

# Enhancing Face Data Diversity with Style-based Face Aging

## Supplementary Material

### 1 Additional qualitative results

We present in Fig. 1 additional samples from the proposed as well as the baseline methods. These results support our conclusion that our method outperforms the baselines, especially for the 0 – 30 and 50+ age classes, which is crucial for diversity-enhancing augmentation methods.

### 2 Intra-class Aging

We present in Fig. 2 further results on intra-class aging. In particular, given an older-looking target, our method is even able to age faces that belong to the oldest age class, by transferring more crude aging patterns.



Figure 2: Intra-class diversity: Given input images (top row) of the age class 50+, we can synthesize even older looking faces by transferring the aging patterns of an older image from the same class.

### 3 Detailed Network Architecture

The specifics of our networks, including our choice of layers and activation functions, can be found in Table 3 and Table 4.

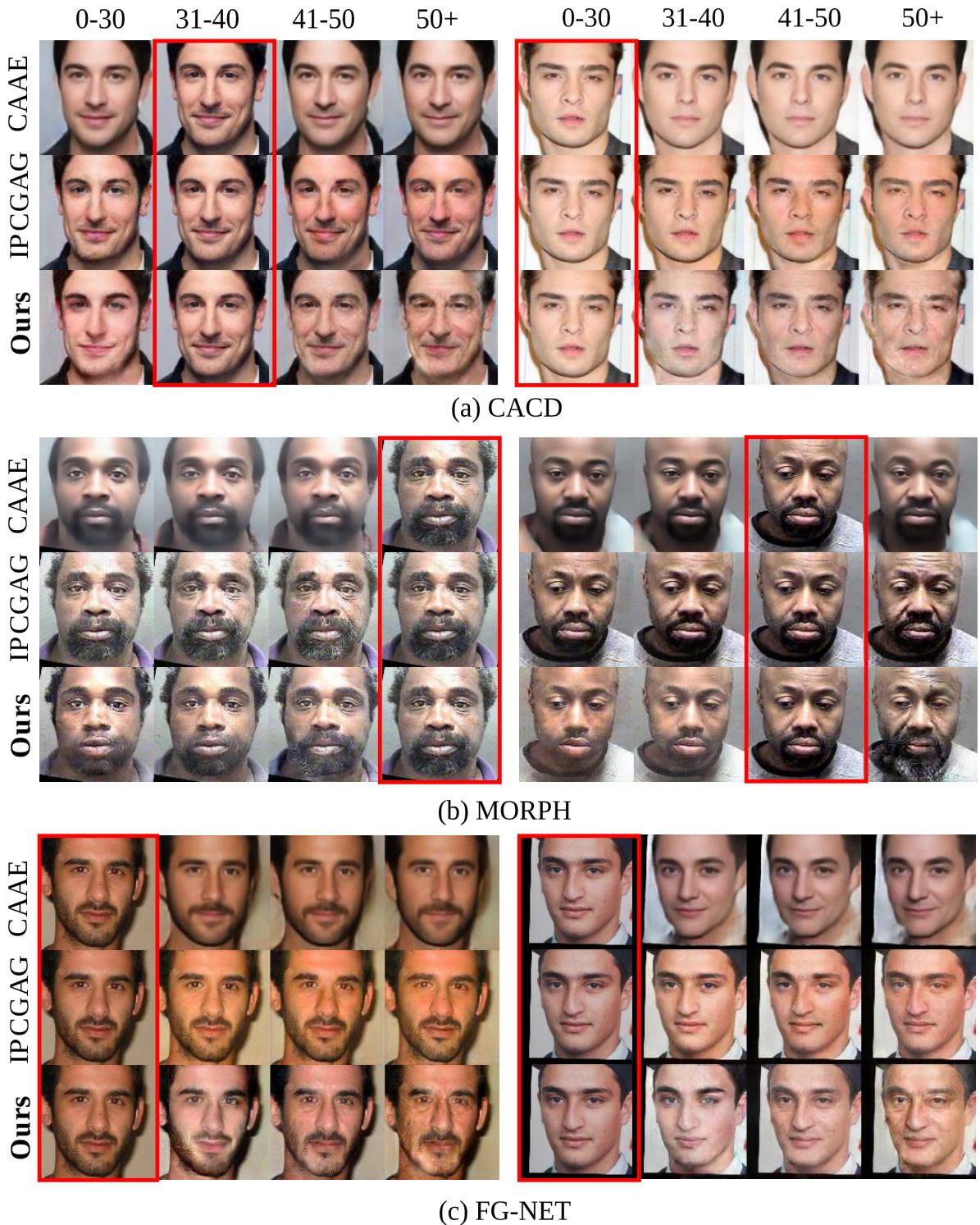


Figure 1: Additional baseline comparisons: translating an image from the test set to all ages classes on CACD, MORPH and FG-NET. The red column highlights the input image, positioned in its corresponding age class.

Section	Name	Dimensions (In)	Dimensions (Out)	Layers
Encoder	e1	( $b$ , 128, 128, 3)	( $b$ , 128, 128, 64)	Conv2d( $f=64$ , $k=7$ , $s=1$ ) → IN
	e2	( $b$ , 128, 128, 64)	( $b$ , 64, 64, 128)	ReLU → Conv2d( $f=128$ , $k=4$ $s=2$ ) → IN
	e3	( $b$ , 64, 64, 128)	( $b$ , 32, 32, 256)	ReLU → Conv2d( $f=256$ , $k=4$ $s=2$ ) → IN
	e4	( $b$ , 32, 32, 256)	( $b$ , 16, 16, 512)	ReLU → Conv2d( $f=512$ , $k=4$ $s=2$ ) → IN
	e5	( $b$ , 16, 16, 512)	( $b$ , 8, 8, 512)	ReLU → Conv2d( $f=512$ , $k=4$ $s=2$ ) → IN
	e6	( $b$ , 8, 8, 512)	( $b$ , 4, 4, 512)	ReLU → Conv2d( $f=512$ , $k=4$ $s=2$ ) → IN
	e7	( $b$ , 4, 4, 512)	( $b$ , 2, 2, 512)	ReLU → Conv2d( $f=512$ , $k=4$ $s=2$ ) → IN
Decoder	z	( $b$ , 2, 2, 512)	( $b$ , 2, 2, 512)	ReLU → Conv2d( $f=512$ , $k=3$ $s=1$ ) → AdaIN → + e7 → ReLu
	d1	( $b$ , 2, 2, 512)	( $b$ , 4, 4, 512)	ConvT2d( $f=512$ , $k=4$ $s=2$ ) → AdaIN → + e6 → ReLu
	d2	( $b$ , 4, 4, 512)	( $b$ , 8, 8, 512)	ConvT2d( $f=512$ , $k=4$ $s=2$ ) → AdaIN → + e5 → ReLu
	d3	( $b$ , 8, 8, 512)	( $b$ , 16, 16, 512)	ConvT2d( $f=512$ , $k=4$ $s=2$ ) → AdaIN → + e4 → ReLu
	d4	( $b$ , 16, 16, 512)	( $b$ , 32, 32, 256)	ConvT2d( $f=256$ , $k=4$ $s=2$ ) → AdaIN → + e3 → ReLu
	d5	( $b$ , 32, 32, 256)	( $b$ , 64, 64, 128)	ConvT2d( $f=128$ , $k=4$ $s=2$ ) → AdaIN → + e2 → ReLu
	d6	( $b$ , 64, 64, 128)	( $b$ , 128, 128, 64)	ConvT2d( $f=64$ , $k=4$ $s=2$ ) → AdaIN → + e1 → ReLu
	d7	( $b$ , 128, 128, 64)	( $b$ , 128, 128, 3)	ConvT2d( $f=3$ , $k=7$ $s=1$ )

Figure 3: Encoder and Decoder architecture:  $b$  denotes the mini-batch size, and ‘IN’ refers to the Instance Normalization operation. We use ‘+e $_i$ ’ to denote a symmetric skip-connection element-wise addition operation from the encoder to the decoder.

Section	Name	Dimensions (In)	Dimensions (Out)	Layers
Discriminator	d1	( $b$ , 128, 128, 3)	( $b$ , 128, 128, 64)	Conv2d( $f=64$ , $k=7$ , $s=1$ ) → LeakyReLu
	d2	( $b$ , 128, 128, 64)	( $b$ , 64, 64, 128)	Conv2d( $f=128$ , $k=4$ $s=2$ ) → LeakyReLu
	d3	( $b$ , 64, 64, 128)	( $b$ , 32, 32, 256)	Conv2d( $f=256$ , $k=4$ $s=2$ ) → LeakyReLu
	d4	( $b$ , 32, 32, 256)	( $b$ , 16, 16, 512)	Conv2d( $f=512$ , $k=4$ $s=2$ ) → LeakyReLu
	d5	( $b$ , 16, 16, 512)	( $b$ , 8, 8, 512)	Conv2d( $f=512$ , $k=4$ $s=2$ ) → LeakyReLu
	d6	( $b$ , 8, 8, 512)	( $b$ , 4, 4, 512)	Conv2d( $f=512$ , $k=4$ $s=2$ ) → LeakyReLu
	d7	( $b$ , 4, 4, 512)	( $b$ , 2, 2, 512)	Conv2d( $f=512$ , $k=4$ $s=2$ ) → LeakyReLu
	logits	( $b$ , 2, 2, 512)	( $b$ , 4)	Flatten → FC(4)

Figure 4: Discriminator architecture:  $b$  again denotes the mini-batch size.