



# IJIRSET

International Journal of Innovative Research in  
**SCIENCE | ENGINEERING | TECHNOLOGY**

e-ISSN: 2319-8753 | p-ISSN: 2320-6710



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 10, Issue 7, July 2021

**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA

Impact Factor: 7.569



9940 572 462



6381 907 438



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# Face Aging Using Generative Adversarial Network

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**ABSTRACT:** Face aging is to render a given face to predict its future appearance, which plays a crucial role within the information forensics and security field because the appearance of the face typically varies with age. Although impressive results are achieved with conditional generative adversarial networks (cGANs), the prevailing cGANs-based methods typically use one network to find out various aging effects between any two different age groups. However, they can't simultaneously meet three essential requirements of face aging—including image quality, aging accuracy, and identity preservation—and usually generate aged faces with strong ghost artifacts when the age gap becomes large. Inspired by the very fact that faces gradually age over time, this paper proposes a completely unique progressive face aging framework supported generative adversarial network to mitigate these issues. Unlike the prevailing cGANs-based methods, the proposed framework contains several sub-networks to mimic the face aging process from young to old, each of which only learns some specific aging effects between two adjacent age groups. The proposed framework can be trained in an end-to-end manner to eliminate accumulative artifacts and blurriness. Moreover, this paper introduces an age estimation loss to require under consideration the age distribution for an improved aging accuracy, and proposes to use the Pearson coefficient of correlation as an evaluation metric measuring the aging smoothness for face aging methods. Extensively experimental results demonstrate superior performance over existing (c)GANs-based methods, including the state-of-the-art one, on two benchmarked datasets.

**KEYWORDS:** Face aging, generative adversarial networks, progressive neural networks, divide-and-conquer, image translation..

## I. INTRODUCTION

Face aging is to render a given young face to predict its future appearance with natural aging effects while preserving his/her personalized features. It's broad applications starting from digital entertainment to information forensics and security; e.g., predicting the longer term appearances of lost children, and therefore the cross-age face verification [1, 2, 3, 4]. Because of the appealing application value of face aging, the literature has proposed numerous methods to deal with this problem within the past 20 years [5, 6], especially the supervised-based deep neural networks explored in [7, 8, 9]. However, these methods Z. Huang, S. Chen, and J. Zhang are with Shanghai Key Lab of Intelligent information science and therefore the School of computing, Fudan University, Shanghai 200433, China (email: zzhuang19@fudan.edu.cn; szchen19@fudan.edu.cn; jpzhang@fudan.edu.cn). H. Shan is with Institute of Science and Technology for Brain-inspired Intelligence and MOE Frontiers Center for neuroscience, Fudan University, Shanghai 200433, China, and Shanghai Center for neuroscience and Brain-Inspired Technology, Shanghai 201210, China (email: hmshan@fudan.edu.cn). Corresponding author: Hongming Shan require massive paired faces of an equivalent subject over an extended period for training, which is impractical and cumbersome. To alleviate the necessity for paired faces, in recent years, generative adversarial networks (GANs) [10] and its variant, conditional GANs (cGANs) [11], are widely used to train a face aging model with unpaired face aging data [12, 13, 14, 15, 16, 17, 18, 19, 20, 21], achieving better aging performance than conventional methods like physical model-based methods [6] and prototype-based methods [22]. The resultant methods are often roughly summarized into two categories: cGANs- and GANs-based methods. The cGANs-based methods [13, 14, 18, 19, 20, 21] typically train one network to find out various aging effects between any two different age groups, with a target age bracket because the condition. However, the generated faces from these methods cannot simultaneously meet three important requirements for face aging: image quality, aging

accuracy, and identity preservation. for instance , the conditional adversarial autoencoder (CAAE) [13] was proposed to find out a face manifold, traversing on which smooth age progression and regression are often achieved simultaneously. Its generated faces cannot preserve the identity well and are susceptible to blurriness. On the contrary, the GANs-based methods [15, 17] plan to improve the performance from different perspectives. as an example , Yang et al. designed a pyramid-architecture discriminator to estimate high-level age-related details [15], and Liu et al. fed the facial attribute vectors into both the generator and discriminator to stay facial attributes consistent.

## II. RELATED WORK

Traditional methods of modeling face age progression are often roughly divided into two categories: physical model-based and prototype-based methods. Physical model-based methods [5, 6] mechanically simulate the changes of facial appearance over time, like muscles and facial skins, via a group of parameters. However, physical model-based methods are usually computationally expensive and don't generalize well thanks to the mechanical aging rules. On the contrary, prototype-based methods [6, 22, 26] compute the typical faces of individuals within the same age bracket because the prototypes. As a result, the testing face are often aged by adding the differences between the prototypes of any two age groups. the most problem of prototype-based methods is that the personalized features can't be preserved well thanks to the utilization of average faces. Recently, deep neural networks have shown their potential for face aging [7, 8, 9]. for instance , Wang et al. proposed a recurrent face aging framework that first maps the faces into eigenface subspace [27] then utilizes a recurrent neural network to model the transformation patterns across different ages smoothly [8]. together of the many supervised-based face aging methods, it requires massive paired faces of an equivalent subject over an extended period for training, which is impractical. On the contrary, We use several sub-networks to find out aging effects with unpaired faces

## III. METHODOLOGY

Assuming that the faces lie on a face manifold residing during a high-dimensional space as shown in Fig. 1, traversing from light to deep color achieves age progression. The change direction on the face manifold corresponds to the natural aging effects within the pixel space at different age stages. However, directly modeling the face manifold complicates the aging process of various races and sexes, leading to low-quality faces and unexpected changes of identity. Therefore, we formulate this complicated aging process into a progressive neural network consisting of several sub-networks, each of which only learns the precise aging effects between two adjacent age groups within the image domain. The geodesic distance between any two age groups on the face manifold are often approximated by several locally linear Euclidean distances, almost like [29, 30]. Following [15, 17, 19], we divide all ages into  $N$  nonoverlapping age groups, where  $N = 4$  during this paper. More specifically, the age ranges in age bracket 1, 2, 3, and 4 correspond to 30-, 31 - 40, 41 - 50, and 51+, respectively. We interchange the age range and therefore the age bracket index supported the context to simplify the expression without confusing. the subsequent subsections present our novel progressive face aging framework, network architectures, and loss functions, respectively. A. Progressive Face Aging Framework before introducing our framework, we first briefly describe the cGAN-based methods. The cGANs-based methods employ one-hot encoding to represent the target age bracket  $t$  as a vector  $c_t \in \mathbb{R}^{1 \times N}$ , whose elements are all 0s apart from one 1 to point the target age bracket. When given an input face image  $X_s \in \mathbb{R}^{w \times h \times 3}$  from source age bracket  $s$ , they first pad the vector  $c_t$  into a tensor  $C_t \in \mathbb{R}^{w \times h \times N}$ , then concatenate  $X_s$  and  $C_t$  along the channel dimension because the input to an aging network  $G$ . Formally, the aged face  $X_t$  belonging to focus on age bracket  $t$  are often expressed as:  $X_t = G[X_s; C_t]$ , (1) where  $[X_s; C_t]$  denotes the concatenation of two tensors  $X_s$  and  $C_t$  along the channel dimension. Although this encoding scheme is convenient to some extent, it enforces one network to find out various aging effects between any two age groups, failing to get high-quality faces when the age gap becomes large

## IV. EXPERIMENTAL RESULTS

Figs. 4 and 5 showcase the aged faces from the datasets, which were generated by our PFA-GAN from the age group 30- to the other three old age groups. Although input faces cover a wide range of the population in terms of race, gender, pose, makeup, and expression, those aged faces are photo-realistic, with natural details in the skin, muscles, wrinkles, etc. For example, the beard turns into grey, and the skin gets wrinkles. Besides, all faces, even at a large age gap, can preserve their original identities.



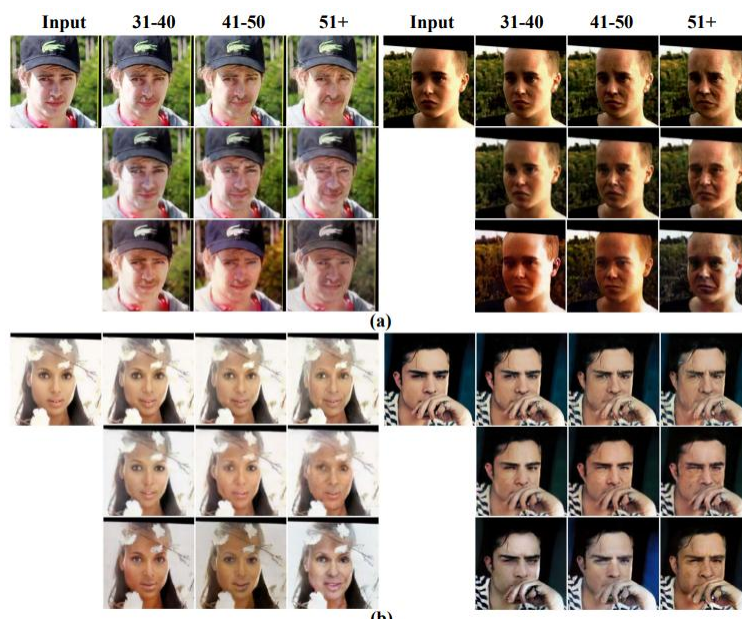


Fig. 4: The generated aged faces by dataset. We show the input faces with their real ages

in the first column, and different aged faces of the same subject in the next three columns corresponding to three age groups 31–40, 41–50 and 51+.

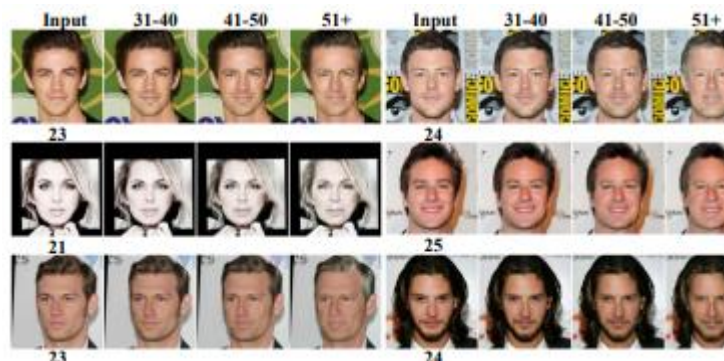


Fig. 5: The generated aged faces by dataset. We show the input faces with their real ages in the first column, and different aged faces of the same subject in the next three columns corresponding to three age groups 31 – 40, 41 – 50 and 51+.

## V. CONCLUSION

In this paper, we proposed a novel progressive face aging framework based on generative adversarial networks to model the age progression by a progressive neural network. In doing so, GAN aged the input young face in a progressive way to mimic the human face age progression. We also introduced a novel age estimation loss and an aging smoothness metric. The PFA-GAN can be optimized in an end-to-end manner to eliminate the accumulative error. Experimental results on two benchmarked datasets demonstrated the superiority of PFA-GAN over the state-of-the-art cGAN based methods in terms of image quality, aging accuracy, aging smoothness, and identity preservation

## REFERENCES

- [1] H. Ling, S. Soatto, N. Ramanathan, and D. W. Jacobs, "Face verification across age progression using discriminative methods," IEEE Trans. Inf. Forensics Security, vol. 5, no. 1, pp. 82–91, 2009.
- [2] U. Park, Y. Tong, and A. K. Jain, "Age-invariant face recognition," IEEE Trans. Pattern Anal. Mach. Intell., vol. 32, no. 5, pp. 947–954, 2010.

- [3] Z. Li, U. Park, and A. K. Jain, "A discriminative model for age invariant face recognition," IEEE Trans. Inf. Forensics Security, vol. 6, no. 3, pp. 1028–1037, 2011.
- [4] T. Wu, P. Turaga, and R. Chellappa, "Age estimation and face verification across aging using landmarks," IEEE Trans. Inf. Forensics Security, vol. 7, no. 6, pp. 1780–1788, 2012.
- [5] A. Lanitis, C. J. Taylor, and T. F. Cootes, "Toward automatic simulation of aging effects on face images," IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 4, pp. 442–455, 2002.
- [6] J. Suo, S. Zhu, S. Shan, and X. Chen, "A compositional and dynamic model for face aging," IEEE Trans. Pattern Anal. Mach. Intell., vol. 32, no. 3, pp. 385–401, 2010.
- [7] C. N. Duong, K. Luu, K. G. Quach, and T. D. Bui, "Longitudinal face modeling via temporal deep restricted boltzmann machines," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2016, pp. 5772–5780.
- [8] W. Wang, Z. Cui, Y. Yan, J. Feng, S. Yan, X. Shu, and N. Sebe, "Recurrent face aging," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2016, pp. 2378–2386.
- [9] C. N. Duong, K. G. Quach, K. Luu, T. H. N. Le, and M. Savvides, "Temporal non-volume preserving approach to facial age-progression and age-invariant face recognition," in Proc. IEEE Int. Conf. Comput. Vis., 2017, pp. 3755–3763.
- [10] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," in Proc. Adv. Neural Inf. Process. Syst., 2014, pp. 2672–2680.
- [11] M. Mirza and S. Osindero, "Conditional generative adversarial nets," arXiv preprint arXiv:1411.1784, 2014.
- [12] G. Antipov, M. Baccouche, and J. Dugelay, "Face aging with conditional generative adversarial networks," in Proc. IEEE Int. Conf. Image Process., 2017, pp. 2089–2093.
- [13] Z. Zhang, Y. Song, and H. Qi, "Age progression/regression by conditional adversarial autoencoder," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2017, pp. 4352–4360.
- [14] X. Tang, Z. Wang, W. Luo, and S. Gao, "Face aging with identity-preserved conditional generative adversarial networks," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., 2018, pp. 7939–7947.
- [15] H. Yang, D. Huang, Y. Wang, and A. K. Jain, "Learning face age progression: A pyramid architecture of GANs," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., 2018, pp. 31–39.
- [16] J. Song, J. Zhang, L. Gao, X. Liu, and H. T. Shen, "Dual conditional GANs for face aging and rejuvenation," in Proc. Int. Joint Conf. Artif. Intell., 2018, pp. 899–905.
- [17] Y. Liu, Q. Li, and Z. Sun, "Attribute-aware face aging with wavelet-based generative adversarial networks," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., 2019, pp. 11 869–11 878.
- [18] P. Li, Y. Hu, R. He, and Z. Sun, "Global and local 15 consistent wavelet-domain age synthesis," IEEE Trans.



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