.46	89.52	81.83
FPGC-1	85.58	81.64	82.82	89.81	**89.25**	**89.76**	82.95
FPGC-5	82.02	79.27	81.02	82.20	87.25	87.78	79.87
FPGC-20	**85.90**	**84.36**	**84.38**	**91.07**	88.57	89.28	**87.82**
FPGC-0.25 + FPGC-20	87.20	86.10	**88.00**	91.63	**91.19**	92.08	89.32
FPGC-0.5 + FPGC-20	87.29	86.04	87.25	**92.81**	91.01	**92.12**	90.13
FPGC-1 + FPGC-20	87.65	**87.01**	87.47	92.08	90.99	91.64	89.46
FPGC-5 + FPGC-20	**87.77**	86.76	86.13	91.12	90.86	91.44	**90.22**

Table 2. **Recognition results for 10K synthetic identities.** TAR@FAR=0.1% results obtained by recognition models with various backbones trained using different synthetic datasets for the case of **10K** synthetic identities. The datasets that were generated by FPGAN-control are denoted by FPGC-w_{app} where w_{app} corresponds to the weight of the appearance loss.

Table 2 present the accuracy results of various recognition models trained on different synthetic datasets, each with 10K synthetic identities. Table 2 supports Table 4 in the main paper, by demonstrating that the superiority of datasets generated by FPGAN-Control compared to the baselines is maintained when using just 10K synthetic identities per dataset.

References

[1] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans Trained by a Two Time-Scale Update Rule Converge to a Local Nash Equilibrium. In *NIPS*, 2017. 1