Deep Feature Interpolation for Image Content Changes: Supplemental

1. Changing Face Attributes

In this section we provide details on the test images. We use attributes predicted by a machine learning model to perform attribute changes on aligned LFW faces. The attributes are in the form of scalar decision values which we convert into boolean attributes by assigning $True$ to the top two-thirds of images whose decision value is positive. The LFW images are aligned using the same code used by AEGAN to facilitate comparison. We first determined whether each attribute was more commonly associated with men or women, since the majority of images in LFW are of men. In a purely data-driven fashion we found 38 test images randomly selected according to attribute constraints, allowing us to apply multiple transformations to the same face. For example, if we wish to transform a test image to have a mustache and separately to have glasses, the test image would ideally not already have a mustache or glasses. Additional test results are shown in Figure 2. Output resolution is $200 \times 200$.


2. High Resolution Face Editing

In Figure 4 and Figure 5 we show additional results on high resolution face images for the tasks of adding facial hair and aging.

3. Perceptual Study Tutorial

In this section we describe the tutorial used to train workers to evaluate face attribute changes. Workers were instructed to pick the image which has the target attribute and preserves the unique characteristics of the original image. They were instructed to use quality only as a tie-breaker.

Workers were required to pass a test before participating. The test image was a picture of Robert Downey Jr. (RDJ) and the 4 pictures to chose from were: A. a RDJ lookalike with facial hair (Jeffrey Dean Morgan), B. the original RDJ picture without facial hair, C. a different picture of RDJ with facial hair, and D. the original RDJ picture edited to add facial hair (Figure 1). If workers picked the wrong image then they were shown an explanation of why it was wrong and were not allowed to proceed until they selected image D.

4. Inpaint Without Attributes

In Figure 3 we show additional inpainting results (random test images). Source and target sets are found by taking the $K = 100$ nearest neighbors (by cosine distance) in VGG-19 pool15 space. Output resolution is $200 \times 200$.

1DeepPy: https://github.com/andersbl/deeppy

Facial Hair

Original A B C D

Figure 1. Perceptual study tutorial test. Workers are instructed to pick the image that adds facial hair to the original image.
Figure 2. *(Zoom in for details.)* Attribute changes on aligned faces with Deep Feature Interpolation. Looking down a column the face should have the target attribute. Looking across a row the image should preserve the unrelated attributes of the original image as much as possible (e.g., the person’s identity, clothing and background).
Figure 3. Image inpainting with DFI. The missing regions are filled with plausible pixel values although partial objects are not completed (e.g., eyeglasses). These results were produced without supervised attributes.
Figure 4. (Zoom in for details.) High resolution results for the task of adding facial hair. Each row shows a different image. Each column represents a different value of $\alpha$. In each row, the first column is the original image.
Figure 5. (Zoom in for details.) High resolution results for the task of aging faces. Each row shows a different image. Each column represents a different value of $\alpha$. In each row, the first column is the original image.