Component Attention Guided Face Super-Resolution Network: CAGFace



What is it about?

• Face Super Resolution (FSR) converts a low resolution (LR) face image to a corresponding high resolution(HR) image. We present the state-of-the-art FSR method results in a broad spectrum of real-life scenarios without inducing perceptual artifacts.



Our Contributions:

- A novel a patch-based, fully convolutional network for face image face super-resolution, where we
- processes patches in original low-resolution throughout its backbone.
- drives networks attention by face component masks.
- Multi stage architecture that recurrently applys the super-resolution stages to leverage on the reconstructed high-resolution outputs from the previous stage to enhance estimated high resolution details progressively.
- The experiments demonstrate **SOTA with best SSIM/PSNR/FID results** compared to existing methods and without much perceptual artifacts!



(b) Skin (c) Hair (d) Other parts (a) Input Figure 3: Sample attention maps from component network.

Ratheesh Kalarot

kalarot@adobe.com

Tao Li taoli@purdue.edu

Method:

- First, facial components are segmented, and component-wise attention maps are generated. For training, random patches are sampled.
- The super-resolution network has two stages:
- The first stage estimates a 2× intermediate HR image;
- The second stage builds on the space-to-depth converted intermediate HR image and uses the original features of the first stem layer through a stage-wise skip-connection while implicitly imposing the component-wise attention.





(a) Input (PSNR / SSIM)

(b) SRCNN [(22.82 / 0.668)

(c) EDSR (21.78 / 0.689)

(d) SRGAN [30] (17.48 / 0.420)

Fatih Porikli

fatih.porikli@anu.edu.au

(e) E-Net [4] (23.08 / 0.679)

(f) SRFBN [32] (21.12 / 0.673)

(g) Ours (26.79 / 0.800)





(b) Bicubic (30.96 / 0.830)





(f) ESRGAN [5: (17.41 / 0.183)

(g) EDSR [33] (27.14 / 0.773)

	PSNR	SSIM	MS-SS
Bicubic	31.87	0.872	0.95
SRCNN [10]	27.40	0.801	0.92
FSRCNN [11]	24.71	0.804	0.95
EDSR [33]	28.34	0.827	0.93
SRGAN [30]	21.49	0.515	0.80
ESRGAN [55]	19.84	0.353	0.78
EnhanceNet [41]	29.42	0.832	0.93
SRFBN [32]	27.90	0.822	0.93
Ours	34.10	0.906	0.97

Table 2: Comparison results for 1024×1024 outputs. Our method is trained with patches.

	PSNR	SSIM	MS-SSIM	FID
Bicubic	25.57	0.766	0.935	135.51
SRCNN [10]	23.12	0.688	0.900	147.21
FSRCNN [11]	22.45	0.709	0.930	139.78
EDSR [33]	22.47	0.706	0.901	129.14
SRGAN [30]	17.57	0.415	0.757	156.07
ESRGAN [55]	15.43	0.267	0.747	166.36
EnhanceNet [41]	23.64	0.701	0.897	116.38
SRFBN [32]	21.96	0.693	0.895	132.59
Ours	27.42	0.816	0.958	74.43

Table 3: Comparison results for 256×256 outputs. Our method is trained with whole-faces.



(c) SRCNN [10] (27.54 / 0.750)



(h) EnhanceNet [4 (29.24 / 0.799)



(d) FSRCNN [] (23.56 / 0.749)





(i) SRFBN [32] (26.65 / 0.765)



(e) SRGAN [3 (22.32 / 0.482)



(j) Ours (33.92 / 0.893)



→ F=256, L=32 → F=128, L=16 → F=32, L=16 Epoch

F=256, L=32 F=256, L=16 F=128, L=32 ■ F=128, L=16 ■ F=64, L=32 F=64, L=16 ■F=32, L=16 Input image size

Figure 7: Effect of different network parameters on speed.