Learning a face space for experiments on human identity

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Learning a face space that captures variation in human identity and appearance requires careful pairing of image set and network architecture.

HUMANAE

Held constant...

- Photographer
- Camera model
- Lens model
- Lens focal length
- Focal point
- Aperture
- Exposure time
- Distance to subject
- Camera placement
- Light design
- Facial expression

...

- Pose
- Background texture
- Ambient lighting
- Level of comfort / arousal
- Image resolution
- Digital format
- Color grading
- White balance
- Gamma correction
- Compression level & quality
- Watermarking (i.e., none)
- Digital alteration & touchups

Varies...

- Age
- Skin tone
- Place of origin
- Gender identity
- Hair style
- Profession
- Economic status
- Disability
- Injury & illness
- Body modification
- Cosmetic surgery
- Makeup
- Hair dying
- Tattooing

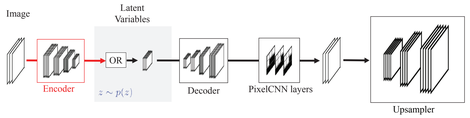
Alignment

(Kazemi & Sullivan, CVPR 2014)

Resultant training set

MODEL

Variational autoencoder with partially autoregressive decoder



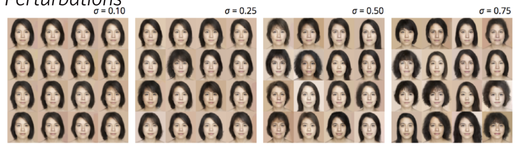
Gulrajani et al. (2016)

RESULTS

EVALUATION

Interpolations

Perturbations



Nearest neighbors

Human-in-the-loop search

$$\theta_t + \alpha \frac{1}{n\sigma} \sum_{i=1}^{n} F_i \epsilon_i$$

PERCEPTUAL COMPARISONS

A head-to-head comparison between different models trained on the same image set

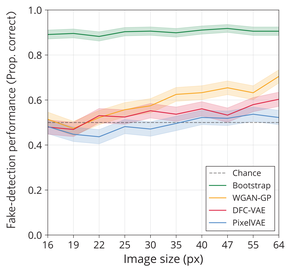


Figure 2: Sample images from the aligned/cropped Humanæ dataset.

Figure 3: Samples from WGAN-GP trained on humanæ.

Figure 4: Samples from DFC-VAE trained on humanæ.

Figure 5: Samples from PixelVAE trained on humanæ.

Pairing a variational autoencoder (having a partially autoregressive decoder) with Humanæ results in a face space that is smooth, navigable, and that renders into realistic portraits with meaningful variation.

www.angelicadass.com/humanae-work-in-progress