

Supplementary Materials to “GAN Prior Embedded Network for Blind Face Restoration in the Wild”

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In this supplementary file, we provide the following materials:

- More visual comparisons of different methods on synthetic face images (referring to Section 4.4);
- More visual comparisons of different methods on real face images in the wild (referring to Section 4.5);
- Some preliminary results on face inpainting and face colorization.

1. Experiments on Synthetic Images

This section shows more visual results of competing methods on the blind face restoration (BFR) and face super-resolution (FSR) tasks. The experimental settings can be found in Section 4.4 in the main paper. As in the main paper, we compare our GPEN method with Pix2PixHD [8], Super-FAN [1], GFRNet [5], GWAInet [2], DFDNet [4] and HiFaceGAN [10] on the task of BFR. As for the task of FSR, we compare with Super-FAN [1], GFRNet [5], GWAInet [2], DFDNet [4], HiFaceGAN [10], mGANprior [3], PULSE [6] and pSp [7]. The visual comparisons on the BFR and FSR tasks are presented in Figure 1 and Figure 2, respectively.

2. Experiments on Images in the Wild

The 1,000 real-world low quality face images we collected from internet and our BFR results will be made publically available. As in Section 4.5 in the main manuscript, the methods Pix2PixHD [8], Super-FAN [1], GFRNet [5], GWAInet [2], DFDNet [4] and HiFaceGAN [10] are used in the comparison. Figure 3 shows the visual comparisons, demonstrating the superior performance of our method on restoring photo-realistic facial details.

3. Face Inpainting and Face Colorization

Though our method is designed for BFR, it can serve as a generic solution for other image-to-image tasks, such as face inpainting and face colorization, in which GAN prior plays a critical role.

Face Inpainting. Face inpainting aims to recover the missing pixels indicated by a binary mask in a face image. In this experiment, we treat the task as a blind face inpainting problem without using the binary mask. During training, we generate random holes with arbitrary shape in the high-quality face images on-the-fly as inputs. The model is updated following the same strategies and settings as in our main paper.

Figure 4 shows the qualitative comparisons of our method with the state-of-the-art face inpainting methods Deepfill v2 [11] and GMCNN [9], both of which require an extra binary mask to indicate the location of missing pixels. Our model demonstrates much better performance and it reproduces high-quality faces in a resolution of 1024².

Face Colorization. Given a grayscale face as input, our model can also hallucinate a plausible color version of it. We update our model by taking a colored face image and its grayscale counterpart as a training pair. The training strategies and settings are inherited from our main paper.

We compare our GPEN with mGANprior [3], which uses the multi-code GAN prior, and the methods in [12, 13], which are specially designed for colorization task. Figure 5 presents the qualitative comparisons. It can be seen that our model can achieve favorably better face colorization results.



Figure 1: Blind face restoration results on synthetic face images. (a) Degraded faces; (b) Super-FAN [1]; (c) GFRNet [5]; (d) GWAInet [2]; (e) Pix2PixHD [8]; (f) DFDNet [4]; (g) HiFaceGAN [10]; (h) GPEN; (i) Ground truth.

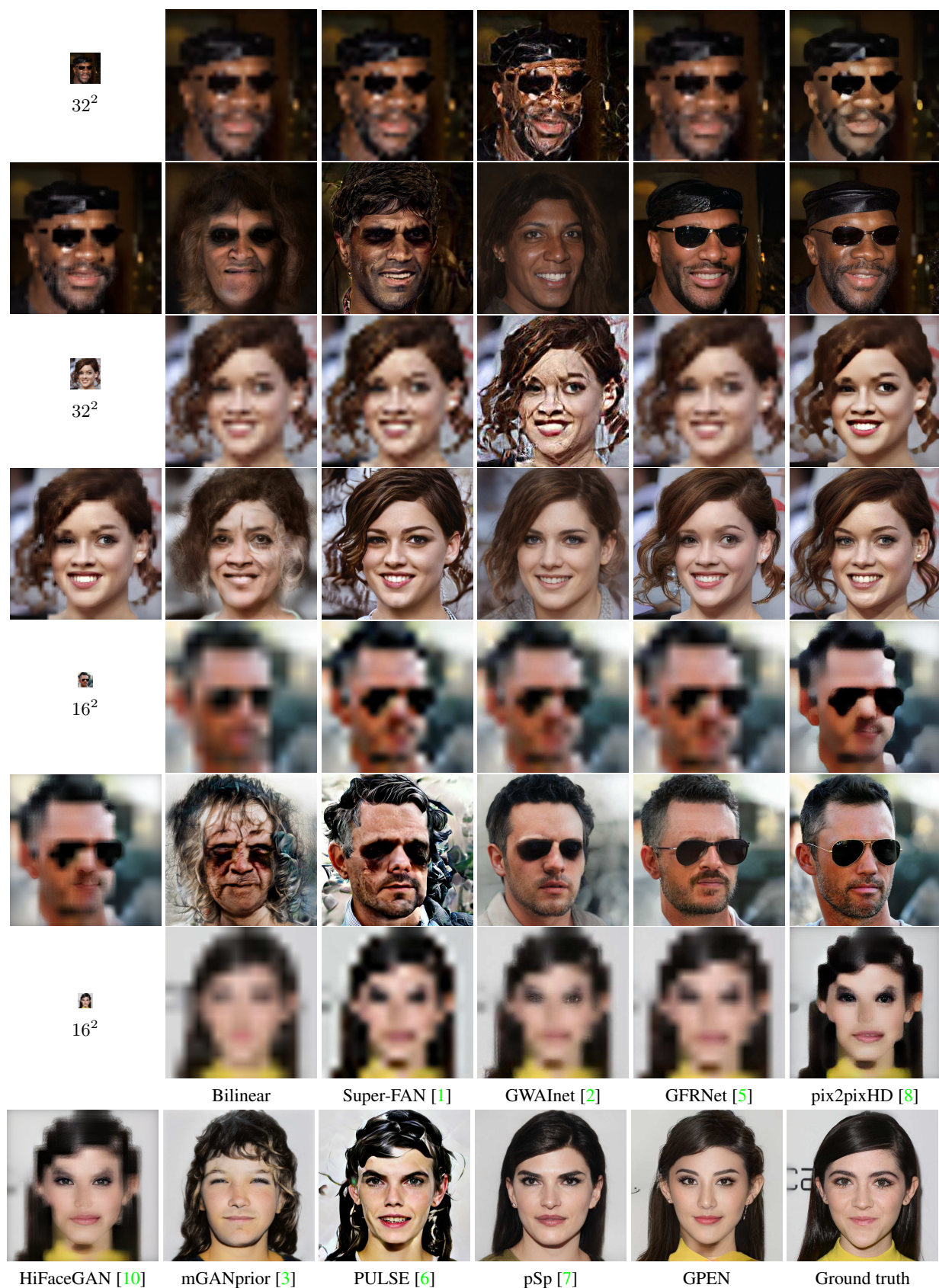


Figure 2: Face super-resolution results by state-of-the-art methods.

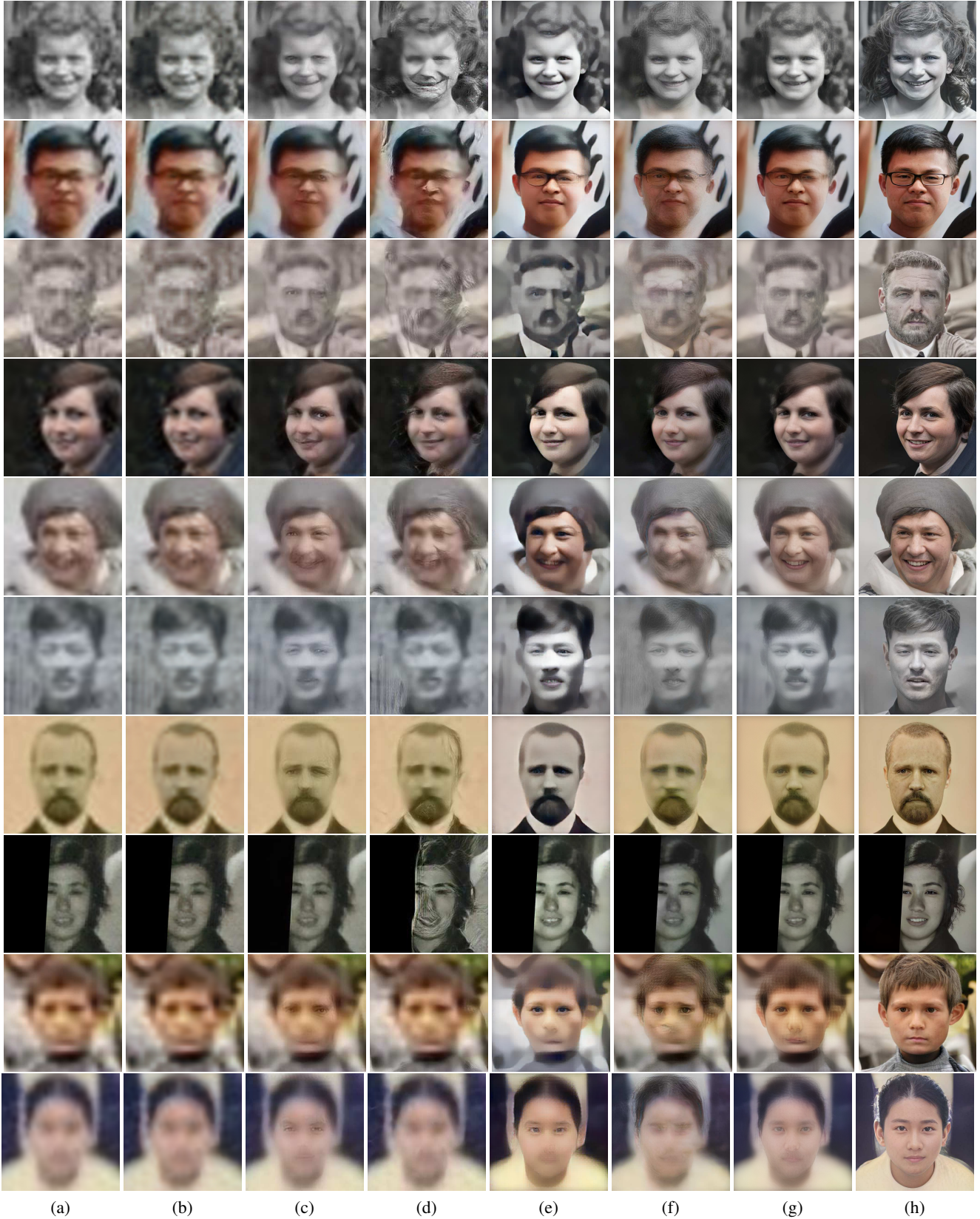




Figure 4: Qualitative comparison of different inpainting methods on high-quality faces (in 1024^2).

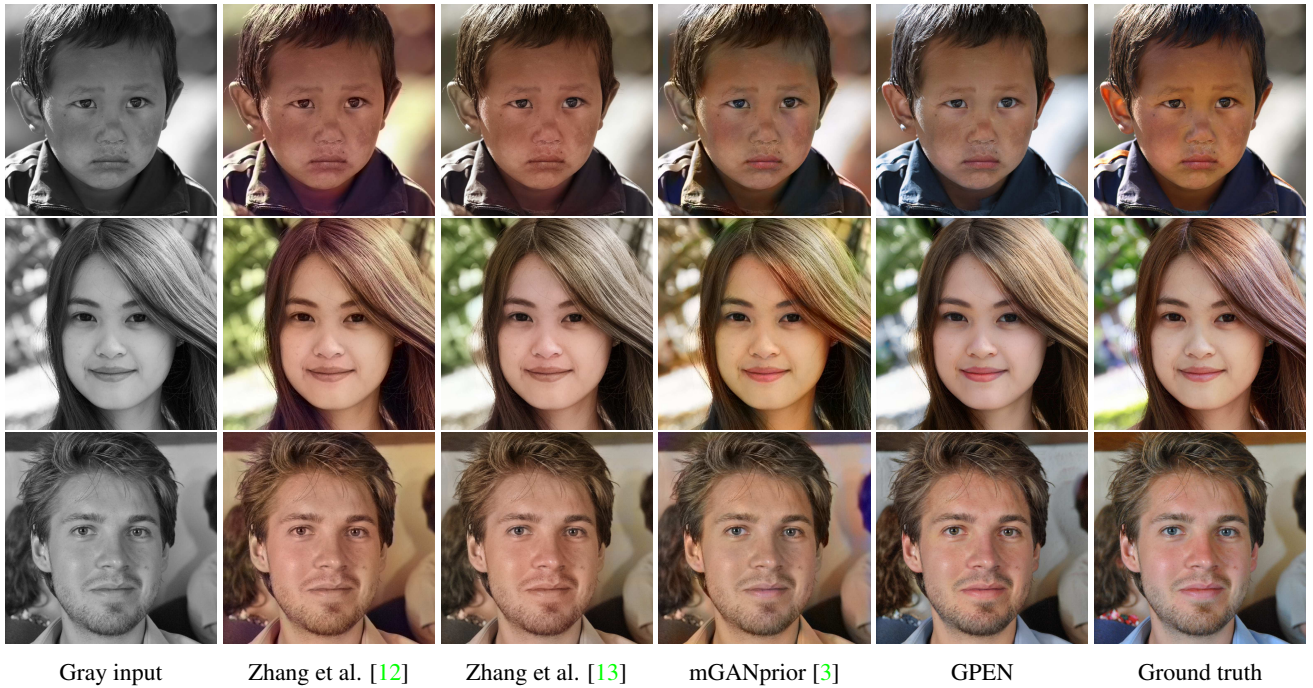


Figure 5: Qualitative comparison of different colorization methods on high-quality faces (in 1024^2).

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