AgingGAN: Age Progression with CycleGAN
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Introduction

Age progression, the process of aesthetically rendering a facial image with simulated effect of growing old, has attracted much attention from the Deep Learning and Computer Vision community. It is a challenging task because the patterns of aging that we want to capture could be easily affected by the various conditions of the input image. Further, the scarcity of paired data two images of the same person taken at different time (20+ years apart) - prevented existing solutions to achieve good performance.

In this project, we propose a simple, yet intuitive deep learning model based on CycleGAN [1] that can generate predictive images of people’s look after certain years based on their current images, without the need of paired dataset.

Dataset & Features

IMDB-WIKI [2]
- Group A (age 20–30)
  - 5,004 images (3,165 male, 1,839 female)
  - filtered with facial_score > 3
- Group B (age 50+)
  - 2,779 images (2,209 male, 570 female)
  - filtered with facial_score > 1.

Cross-Age Celebrity (CACD) [3]
- Group A (age 20–30)
  - 2,200 images randomly taken from pool of 39,069.
- Group B (age 50+)
  - 2,200 images randomly taken from pool of 33,872.

Modifications
- Resized to 256 x 256
- Removed Grayscale images
- Removed images that are not pictures (e.g. drawings).

Method and Model

In practice, using least-squares loss, e.g. \( L_{\text{cycle}}(G, D, X, Y) \):
Train \( C \) to minimize \( E_{x\sim\mathcal{X}}[D^c(G(x) - y)] \)
Train \( D \) to minimize \( E_{y\sim\mathcal{Y}}[D^c(G(x) - y)] + E_{x\sim\mathcal{X}}[D^d(G(x)) - 1]^2 + E_{x\sim\mathcal{X}}[D^d(G(x)) - 1]^2 \)

Results

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Conclusions

1. CycleGAN can generate quality age progression images.
2. The aging effects will increase as # of epochs increases, but such effect become less and less apparent after 200 epochs.
3. Transfer learning and fine tuning using other trained model (Horse2Zebra model in our case) can be applied to accelerate training but will slightly compromise the quality of the output.
4. The choice of dataset can severely affect the performance of the model (CACD dataset has horrible results).

Future Work

- Investigate the correlation between the Cycle-Consistency cost and image quality.
- Increase training set size to 20–50K.
- Explore models support facial geometric changes.

References