Re-Aging GAN: Re-Aging GAN: Toward Personalized Face Age Transformation

Contents

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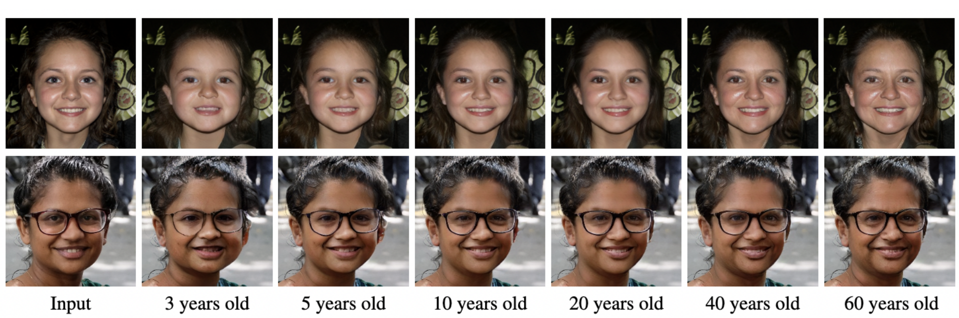
Abstract

Face age transformation aims to synthesize past or future face images by reflecting the age factor on given faces. Ideally, this task should synthesize natural-looking faces across various age groups while maintaining identity. However, most of the existing work has focused on only one of these or is difficult to train while unnatural artifacts still appear.

Thus, the Re-Aging GAN (RAGAN) was proposed in ICCV 2021, a novel single framework considering all the critical factors in age transformation. Our framework achieves state-of-the-art personalized face age transformation by compelling the input identity to perform the self-guidance of the generation process. Specifically, RAGAN can learn the personalized age features by using high-order interactions between given identity and target age.



Our role in this project is to implement this paper, and try to replicate the results of the paper as much possible. The code with which they have implemented is neither open-sourced nor publically available.

Literature Survey

A face age transformation task is dedicated to learning age progression or regression of a given face according to the target age. Here, the target age implies an explicit conditioning factor that guides the transformation to produce facial images with a certain age. That is, we can set any target age for an input face image, and expect to have an output face depicting the target age characteristics, as shown in the previous slide.

Ideally, age transformation models should satisfy the following properties.

1. A model should take into account the identity of the person while progressing/regressing the face age and systeain it mostly unaltered, *i.e.*, identity preservation.
2. A model should be able to generate natural looking faces corresponding to the target age across various age group.

In this regard, a number of works on face age transformation have been introduced. These methods, on the basis of powerful generative adversarial networks (GANs). train deep neural networks to perform a robust age transformation of the input face. Aside from this, several mechanisms have been adopted (*i.e.* networks and constraits) for identity preservation to ensure that face identity is unaltered during the age transformation process. However, even with improved approaches, existing methods tend to generate images with visible artifacts and/or unnatural-looking faces which surely lowers down the image quality and its perception.

Another important aspect that should be considered is a wide-range age transformation, specifically, an age regression process for rejuventating input face. Most existing works scarcely emphasise on this. Although a few methods can operate on face age regression and provide good performance, their results still suffer from artifacts near and/or on face regions and contain no background due to the tight face cropping.

The main contributions of this RAGAN are:

- They introduce a personalized self-guidance scheme that enables transforming the input face across various target age groups while preserving identity.
- They successfully perform age transformation using only a single generating and discriminative model trained effectively in an unpaired manner.
- They quantitatively and qualitatively demosntrate the superiority of RAGAN over state-of-the-art methods through extensive experimnents and evalutations.

Datasets Used

For training the framework, the paper uses FFHQ dataset labelled for age transformation task. This dataset provides image of 70,000 people in 10 age groups. Then they split it to training and test set and prune the dataset images that have a low label confidence score. In addition this dataset provides face semantic maps. They use these semantic information to mask out images and so separate face-region and background information for reliable transformation. To evaluate their generalization of the model to unseen images, they use the CelebA-HQ and the CACD datasets in their own qualitative evaluations. Both of these datasets provide face images of celebrities with diversity in age, pose, illumination and expression. All images used in our training and evaluations are at the resolution of 256 × 256 which is a commonly used resolution in existing works.

Existing Algorithms

Modules present in the Code

Overview

Let $\mathcal{X}$ and $\mathcal{Y}$ be the set of images and possible ages respectively. Given a face image $x\in\mathcal{X}$ and a target image $y'\in\mathcal{Y}$, our goal is to train a single Generator G such that it can generate a face image x' of a particular age y' corresponding to the identity in x. In addition, we introduce an age modulator within G to reshape identity features by considering the target age and utilize it as a self-guiding information.

In comparison to prior works, the main objkect is to robustly transform face age as well as maximum retention of age-unrelated information in x', such as background, hairstyle, expression, etc. This means this framework should preserve the age-unrelated information contained in the input image during the age transformation process. Therefore, we consider a simple strategey on encoder and decoder networtks to share some of the valuable information.

Proposed Framework

The proposed GAN-based frame is divided into the generator consiting of an encoder, a modulator, and a decoder, and the discriminator. Since the discriminator follows exisiting approaches, it was not very broadly elaborated, only the generator part is described in depth. The generator makes use of encoder-decoder architecture for image generator and is made of an identity encoder Enc, an age modulator AM, and a decoder Dec. In a superficial view, the encoder and decoder networks perform the same procedyre as existing works, yet they have a few modifications.

One of the difference the proposed and the existing works is the indegration of addition sub-network at the bottleneck of the generator. By this networtk, we can obtain features providing information on how a particular person should look like at the age under consideration. Given that such age-ware features are learned based ona given input image, then it can be used for further generation process.

Identity Encoder

Given an image x for age transformation, our identity encoder Enc extracts identity-related feature f_{id} of the image, where $f_{id}=Enc(x)$. Particularly, the encoder provides such features that supply facial structures at the local level and general information on face shape. These features are necessary to generate the same-looking face and thus have high importance, as discussed eqarlier. In turn, this importance intuitively leads us to focus on the face region only. Therefore, they proposed to perform a masking operation after transferring x into the feature domain. To this, we utilize a network trained on sophisticated mask-based dataset. We delibrately perform masking at this stage such that we can obtain face as well as background-related features to operate on the face region only while maintaining the background informaion simultaneously. At the architecture level, the idenetity encoder is designed to have an image-to-featur level convolutional layer followed by downsampling blocks.

Age Modulator

Age modulator AM is constructed in the form of CNN, which is widely used in learning a low-dimensional vector of an input. It takes identity vectors f_{id} from the encoder and by, considering given age information y', outputs its reshaped version $f_{aw} = AM(f_{id}, y')$, where f_{aw} is an element age-aware vector. To embed target age into AM, we add conditional batch normalization (CBN) layers used as a way to incorporate label information into the network. By doing so, AM learns optimal age-aware features for input identity, which enables satisfying both identity and age properties. Given that the network is integrated into G, it can be trained alongside the generator in an end-to-end manner. We implement AM as a set of downsampling layers with CBN technique producing a compact feature-vector used to modulate decoder layers

Version 1: Re-Aging GAN

```python
import os
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'

import tensorflow as tf
import tensorflow.keras as keras
from tensorflow.keras import layers, regularizers, initializers
import tensorflow_datasets as tfds
import tensorflow_addons as tfa

import numpy as np
import matplotlib.pyplot as plt
import matplotlib
import cv2
import pandas as pd

from tqdm import tqdm
import warnings
warnings.simplefilter('ignore')
%matplotlib inline

print(f'''Import Versions:-
* TensorFlow: {tf.__version__}
* TensorFlow Datasets: {tfds.__version__}
* TensorFlow Addons: {tfa.__version__}
* NumPy: {np.__version__}
* Pandas: {pd.__version__}
* cv2: {cv2.__version__}
* Matplotlib: {matplotlib.__version__}''')
```

```
Import Versions:-
* TensorFlow: 2.9.2
* TensorFlow Datasets: 4.6.0
* TensorFlow Addons: 0.17.1
* NumPy: 1.22.4
* Pandas: 1.4.3
* cv2: 4.6.0
* Matplotlib: 3.5.2
```

Expected Output