CONTINUOUS FACE AGING GENERATIVE ADVERSARIAL NETWORKS

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ABSTRACT

Face aging is the task aiming to translate the faces in input images to designated ages. To simplify the problem, previous methods have limited themselves only able to produce discrete age groups, each of which consists of ten years. Consequently, the exact ages of the translated results are unknown and it is unable to obtain the faces of different ages within groups. To this end, we propose the continuous face aging generative adversarial networks (CFA-GAN). Specifically, to make the continuous aging feasible, we propose to decompose image features into two orthogonal features: the identity and the age basis features. Moreover, we introduce the novel loss function for identity preservation which maximizes the cosine similarity between the original and the generated identity basis features. With the qualitative and quantitative evaluations on MORPH, we demonstrate the realistic and continuous aging ability of our model, validating its superiority against existing models. To the best of our knowledge, this work is the first attempt to handle continuous target ages.

Index Terms— Face aging, Image-to-Image translation, Unsupervised Learning, Generative adversarial networks

1. INTRODUCTION

Someone would imagine how the appearance of people changes as time goes forward or backward. To make this possible in reality, the face aging problem has been actively studied, which aims at translating a facial image into an older (or younger) facial image while preserving the personal identity. Face aging has drawn much attention due to its broad use in photo-editing [1] or finding missing children [2].

Recent studies on face aging [3, 4, 5, 6, 7] utilize the image-to-image translation techniques [8, 9], thanks to its ability of translating source images to the target domain while preserving the context. However, directly mapping face aging to image-to-image translation is challenging, since most of existing face datasets do not contain sufficient images for each age point. To alleviate this problem, existing face aging studies [4, 5, 6, 7, 10, 11] group several continuous ages into discrete age groups (e.g., 20s, 30s, and so on). However, using discrete age groups leaves obvious limitations behind. Because the model learns only one representative aging factor for each age group, translated results are deterministic in each target age group and thus are discrete, e.g., only one result can be obtained in the target age group of 30s as shown in the Figure 1(a). Moreover, due to the absence of any clue on the exact age of the translated image, continuous face aging cannot be achieved. One would try directly applying interpolation between encoded features of a generator, but the interpolated samples are not likely to correspond to the target age because the learned age domains are discrete.

To overcome the limitations, we introduce a novel method to translate a facial image to the continuous target age while preserving the personal identity, named continuous face aging generative adversarial networks (CFA-GAN). To learn continuous aging factors, we propose to extract age-invariant personal features by disentangling the features into the identity basis feature and the age basis feature. To make the decomposed features contain the appropriate information, we train an auxiliary age regressor and an identity classifier by the joint learning strategy. Moreover, to preserve the original identities of input images, we design a loss maximizing the similarity between the identity basis features of real and translated image. Consequently, our CFA-GAN is able to generate realistic and smooth images given continuous target ages, as shown in Figure 1(b).

The main contributions of this paper are as follows.

• We present the novel framework that is capable of generating face images of continuous target ages. Note that this is the first attempt to handle continuous target ages.

• We propose to disentangle the identity and the age basis features for continuous aging. Moreover, a novel loss is designed to preserve the identity of an input image.

• We demonstrate the efficacy of our method on continuous aging with the experiments on MORPH [12].
2. PROPOSED METHOD

In this section, we introduce the proposed model, Continuous Face Aging Generative Adversarial Network (CFA-GAN). As described in Figure 2, CFA-GAN consists of a generator and a discriminator. The generator is designed based on the U-Net architecture with skip-connections. Each of the generator and the discriminator has an age regressor and an identity classifier. It is worth noting that their weights are not shared by the generator and the discriminator.

**Input details.** The training dataset contains \( N \) images \( \{ x^{(i)} \}_{i=1}^{N} \) and the corresponding labels \( \{ y^{(i)}, a^{(i)} \}_{i=1}^{N} \), where \( y^{(i)} \) is an identity number and \( a^{(i)} \) is an original age.

### 2.1. Face Aging by Disentangling Age and Identity

We first extract the feature of an input image using the encoder of the generator \( G \). Formally, \( z^{(i)} = Enc_{G}(x^{(i)}) \), where \( x^{(i)} \) and \( z^{(i)} \) represent the \( i \)-th input image and the corresponding personal feature, respectively. Then, since the personal feature is likely to be entangled with the age-related feature, we propose to decompose the personal feature so that the age-related feature and the age-invariant personal feature are orthogonal. This is formalized as:

\[
\begin{align*}
    z^{(i)} &= \frac{z_{age}^{(i)}}{\| z_{age}^{(i)} \|_2} \cdot z_{id}^{(i)},
\end{align*}
\]

where \( z_{age}^{(i)} = \| z^{(i)} \|_2 \), \( z_{id}^{(i)} = \{ \frac{z_{1}}{\| z_{1} \|_2}, \frac{z_{2}}{\| z_{2} \|_2}, \ldots, \frac{z_{C}}{\| z_{C} \|_2} \} \), with \( \| z_{id} \|_2 = 1 \), \( C \) denotes the number of channels and \( \| \cdot \|_2 \) is the \( \ell_2 \)-norm operator. The identity basis feature is the age-invariant feature representing the personal identity, while the age basis feature is the age-related features of person.

To ensure that each decomposed feature contains intended information, we take the advantage of multi-task learning. Specifically, we predict the age of an input image with \( z_{age} \), and classify the identity number of an input image with \( z_{id} \). The loss functions of multi-task learning are as follow.

\[
\begin{align*}
    L_{reg} &= \frac{1}{N} \sum_{i=1}^{N} (a^{(i)} - f_{age}(z_{age}^{(i)}))^2, \\
    L_{cls} &= -\frac{1}{N} \sum_{i=1}^{N} y^{(i)} \log(f_{id}(z_{id}^{(i)})),
\end{align*}
\]

where \( a^{(i)} \) and \( y^{(i)} \) denote the ground-truth age and the identity number of the \( i \)-th input image respectively. The age regressor \( f_{age} \) and the identity classifier \( f_{id} \) are composed of several fully-connected layers.

Our goal is to translate the aging factor of an input image according to the target age while preserving the personal identity. Hence, after decomposing the feature of an input image,
we feed the identity basis feature $z_{id}^{(i)}$ and the target age as inputs to the decoder of the generator. The synthesized images can be obtained by:

$$\tilde{x} = Dec(z_{id}, a_{trg}),$$

where $a_{trg}$ denotes the target age.

### 2.2. Generating Images with Fidelity

To generate aged images with fidelity, we adopt the adversarial training, following the training process of Generative Adversarial Networks (GAN) \cite{14, 15, 16}. The discriminator is trained not only to discriminate the generated images from the real images, but also to predict their ages and identities. We disentangle features as in Eq. 1, and adopt multi-task losses as in Eq. 2 and Eq. 3. The multi-task losses are calculated with decomposed features of $Enc_D(x)$, where $Enc_D$ denotes the encoder of the discriminator. For quality and stability, we adopt Wasserstein GAN with gradient penalty \cite{15} as our adversarial loss, which is formulated as:

$$L_{adv} = \mathbb{E}_{\tilde{x} \sim P_g} [D(\tilde{x})] - \mathbb{E}_{x \sim P_r} [D(x)]$$

$$+ \gamma \mathbb{E}_{\tilde{x} \sim P_g} [\|\nabla D(\tilde{x})\|_2 - 1]^2,$$

where $D$ denotes the discriminator. With the adversarial training, the generator learns to produce realistic results.

The translated image $\tilde{x}$ should also be estimated same as the target age while preserving the personal identity. Hence, we adopt an age error loss of fake images to optimize the generator. The age error loss is the mean squared error (MSE) between the estimated age and the target one, defined as:

$$L_{age} = \frac{1}{N} \sum_{i=1}^{N} (a_{trg} - f_{age}(\tilde{z}_{age}^{(i)}))^2,$$

where $a_{trg}$ indicates the randomly sampled target age.

To preserve the original personal identity, we propose to minimize the verification loss by maximizing the cosine similarity between the identity basis feature of the original and translated images as follows.

$$L_{id} = 1 - \frac{z_{id} \cdot \tilde{z}_{id}}{\|z_{id}\| \|\tilde{z}_{id}\|},$$

where $\tilde{z}_{id}$ denotes the identity basis feature of the generated image $\tilde{x}$. The identity preservation loss is minimized when the angle between two feature vectors are 0.

Lastly, to train without ground-truth, we adopt the reconstruction loss and the cycle consistency loss \cite{9} as follows.

$$L_{recon} = \frac{1}{N} \sum_{i=1}^{N} (x^{(i)} - G(x^{(i)}, a_{trg}))^2,$$

$$L_{cycle} = \frac{1}{N} \sum_{i=1}^{N} (x^{(i)} - G(G(x^{(i)}, a_{trg}), a^{(i)}))^2,$$

where $\{\lambda_i\}$ are hyper-parameters for weighing loss functions.

### 3. EXPERIMENTS

In this section, we provide the implementation details of our CFA-GAN and report evaluation results on the MORPH \cite{12} dataset. MORPH contains 55,000 face images of 13,617 identities from 16 to 77 years old. Following the prior works \cite{10, 11, 17}, we first extract facial regions of $200 \times 200$ pixels using MTCNN \cite{13}, and then resize them to $128 \times 128$ resolution. We split the dataset into training and test set in a ratio of 90:10 respectively. To demonstrate the effectiveness of our CFA-GAN, comparative experiments are conducted with the state-of-the-art face aging methods.
Table 1. Evaluation on the regressed ages of translated images. “Generic” denotes the ground-truth age distribution. We report the average estimated age distributions and the mean squared errors between the target and the estimated ages.

| Age group | 21-30 | 31-40 | 41-50 | 50+ |
|-----------|-------|-------|-------|-----|
| Generic   | 25.12 | 35.43 | 44.72 | 54.88 |
| CAAE [10] | 24.31 | 31.02 | 39.03 | 47.84 |
| IPCGAN [11] | 22.38 | 27.53 | 36.41 | 46.42 |
| AcGAN [17] | 25.92 | 36.49 | 40.59 | 47.88 |
| Ours      | 26.88 | 36.96 | 48.85 | 59.28 |

Table 2. Evaluation on identity preservation. The upper part presents the average confidence scores of the translated images from the original age (row) to the target age (column). The lower part shows verification rates, where a pair is considered true positive if its confidence surpasses the threshold.

| Age group | 21-30 | 31-40 | 41-50 | 50+ |
|-----------|-------|-------|-------|-----|
| Verification Confidence (%) | 99.38 | 97.82 | 92.72 | 80.56 |
| Verification Rate (%) | 99.38 | 97.82 | 92.72 | 80.56 |
| CAAE [10] | 100 | 100 | 100 | 100 |
| IPCGAN [11] | 100 | 100 | 100 | 100 |
| AcGAN [17] | 100 | 100 | 100 | 100 |
| Ours | 100 | 99.93 | 99.68 | 98.91 |

3.3. Quantitative Results

Face aging aims to translate the faces of input images to target ages while preserving personal identities. Therefore, one can evaluate face aging models from two perspectives: (1) how much the age of the translated image matches the target age and (2) how well the identity of the original image is preserved. Following the previous studies [11, 17], we evaluate our CFA-GAN by employing Face++ API [20] that offers age regression and face verification.

4. CONCLUSION

Since previous face aging studies were limited in discrete age group labels, the ages of their result images were in black box. In this paper, we proposed CFA-GAN for continuous face aging, where the age-related features are isolated from the age-invariant features. Moreover, we proposed a novel loss function to preserve original personal identity. As a result, the translated images by our method correspond well to the target ages (not groups). Through the experiments, we validated the superiority of our method against the existing work.
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