Dual-reference Age Synthesis

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\section*{Abstract}
Age synthesis has received much attention in recent years. State-of-the-art methods typically take an input image and utilize a numeral to control the age of the generated image. However, different people have different age appearance even though they are in the same age, and different observer has different understanding about "young" or "senior". In this paper, we revisit the age synthesis and ask: is a numeral capable enough to describe the human age? The answer is that his/her images can tell the age information. Furthermore, aging synthesis being implemented with two images as a potential and novel task is proposed. We propose a novel framework to meet the requirements of this task, which takes two images as inputs to generate an image which shares the same identity of the first image and has the similar age with the second image. In the proposed framework, a generate adversarial network is training and competes against an age agent and an identity agent, the output of these two agents form a joint manifold feature as the input of the generator and the final images are generated by the generator. Experimental results demonstrate the appealing performance and flexibility of the proposed framework by comparing with the state-of-the-art and ground truth.

\section{Introduction}
Age synthesis, which is also referred to as face aging and rejuvenation or age progression and regression, aims to predict the aging or rejuvenating effects for an individual face while preserve the personality features. It has received many research interests for its importance to wide range applications, \textit{e.g.} finding missing people, face verification, security surveillance and entertainment, \textit{etc}. To synthesize aging image, conventional methods can be categorized into three folds: physical model-based methods, prototype-based methods and generate adversarial network (GAN) based methods. Physical model-based methods use a parametric anatomical model to describe face aging procedure including faces, skin, physical mechanism on profile growth and facial muscle changes, \textit{etc}. which are expensive computational-cost and complex [Mark \textit{et al.}, 1980; O’toole \textit{et al.}, 1997; O’Toole \textit{et al.}, 1999]. The prototype-based methods use prototype images to define the salient feature of different ages and the differences between two prototypes depict the transformation of age, then these changes are applied to a given input face and its age can be changed. However, prototypes are the average facial features which can not preserve identity information [Benson and Perrett, 1993; Liu \textit{et al.}, 2004; Tiddeman \textit{et al.}, 2001]. Then in the latest decade, thanks to the development of General Adversarial Networks (GANs) [Goodfellow \textit{et al.}, 2014], GAN-based methods has got great progress [Yang \textit{et al.}, 2017; Antipov \textit{et al.}, 2017]. The GAN-based methods learn identity features of an individual firstly, transform a given number to a one-hot vector to describe age information, and then use a generator to synthesize images using these identity features with a given number as its target age. A discriminator classifies the synthesized aging images as “fake” and those wild-life images in target ages or “young”/“senior” people images as “real”, and the generator tries to generate indistinguishable images, then generator and discriminator are optimized alternately in adversarial manner. To achieve the best performance, GAN-based methods need to collect a large number of pair-wise images (\textit{i.e.}, face images of the same person at large age spans) in the real world as ground-truth which is difficult and even infeasible.

No matter the parametric model in physical model-based methods or the average depiction in prototype-base methods or the one-hot vector in GAN-based methods, these three categories methods all use a fixed number or average depiction to describe age feature. However, as we all know, different people has different age appearance even though they are in the same age, moreover, “young” or “senior” is abstract conception and there has no unified baseline for them. Those numeral age or average depiction is not capable enough to describe human age features, but the image itself includes all age information. Therefore, a potential and novel task is proposed: age synthesis only with images which means taking two images as inputs to generate an image shares the same identity of the first image and has the similar age with the second image. The main motivation behind this paper is to tackle the new task, synthesize images with age features from images rather than with a given number.

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In this work, we propose a duo-reference age synthesis (DRFA) framework, the comparison of our framework and conventional framework is illustrated in Figure 1.

Contributions of this paper are summarized in three-fold:

1. We propose an unified age synthesis framework with two reference images as input, and age features are presented from reference images including more age information and is more sensible than a number or an average description.

2. The proposed framework focuses on an end-to-end age feature learning and identity feature learning, which is feasible without ground-truth labeled data or pair-wise data.

3. Extensive experiments and detailed analysis are conducted and validate the advantage of our framework over the age synthesis with identity preservation.

2 Related Works

As far back as 2002, Lanitis et al. investigated three aging formulations: linear, quadratic and cubic, respectively, with 50 raw model parameters and described how the effects of aging on facial appearance can be explained using learned age transformations [Lanitis et al., 2002]. N Ramanathan et al. characterized the shape and textural variations of adult faces undergo with age which developed the computational physical models [Ramanathan and Chellappa, 2006]. To tackle the lack of sufficient long-term face aging sequences for model learning, J Suo et al. proposed a CONcatenational GRaph Evolution (CONGRE) aging model, which decomposed human faces into mutually interrelated subregions under anatomical guidance, and then the long-term evolution of the above graphical representation is then modeled by connecting sequential short-term patterns following the Markov property of aging process under smoothness constraints between neighboring short-term patterns and consistency constraints among subregions [Suo et al., 2012]. Then P Kaur et al. [2017] proposed face texture transfer (FaceTex) framework augmented the prior work. FaceTex suppresses facial texture comprising skin texture details around facial meso-structures (e.g. eyes, nose and mouth) and synthesizes a facial image with different facial textures while maintaining the identity of the original one. However, these physical model-based methods cannot be generalized since their computational cost and complexity, prototype model-based methods got improved. B Tiddeman et al. use the difference between two prototypes(2D shapes) to define an axis of transformation, such as younger to older [Tiddeman et al., 2001]. Liu et al. proposed a novel technique: image-based surface detail transfer (IBSDT) which can be used to age synthesis by transferring the bumps from an old person’s skin surface to a young person’s face. IBSDT is simple to implement but needs first manually put markers on the boundaries and the feature points, and then obtain pixel alignment through image warping [Liu et al., 2004]. Without markers but accounting for the nature of multimodalities in the face image set, Wang et al. introduced multilinear algebra to represent and process the aging image in tensor space [Wang et al., 2012]. Kemelmacher-Shlizerman et al. proposed an illumination-aware age progression approach to compute average image subspaces and apply these average depictions (shape, texture) to a new photo yields an age progressed result [Kemelmacher-Shlizerman et al., 2014]. Thereafter, Shu et al. proposed a Kinship-Guided Age Progression (KinGAP) approach which can generate personalized aging images by computing average face and using the senior family members as a prior guidance [2016]. As we all know, the average depictions cannot maintain the personality well.

Meanwhile, the conditional generate adversarial network (cGAN) introduces condition into original GAN to control the generated results with a given condition [Mirza and Osindero, 2014], this controllable character made CGAN as the main network for age synthesis and speed up the deep learning-based methods development. Loss function of cGAN is as Eq.(1).

\[
\min_G \max_D E_{x \sim P_{data}(x)} \log D(x, y) + E_{z \sim P(z)} \log (1 - D(G(z, y)))
\]

where \(G(\cdot)\) and \(D(\cdot)\) denote generator and discriminator.

Different from the other type methods, GAN-based methods are trying to learn individual personality use the age label as the condition. Makhzani et al. [2015] proposed an Adversarial Autoencoders (AAE) using an adversarial training procedure to learn the latent vector, which inspired most of the state-of-the-art face aging methods. [Antipov et al., 2017; Lample et al., 2017; Liu et al., 2017] investigate age synthesis based on GAN and AAE which can generate the personalized aging images at the tender age. To disentangle the personality and age, Zhang et al. proposed a conditional adversarial auto-encoder (CAAE) and described a synthesis framework based on GAN and AAE; personalized identities are indicated by map the original face image to a latent vector via an encoder, then these identities and a corresponding numeral (age) are fed into the generator to synthesize face images [Zhang et al., 2017]. Antipov et al. proposed an Age Conditional Generative Adversarial Network (Age-GAN) to generate identity-preserving synthetic images within required age categories, which use the Facenet to optimize latent vectors [Antipov et al., 2017], it can be considered as a part of CAAE. Recently, Wanget al. proposed an identity-preserved conditional generative adversarial networks (IPCGANs), which use an age classifier forces the generated face with the target age and use the multi-layer feature of age classifier as identity feature [Wang et al., 2018]. To obtain more realistic image, Liet al. proposed a Wavelet-domain Global and Local Consistent Age Generative Adversarial Network (WaveletGLCA-GAN) which adopt wavelet transform to depict the textual information in frequency-domain with given age labels, WaveletGLCA-GAN abstract age information from local patches of a given age face image and generate an image with the target age, but it needs forehead, eyes and mouth local patches of the target age images and consists five sub-networks which are complex [Lì et al., 2019]. There still has a lot of endeavors promoting the GAN-based methods [Yang et al., 2017; Song et al., 2018; Tang et al., 2017]. Despite of focusing on...
face aging synthesis, Expression Generative Adversarial Network (ExprGAN) [Ding et al., 2017] and StarGAN [Choi et al., 2018] can also be used for face aging synthesis. To our knowledge, these methods need pair-wise data or annotated data.

3 Proposed method

In this section, we first describe the framework of our proposed method, then two main modules of the framework are discussed in Sec.3.2 and Sec.3.3, respectively. Finally, the objective functions are introduced.

3.1 Overview

With a given age reference image, can you imagine what did Emma Stone look like when she was young? Or a baby will look like when he/she grows up? We can tell you in Figure 2.

Figure 2: Demonstration of our age synthesis result(images with black dotted box are the original ones.)

Different people in the same age has different age appearance, for example, those people well-educated and grew up in a wealthy family looks younger than those homeless. Therefore, synthesizing face aging or rejuvenating with reference faces rather than with a numerical age, which is more reasonable since a reference image expresses what kind of age effect exactly and includes more age information than a number. To tackle the new task, age synthesis only with images, our framework consists of three parts: an age agent, an identity agent and a GAN. The age agent is used to learn the reference age features, the identity agent is used to learn the identity information, and a GAN is used to synthesize the face image. Figure 3 describes the framework of our proposed method.

For convenience, we define $I^m$ as an image of the individual with identity $i$ at age $m$, and the age reference image is $I^a_j$ and the identity reference image is $I^{i_j}$. We assume that the face image is sampled from two low dimensional manifolds where the identity and age change smoothly along respective dimensions. The identity agent and the age agent map the two reference images into two manifold features respectively. The identity feature and age feature are joint and then are fed to generator, as the age feature be a condition.

3.2 Age Agent

An age agent is designed for the proposed framework based on the deep expectation of apparent age (DEX) [Rothe et al., 2015; Rothe et al., 2016] (the winner of LAP challenge on apparent age estimation) which is pretrained on ImageNet [Deng et al., 2009]. There are 13 convolution layers with 1-stride in the age agent, every convolution layer is followed with a ReLU layer. The size of kernel is $3 \times 3$, and the number of kernels are 64, 64, 128, 128, 256, 256, 256, 512, 512, 1024, 1024, and 1024, respectively. Since age features and identity features will be joint, we remove the last fully-connected layer and append two fully-connected layers to output 50 dimensions age feature.

Comparing with conventional researches, the 50-dimension age embedding has more age information than a one-hot vector or a numerical age label. Moreover, the 50-dimension feature makes our framework light-weighed rather than those conception features (congregate multi-layers outputs of deep networks as the final feature) [Yang et al., 2017; Ding et al., 2017]. With the back-propagation of $L_{age}$, age agent can be optimized for learning age feature better.

Age preserving Specially, an age preserving function $L_{age}$ guarantees the synthesized image has the same age with
the age reference image.

\[ \mathcal{L}_{\text{age}} = ||E_A(I^n_j), E_A(\tilde{I}^n_i)||_2 \]  \hspace{1cm} (2)

where \( E_A(\cdot) \) is the age feature.

### 3.3 Identity Agent

The identity agent is inspired by the CAAE method [Zhang et al., 2017], however, different from CAAE, an identity preserving loss is injected into the identity agent. There are an encoder \( E_I \) and a discriminator \( D_I \) in the identity agent. Five convolution layers extract hierarchical identity features with 2-stride, the size of kernel is 5 × 5 and the number of kernels are 64,128,256,512 and 1024, respectively. In identity agent, a ReLU layer follows after each convolution layer. A full connection layer project the convolution features into a 50 dimensions latent vector which is the final identity feature.

**Reconstruction** Aim to extract identity features from reference images without pair-wise or labeled training data, a reconstruction loss is used:

\[ \mathcal{L}_{\text{rec}} = ||I^n_i, \tilde{I}^n_i||_1 \]  \hspace{1cm} (3)

where \( \tilde{I}^n_i = G(E_I(I^n_i), E_A(I^n_j)) \).

We assume the identity manifold obey the uniform distribution and then an adversarial process force the identity manifold with no “holes” [Zhang et al., 2017]. Denote \( p_{\text{data}}(I) \) as the distribution of the identity reference data \( I \), assume \( p_z \) as the prior uniform identity feature distribution and \( z_i \sim p_z \). The latent code is trained to approach the uniform distribution by:

\[ \mathcal{L}_{z_i} = \min_{E_I} \max_{D_I} \mathbf{E}_{z_i \sim p_z} \log[D_I(z_i)] + \mathbf{E}_{I \sim p_{\text{data}}(I)} \log[1 - D_I(E_I(I))] \]  \hspace{1cm} (4)

where \( E_I \) and \( D_I \) denote the identity encoder and identity discriminator.

**Identity preserving** Furthermore, our method aim to synthesize image in a unsupervised manner, an identity preservation function forces the synthesized image \( \tilde{I}^n_i \) has the same identity with \( I^n_i \):

\[ \mathcal{L}_{\text{id}} = ||E_I(I^n_i), E_I(\tilde{I}^n_i)||_2 \]  \hspace{1cm} (5)

where \( E_I(\cdot) \) is the identity feature.

### 3.4 Generator and Discriminator

In Figure 3, a 128 × 128 × 3 image \( I^n_i \) as identity reference and a 224 × 224 × 3 image \( I^n_j \) as age reference are inputted into our model. The generator \( G \) is a decoder actually, and the task of the generator is to synthesize images \( G(E_I(I^n_i), E_A(I^n_j)) \) with identity reference image \( I^n_i \) and age reference image \( I^n_j \). The discriminator \( D \) discriminates whether a image is a ground-truth or a synthesized one using 4 de-convolution layers and 2 full connection layers.

### 3.5 Objective function

To generate a photo-realistic face image, the discriminator tries to discriminate the two reference images as real and the generated image as fake. Thus the discriminator’s objective function can be derived as:

\[ \mathcal{L}_{\text{adversarial}} = \min_G \max_D \mathbf{E}_{I^n_i \sim p_{\text{data}}(I^n_i)} \log[D(I^n_i)] + \mathbf{E}_{\tilde{I}^n_i \sim p_{\text{data}}(\tilde{I}^n_i)} \log[1 - D(\tilde{I}^n_i)] \]

\[ + \mathbf{E}_{I^n_j \sim p_{\text{data}}(I^n_j)} \log[D(I^n_j)] + \mathbf{E}_{\tilde{I}^n_j \sim p_{\text{data}}(\tilde{I}^n_j)} \log[1 - D(\tilde{I}^n_j)] \]  \hspace{1cm} (6)

where \( \tilde{I}^n_i = G(E_I(I^n_i), E_A(I^n_j)) \).
Finally, the overall objective function is:
\[
\min_{E, G, D_1, D_2} \max_{I, D_1, D_2} \lambda_{\text{adversarial}} L_{\text{adversarial}} + \lambda_{\text{id}} (L_{zI} + L_{\text{rec}} + L_{\text{id}}) + \lambda_{\text{age}} L_{\text{age}}
\]
where \( \lambda_{\text{adversarial}}, \lambda_{\text{id}} \) and \( \lambda_{\text{age}} \) are weights to control the impact of these loss terms.

4 Experiments

4.1 Data Description

We conducted experiments on two widely used benchmark face datasets UTKFace [Zhang et al., 2017] and Cross-Age Celebrity Dataset (CACD) [Chen et al., 2014]. The age of UTKFace dataset ranges from 0 to 116 years old and has no identity annotation. CACD dataset covers 2,000 celebrities, its age labels were estimated by simply subtract the birth year from the year of which the photo was taken, so we chose those images whose ranks are smaller than or equal to six as the training data. Specially, different with UTKFace images in the wild, CACD face images are exquisite photos which have low qualities. We made an intuitive static on UTKFace and CACD via their age ranges, i.e. 0-5, 6-10, 11-15, 16-20, 21-30, 31-40, 41-50, 51-60, 61-70 and 70+. As Figure 4 shows, only UTKFace includes baby (zero to five-year-old), child (six to ten-year-old) and those senior people above 70-year-old images. Furthermore, the amount of person at age from 20 to 40-year-old is about as twice as that of other age ranges.

In the training step, we random chose two images, one is the identity reference image and the other one is age reference image. In other word, the same image can be chosen as an identity reference image or an age reference image in different epoch randomly. Therefore, the reconstruction and generated loss functions of age reference image are not involved in our method, that is different from other typical methods [Song et al., 2018].

Empirically, it is hard to archive good performance if we train the model with multiple loss functions in Eq.(7) directly. To tackle this difficulty, we applied a joint-training strategy for training. At first, in order to preserve identity information and make sure that the identity manifold covers all feature space, we set \( I_i^m = I_j^n \), and then train the identity agent and the generator by minimize reconstruction loss (Eq.(3)) and adversarial loss of identity agent (Eq.(4)). Then we introduced the adversarial loss of generator and discriminator (Eq.(6)) into the training loss to guarantee the generated images be photo-realistic. Subsequently, after the identity agent loss converged, we fixed \( E_i \) and \( D_i \), set \( I_i^m \neq I_j^n \), and used the two preserve functions (Eq.(5), Eq.(2)) to optimize the generator.

For CAAE, we retrained CAAE on UTKFace with the released code, fine-tuned the CAAE model on CACD, and then we got ten age groups images of UTKFace and CACD. For IPCGAN, we got the test results on UTKFace and CACD with the released pretrained model which were trained on CACD and can only synthesize five age groups images (11-20, 21-30, 31-40, 41-50 and 50+).

4.2 Implementation Details

In term of morphology, children (baby and child younger than ten-year-old) have different facial appearance from the teenagers and adults. Aiming to learn age features from children and senior person and avoid over-fitting in the range of 20-year-old to 40-year-old, we augmented UTKFace and CACD by flipping those images in other age ranges. Then we used 80% images as training data, 10% as validation data and the left 10% as test data. All images were aligned and cropped, and were normalized to [-1, 1]. We trained our networks on an NVIDIA TITAN X GPU using a random sample of 100 as one batch from training data, with learning rate \( 2e^{-3} \), \( \lambda_{\text{adversarial}} = 1 \), \( \lambda_{\text{id}} = 1e^{-3} \) and \( \lambda_{\text{age}} = 1e^{-2} \).

Ten images from UTKFace were chosen as the age reference images in test step whose ages cover a range from baby to senior people and are distinct from the training images (shown in Figure 5).

In the training step, we random chose two images, one is the identity reference image and the other one is age reference image. In other word, the same image can be chosen as an identity reference image or an age reference image in different epoch randomly. Therefore, the reconstruction and generated loss functions of age reference image are not involved in our method, that is different from other typical methods [Song et al., 2018].

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4.3 Experimental Performance and Analysis

Generative Performance Comparison
IPCGAN trains model on five age groups, for fair, the result comparisons are taken in the five age groups as shown in Figure 6. The identity reference images cover young person, mid-age person and senior person.

Figure 6 shows the synthesized faces in different five age groups. All generated images have the same expression and same pose as the identity reference images. For identity preserving and age classifier in IPCGAN share one deep convolutional network which is not reasonable, we can see that age appearances change slightly and the generated images look similar as the input images in IPCGAN. For CAAE, there only has reconstruction loss on pixel level and has no age preserving strategy, the synthesized images in CAAE look blurry and have artifacts, for example, in the left top dotted box of Figure 6, pupils of CAAE images changed and the mid-age one looks the same as young one. Compared with CAAE and IPCGAN, DRAS can synthesize higher quality face images with the same identity and age with the references images.

Furthermore, we compare our results with those ground truth. First, we use the same image as identity reference image and age reference image, and reconstruct the reference image as Figure 7. The reconstruction images of IPCGAN have the best performance on some details, for example the illumination and curl hair on face (show in green boxes). Images with blue boxes mostly look like real images since these three methods are all considering reconstruction loss.

Then we synthesize Emma Waston and Isabella Rossellini’s images with different age reference images, choose the real images from CACD, and the real images are in the same age group with age reference images. The IPCGAN can generate images which most like the identity reference images, but still has slight age appearance difference. Our proposed model can synthesize images which have the same identity feature and age feature with the reference images (as Figure 8 shows).

Disentangled Identity Feature Learning Performance
The identity agent in our model learns the disentangled identity feature. To validate the identity agent, we choose 11 celebrities from CACD, collect their images which cover age range from teenage to mid-age. The 11 subsets are described in Table 1.

We use t-Distributed Stochastic Neighbor Embedding (t-SNE) [Maaten and Hinton, 2008; Van der Maaten and Hinton, 2012] to visualize the identity feature map. The output of t-SNE, which models similar objects by nearby points and dissimilar objects by distant points, can depict the similarities of identities.

First, we choose 9 subsets (id0, id1, id2, id4, id5, id6, id8, id9 and id10) from Table 1 that every three locate in the same age range, retrieve their identity features via the identity agent, and then feed them to t-SNE. These 9 person can almost be categorized by their identity as Figure 9 showing. Some overlapped identities are similar on pose (e.g. side face in Figure 9(a)), expression (e.g. smiling or being serious in Figure 9(b)) or shape of face (e.g. in Figure 9(b) and 9(c)), which is in consistent with the discussion in the "generate performance comparison" subsection. As shown in Figure 9(c), the three people are separated well for they have different ethnicity and different gender, which are parts of identity features. Especially, in the left bottom of Figure 9(a), Clave Lively (id3) has the "similar" identity feature with Zac Efron(id0), it is notable that Zac has sun glasses and has same expression with Clave that mislead our identity agent. Some overlapped images are shown in Figure 10.

Furthermore, we choose six subsets to study the disentangled identity feature map in different age ranges. Most identity features are separated well as Figure 11 showing. However, there still have some features overlapped. By observing Figure 12 we find identity features are also affected by gender, expression and occlusion. For example, in Figure 12(a), id6 and id10 are females and have red lips, then some of their identity features are overlapped even though they are not in the same age range; one of id9 looks serious as id6 and id10, and his identity feature is mixed with id6. In Figure 12(b), id0 and id2 are young people, the identity feature of id0 who has sun glasses is overlapped with id2, that has been found in Figure 10. That is reasonable, for people in same age or adjacent age sometimes have similar appearance feature: young people’s eyes always bigger than that of senior people and they have less wrinkle on the face, which can be seems as the identity feature.

In short, the identity agent can disentangle identity feature from age feature.

Identity Preservation Comparison
We synthesize images by CAAE, IPCGAN and DRAS, and then retrieve their identity feature using our identity agent. The three methods all have identity preservation strategy to keep the generated images look like the identity reference images: IPCGAN uses conceptual loss and reconstruction loss, CAAE uses reconstruction loss and DRAS has identity preserving function and reconstruction loss. Therefore the generated images idn* of these three methods are almost around their identity reference images idn as shown in Figure13 and Figure14. Since DRAS and IPCGAN have both identity preserving loss and reconstruction loss, identity features of DRAS and IPCGAN have more intra-cluster compactness which means they can learn identity feature better than CAAE. Furthermore, DRAS has more between-cluster
Figure 6: Some synthesized faces on UTKFace and CACD. Each dotted box denotes the same one person’s images. The first left column is the identity reference images for DRAS (the input images for CAAE and IPCGAN).

As discussed before, some age appearance such as wrinkle and moustache are part of identity features, and identity feature layers are shared with age classifier in IPCGAN, therefore there are some “outliers” with dotted circle in Figure13 in IPCGAN. The identity features of three person learned by CAAE are overlapped more than that of IPCGAN and DRAS, since CAAE only focuses on the difference between reconstructed images and the original ones rather than the difference in feature space.

Figure 13 and Figure 14 show that our DRAS perform outstanding both on those identity in same age range and those in different age ranges.

**Age Preservation Performance**

To discern whether a synthesized image fells in the same age range with the age reference image, we use a pre-trained AlexNet model which is fine-tuned to classify 10 classes on UTKFace and CACD. For every identity reference image, it has 10 synthesized images with 10 different age reference images by CAAE and DRAS, respectively, and it has 5 synthesized images which locate in 5 age groups in IPCGAN. Therefore, the number of synthesized images in every age group is same and the data is balance, then we use the accuracy to describe age preservation performance. We use the fine-tuned classifier to validate CAAE and DRAS and use the formal released trained model [Wang et al., 2018] to validate IPCGAN. The quantitative comparison result is shown in Table 2 and Table 3. Obviously, our model gets the best age preserving performance in 9 age groups except age group 5# and outperform the other two methods in age preserving view.

| Age Groups | Accuracy of CAAE (%) | Accuracy of DRAS (%) |
|------------|---------------------|---------------------|
| 0# (0-5)   | 99.94               | 99.93               |
| 1# (6-10)  | 97.59               | 99.63               |
| 2# (11-15) | 79.03               | 92.47               |
| 3# (16-20) | 84.83               | 93.12               |
| 4# (21-30) | 99.91               | 100                 |
| 5# (31-40) | 97.27               | 93.9                |
| 6# (41-50) | 75.64               | 84.71               |
| 7# (51-60) | 90.53               | 90.1                |
| 8# (61-70) | 96.65               | 97.02               |
| 9# (70+)   | 96.46               | 99.97               |
| **Average**| **91.78**           | **96.04**           |

Table 2: Age preservation performance of the three methods. Bold number is the maximum.

The generated images which are infant(0#), toddler(1#), 20-30 years old people (4#) and those over 60-year-old(8# and 9#) have more age feature consistent with the reference age images than other groups. By observing Figure 4, only UTKFace has data in age group 0#, age group 1#, age group 8# and age group 9#, and UTKFace has more 20-30 years
Figure 7: Reconstruction results of three methods. The left dotted box is UTKFace and the right one is CACD. In each box, from top to bottom, they are ground truth, then images generated by CAAE, IPCGAN and DRAS. The green box is the best performance on details and the blue box is the photo-realistic ones.

Figure 8: Synthesized faces with different identity reference images and age reference images. The first row is the age reference images and the first left column is the identity reference images. In each box, from top to bottom, they are real images in the same age with age reference images, and images generated by CAAE, IPCGAN and DRAS.

Table 3: Age preservation performance of IPCGAN.

| Age Groups | Accuracy of IPCGAN(%) |
|------------|-----------------------|
| 2# and 3# (11-20) | 10.57 |
| 4# (21-30) | 25.92 |
| 5# (31-40) | 30.89 |
| 6# (41-50) | 20 |
| 7#, 8# and 9# (50+) | 78.12 |
| Average Accuracy(%) | 33.10 |

Table 4: Description of four training scenarios.

| Scenario | Description |
|----------|-------------|
| S1       | with the two preserving functions |
| S2       | without the two preserving functions |
| S3       | with only identity preserving function |
| S4       | with only age preserving function |

old face images (age group 4#) than CACD. In other word, in age group 3#, 5#, 6# and 7#, the amount of data in CACD is more than that of UTKFace. Moreover, CACD images are about celebrities who are various in pose and heavy makeup, that affects the age effect learning. Furthermore, in IPCGAN, age constraint and identity constraint share the same convolution layers which results in the lowest performance of IPCGAN in age preservation.

Ablation Study

For analyzing the effect of age preserving function and identity preserving function, we set four training scenarios in Table 4.

Under the four training scenarios, we trained our model and got test results shown in Figure 15. Face images with red boxes are blurry that look younger than the reference age, which means the trained model without age preserving function will lose some age information. And those images with yellow boxes don’t look like the identity reference images, which means the model without identity preserving function will lose the personality information in some degree. Moreover, by checking those images synthesized under scenario S2 and S3, images with age preserving function have artifacts but those S2 images haven’t. Age information usually appears in local facial parts, such as wrinkles at the eyes corner, the width between two eyes is large and the face shape is round like an apple for baby, therefore age feature consists texture features, shape features etc., which can be seen as ar-
Figure 9: Visualization of identity feature. (a) age ranges from 14 to 26 years old (b) age ranges from 20 to 33 years old (c) age ranges from 43 to 58 years old

Figure 10: Description of overlapped points. Face images with colour boxes belong to the identity with same colour.

Figure 11: Visualization of identity feature in different age ranges. (a) identity in three age ranges (b) identity in two age ranges

Figure 12: Description of overlapped points. Face images with colour boxes belong to the identity with same colour.

Effect of identity preserving function

Effect of identity preserving function

Effect of age preservation function

Effect of age preservation function

that DRAS only has identity preservation function, the identity feature of each person is more compact as the third row show in Figure 16. Only considering age feature coincidence cannot guarantee the synthesized images share the same identity feature with the identity reference images, as the last row in Figure 16 showing the three person’s identity features are joint together.

Effect of age preservation function

We also take an age evaluation under S1, S2, S3 and S4 scenarios respectively and the result is shown in Table 5. The
Figure 13: Identity preservation comparison of the three methods. From left to right, they are identity feature visualizations of DRAS, IPCGAN and CAAE respectively. Annotation idn* is the synthesized image with identity reference image idn. Points with dotted circle are those far away from their feature centers. (a) 14-26 years old (b) 20-33 years old (c) 43-58 years old

age preservation function can guarantee the synthesized images lie in the same age range with the age reference images, and DRAS with age preserving gets higher accuracy than that without age preserving.

DRAS combines identity preserving and age preserving to synthesize images share the identity feature with identity reference images and the age feature with age reference images, which leads the compromise between identity and age. Therefore, the average accuracy of DRAS with age preservation function and identity preservation function is the highest.

5 Conclusion

This paper studied a new age synthesis task: dual-reference age synthesis. Given two reference face images, synthesize a face image which has the same identity information with identity reference image and at the same age with the age reference image. In the proposed framework, a joint manifold embedding is abstracted from training data through the identity agent and age agent, then the proposed model is trained on adversarial way with the joint manifold embedding, and is optimized with identity preserving function and age preserving function. Detailed training strategy was discussed in this paper, the experimental results on UTKFace and CACD are given and are analyzed thoroughly. The corresponding results show that the proposed approach achieves promising results on this new task.

Acknowledgements

This work was supported by the Jiangsu Overseas Visiting Scholar Program for University Prominent Young
Figure 14: Identity preservation performance of the three methods for different age ranges. From left to right, they are identity feature visualizations of DRAS, IPCGAN and CAAE respectively. Annotation idn* is the synthesized image with identity reference image idn. (a) three age ranges (b) two age ranges

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| Age Groups | Accuracy of S1(%) | Accuracy of S2(%) | Accuracy of S3(%) | Accuracy of S4(%) |
|------------|------------------|------------------|------------------|------------------|
| 0# (0-5)   | **99.93**        | 99.8             | 99.86            | **99.93**        |
| 1# (6-10)  | **99.63**        | 92.85            | 93.32            | 99.49            |
| 2# (11-15) | 92.47            | 74.44            | 74.88            | **93.86**        |
| 3# (16-20) | **93.12**        | 78.98            | 80.41            | 92.17            |
| 4# (21-30) | 100              | 99.97            | 99.9             | 100              |
| 5# (31-40) | **93.90**        | 89.97            | 90.54            | 93.83            |
| 6# (41-50) | 84.71            | 71.59            | 74.1             | **85.12**        |
| 7# (51-60) | 90.1             | 92.51            | **97.63**        | 97.02            |
| 8# (61-70) | 97.29            | 98.2             | 99.53            | **99.66**        |
| 9# (70+)   | **99.97**        | 98.58            | 99.56            | 99.9             |
| Average Accuracy (%) | 96.04 | 89.36 | 90.33 | **96.15** |

Table 5: Effect of age preservation function. Bold number is the maximum.

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Figure 15: The effective of identity and age preserving functions. There are face images generated under S1, S2, S3 and S4 respectively from top to bottom. Images with red boxes are those look younger than the age reference images, and images with yellow boxes look different with the identity reference images.
Figure 16: Effect of identity preservation function. From top to bottom, they are identity feature visualizations under S1, S2, S3 and S4 occasions respectively. Annotation idn* is the synthesized image with identity reference image idn. (a) 14-26 years old (b) 20-33 years old (c) 43-58 years old
Figure 17: Effect of identity preservation function. From top to bottom, they are identity feature visualizations under S1, S2, S3 and S4 occasions respectively. Annotation idn* is the synthesized image with identity reference image idn. (a) three age ranges (b) two age ranges