

Learning Face Age Progression: A Pyramid Architecture of GANs

Wenjie Niu

June 12, 2018

Abstract

[10]The two underlying requirements of face age progression, i.e. aging accuracy and identity permanence, are not well studied in the literature. In this paper, we present a novel generative adversarial network based approach. It separately models the constraints for the intrinsic subject-specific characteristics and the age-specific facial changes with respect to the elapsed time, ensuring that the generated faces present desired aging effects while simultaneously keeping personalized properties stable. Further, to generate more lifelike facial details, high-level age-specific features conveyed by the synthesized face are estimated by a pyramidal adversarial discriminator at multiple scales, which simulates the aging effects in a finer manner. The proposed method is applicable to diverse face samples in the presence of variations in pose, expression, makeup, etc., and remarkably vivid aging effects are achieved. Both visual fidelity and quantitative evaluations show that the approach advances the state-of-the-art.

1. Introduction

Age progression is the process of aesthetically rendering a given face image to present the effects of aging. It is often used in entertainment industry and forensics, e.g., forecasting facial appearances of young children when they grow up or generating contemporary photos for missing individuals.

The intrinsic complexity of physical aging, the interferences caused by other factors (e.g., PIE variations), and shortage of labeled aging data collectively make face age progression a rather difficult problem. The last few years have witnessed significant efforts tackling this issue, where aging accuracy and identity permanence are commonly regarded as the two underlying premises of its success [7][11][5][2]. The early attempts were mainly based on the skins anatomical structure and they mechanically simulated the profile growth and facial muscle changes w.r.t. the elapsed time [8][4]. These methods provided the first insight into face aging synthesis. However, they generally worked in a complex manner, making it difficult to gen-

eralize. Data-driven approaches followed, where face age progression was primarily carried out by applying the prototype of aging details to test faces [1][7], or by modeling the dependency between longitudinal facial changes and corresponding ages [6][9][3]. Although obvious signs of aging were synthesized well, their aging functions usually could not formulate the complex aging mechanism accurately enough, shown as Fig 1, limiting the diversity of aging patterns.

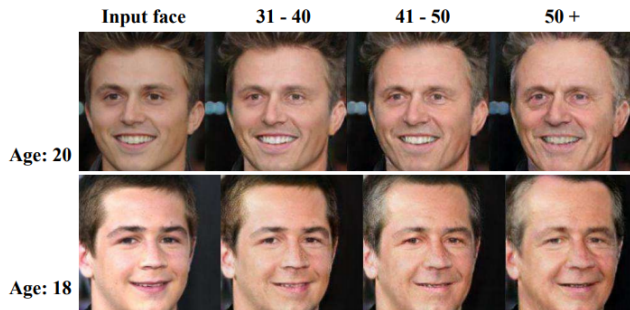


Figure 1. Demonstration of our aging simulation results (images in the first column are input faces of two subjects).

References

- [1] I. Kemelmacher-Shlizerman, S. Suwajanakorn, and S. M. Seitz. Illumination-aware age progression. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2014. 1
- [2] A. Lanitis. Evaluating the performance of face-aging algorithms. In *IEEE International Conference on Automatic Face and Gesture Recognition*, 2009. 1
- [3] U. Park, Y. Tong, and A. K. Jain. *Age-Invariant Face Recognition*. IEEE Computer Society, 2010. 1
- [4] N. Ramanathan and R. Chellappa. Modeling shape and textural variations in aging faces. In *IEEE International Conference on Automatic Face and Gesture Recognition*, 2008. 1
- [5] X. Shu, J. Tang, H. Lai, and L. Liu. Personalized age progression with aging dictionary. In *IEEE International Conference on Computer Vision*, 2015. 1

- [6] J. Suo, X. Chen, S. Shan, W. Gao, and Q. Dai. A concatenational graph evolution aging model. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 34(11):2083–2096, 2012. [1](#)
- [7] J. Suo, S. Zhu, S. Shan, and X. Chen. A compositional and dynamic model for face aging. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32(3):385–401, 2010. [1](#)
- [8] J. T. Todd, L. S. Mark, R. E. Shaw, and J. B. Pittenger. The perception of human growth. *Scientific American*, 242(2):132–134, 1980. [1](#)
- [9] Y. Wang, Z. Zhang, W. Li, and F. Jiang. Combining tensor space analysis and active appearance models for aging effect simulation on face images. *IEEE Systems Man and Cybernetics Society*, 42(4):1107–18, 2012. [1](#)
- [10] H. Yang, D. Huang, Y. Wang, and A. K. Jain. Learning face age progression: A pyramid architecture of GANs. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2018. [1](#)
- [11] H. Yang, D. Huang, Y. Wang, H. Wang, and Y. Tang. Face aging effect simulation using hidden factor analysis joint sparse representation. *IEEE Transactions on Image Processing*, 25(6):2493–2507, 2016. [1](#)