Synthesizing Normalized Faces from Facial Identity Features

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Presented by: Kapil Krishnakumar
Problem

- Want method for synthesizing a frontal, neutral expression image of a person’s face given an input face photograph
- One-to-one mapping from identity to image
- Method of pre-processing images to remove irregularities

Image Credit: Cole et al.
Related Work

Zhmoginov and Sandler et al.

Blanz and Vetter et al.

Cootes et al.

Hassner et al.

Image Credit: Zhmoginov and Sandler. Inverting face embeddings with convolutional neural works.
Blanz and Vetter et al. A Morphable Model For The Synthesis Of 3D Faces
Cootes et al. Active Appearance Models
Hassner et al. Effective Face Frontalization in Unconstrained Images
Approach

- Morphing of Images (Data Augmentation)
- Encoder (Image to Feature Vector)
- Decoder (Feature Vector to Normalized Image)
  - Landmarks
  - Texture

Image Credit: Cole et al.
Architecture

Image Credit: Cole et al.
FaceNet (Background) (Schroff et al. 2015)

- Face Images -> 128-D vectors
- Trained using triplet loss. Embeddings of two pictures of A should be more similar than picture of person A and person B.
- Uses GoogLeNet’s NN2 Architecture

Image Credit: Cole CVPR 2017 Talk (https://www.youtube.com/watch?v=jVAClXpHgAI) | Szegedy et al. Going deeper with convolutions
Encoder

- Use pretrained FaceNet
- Extract 1024-D “avgpool” layer of “NN2” architecture
- Append and train Fully Connected Layer from 1024 to F dimensions on this layer.

Image Credit: Szegedy et al. Going deeper with convolutions
Encoder

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Decoder

- Separating landmarks and textures more effective than just predicting image
- Landmarks estimated using shallow MLP with ReLUs applied on feature vector
  - FV -> [(x,y),.....]
- Textures estimated using fully connected or CNN
  - FV -> Image

Image Credit: Cole et al
Decoder

- Use differentiable image warping to combine landmarks and textures

Image Credit: Cole et al
Decoder

Image Credit: Cole et al
Differentiable Image Warping

Input Image with Landmarks

Final Landmarks

Textures with Landmarks

Mean Landmarks of training data

Dense Flow Field with Spline Interpolation

Final Output

Image Credit: Cole et al
Differentiable Spline Interpolation

Input Landmarks

Final Landmarks

Distance Matrix

Polyharmonic Interpolation

Displacement Flow Field X,Y, Magnitude

Image Credit: Cole et al
Training

Image Credit: Cole et al.
Training

Ground Truth Landmarks

Facenet

MLP

Landmarks

Ground Truth Textures

FC/CNN

Textures

Image Credit: Cole et al.
Training with FaceNet Loss

Ground Truth Landmarks

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Ground Truth Textures

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Image Credit: Cole et al.
Training Loss

- Separately penalize predicted landmarks and textures using mean squared error
- Penalize differences in resulting encodings from input image and rendered image when passed through FaceNet
  - Highly expensive to train

Image Credit: Cole et al
Data Augmentation: Random Morphs

- Problem: Don’t have database of normalized face photos to train decoder network on
- Solution: Morphing Data Augmentation

Select one of $k=200$ Nearest Neighbors using distance defined by Landmarks and Textures

Image Credit: Cole et al
Data Augmentation: Gradient Domain Compositing

- Morphing cannot capture hair and background detail
- Combine morphed image onto an original background using gradient domain compositing

Image Credit: Cole et al
Data Augmentation

Image Credit: Cole et al
Data Augmentation

CNN w/o Data Aug.  FC w/ Data Aug.  CNN w/ Data Aug.

Image Credit: Cole et al
Training Data

- Dataset used to train VGG-Face network. 2.6M photos
- Processing:
  - Average all images for each individual by morphing
  - Each image is then warped to average landmarks of individual
  - Pixel values are averaged to form average image of individual.
- Gives 1K unique identities images
- Use Kazemi and Sullivan for extracting groundtruth Landmarks
- Augmentation produces 1M images

Image Credit: Cole et al
Experiments: Labeled Faces in the Wild

- Identities mutually exclusive to VGG face dataset
Experiments: Labeled Faces in the Wild

- Histograms of FaceNet L2 error between input and synthesized images.
- 1.242 is threshold for clustering identities in FaceNet feature space
- **Blue**: With Facenet Training Loss
- **Green**: Without Facenet Training Loss

Image Credit: Cole et al
Robustness to Occlusions
Extensions: 3-D Model Fitting

- Easier to fit normalized face image on 3D morphable model.

Image Credit: Cole et al
Extensions: Automatic-Photo Adjustment

Input Images

Our Method

Barron [38]
Extensions: Automatic-Photo Adjustment

Input Images

Our Method

Barron [38]

Image Credit: Cole et al
Advantages

- Splitting of generative tasks (Landmarks and Textures) can be better than directly outputting result
- Fresh use of spline interpolation as differentiable module in NN
- Augmentation technique allows training of decoder with only 1K images to perform extremely well.
- Tough features like hair and eyes are well defined in normalized images
- Robustness to occlusions
Disadvantages

● No “ground truth” to compare Normalized Images
  ○ Though measure of performance can be defined as FaceNet closeness between image and normalized image
  ○ Cannot get human annotated ground truth

● Dependent on out of box methods for getting Landmarks and Textures labels
  ○ Paper doesn’t show experiments on other techniques other than Kazemi
  ○ Unclear on how Texture labels are generated.

● Backgrounds are unrealistic and blurry