Attribute Controllable Beautiful Caucasian Face Generation by Aesthetics Driven Reinforcement Learning

Xin Jin  
Beijing Electronic Science and Technology Institute

Shu Zhao  
Beijing Electronic Science and Technology Institute

Le Zhang∗  
Beijing Electronic Science and Technology Institute

Xin Zhao  
Beijing Electronic Science and Technology Institute

Qiang Deng  
Beijing Electronic Science and Technology Institute

Chaoen Xiao  
Beijing Electronic Science and Technology Institute

Figure 1: Top: the original faces generated by EigenGAN [3]. Bottom: aesthetically improved ones by aesthetics-driven reinforcement learning over semantic attributes of the generator.

ABSTRACT

In recent years, image generation has made great strides in improving the quality of images, producing high-fidelity ones. Also, quite recently, there are architecture designs, which enable GAN to unsupervisedly learn the semantic attributes represented in different layers. However, there is still a lack of research on generating face images more consistent with human aesthetics. Based on EigenGAN [He et al., ICCV 2021], we build the techniques of reinforcement learning into the generator of EigenGAN. The agent tries to figure out how to alter the semantic attributes of the generated human faces towards more preferable ones. To accomplish this, we trained an aesthetics scoring model that can conduct facial beauty prediction. We also can utilize this scoring model to analyze the correlation between face attributes and aesthetics scores. Empirically, using off-the-shelf techniques from reinforcement learning would not work well. So instead, we present a new variant incorporating the ingredients emerging in the reinforcement learning communities in recent years. Compared to the original generated images, the adjusted ones show clear distinctions concerning various attributes. Experimental results using the MindSpore, show the effectiveness of the proposed method. Altered facial images are commonly more attractive, with significantly improved aesthetic levels.

1 INTRODUCTION

In recent years, Generative Adversarial Networks (GANs) [2] show promising performance on image synthesis. A parallel line of research tries to learn interpretable GAN generators, which can discover explicit dimensions controlling the semantic attributes. InfoGAN in [1] learns disentangled representations by decomposing the conventional single unstructured noise vector into incompressible noise and a set of structured latent variables. Motivated by style transfer literature, Karras et al. proposed StyleGAN in [4], enabling separations of high-level attributes like pose and identity.
Most recently, He et al. proposed EigenGAN [3], which for each generator layer directly embeds in one linear subspace model with an orthogonal basis. During the training, EigenGAN automatically learns a set of “eigen-dimensions” corresponding to interpretable semantic attributes. So until now, people have several ways to manipulate the semantics within the GANs, or said in other words, semantically edit them. One problem followed is how to enhance the generated face images positively.

In this paper, we incorporate the techniques of reinforcement learning (RL) into the attribute values searching in EigenGAN. The first requirement of the RL agent is the design of the reward function. The objective is to enhance the images to the ones more aesthetically attractive. So for this, we trained an aesthetics score network based on SCUT-FBP5500 released in [5]. By this, we give a multi-attribute model using MindSpore[8], which can conduct automatic Caucasian face beautification for the generated images, as shown in Fig. 1. The user can select different facial attributes in the interaction section to change the generated image.

2 EIGENGAN + RL
2.1 Preliminaries for RL
In RL, the agent constantly interacts with the environment, and this process is described as a Markov Decision Process (MDP). The objective is to learn a stochastic policy, such that when taking actions, the expected reward of the trajectories is maximized. In this paper, the discounting factor equals $1$. Also, no rewards exist for intermediate states. The agent only gets a reward for the terminal state. The reward value is the aesthetic score of the image after a series of adjustments.

2.2 Generator of EigenGAN
The controlling parameters of the generator consist of not only the conventionally noise input $\epsilon \in \mathcal{N}(0, I)$, but also a sequence of latent variables $z_i \in \mathbb{R}^q$, which are similarly sampled from $\mathcal{N}_q(0, I)$ (for EigenGAN, $q$ is set to 6). Six blocks of transposed convolution layers constitute the main part of the neural architecture. For the input part, it is a fully connected layer mapping $\epsilon$ into a $4 \times 4 \times 512$ image. Correspondingly for the output, it is passed into a convolutional layer, getting a generated $256 \times 256$ image of 3 channels.

2.3 Learn to set semantic attributes
For EigenGAN, dimensions from latent variables $z_i$ correspond to interpretable or controllable semantic attributes. So as we move along these dimensions, the generator produces a sequence of images with continuous changes corresponding to the relevant semantic attributes. Six layers in EigenGAN brings us six such $z’s. We only adopt a subset of these controllable semantic attributes, as the others are a bit entangled or drastic. We first set the dimensions corresponding to the attributes as zero. The agent learns how to select this dimension during the training process. After these setting zero operations, we concatenate these altered $z_i$’s into one single vector. Let it be $y$. We clone the single vector five times. The value of five caters to the five trajectories or decision sequences sampled by the RL agent. Intuitively, we train the agent over these sampled trajectories. The agent then gradually learns to select the preferred one.

2.4 Soft policy gradient + self-critical
The standard objective in reinforcement learning is the expected sum of rewards. Most RL algorithms are working on the conventional notion of deterministic optimality. However, intuitively the conventional objective does not consider the importance of stochasticity for exploration. In this paper, we instead follow the framework of maximum entropy reinforcement learning (see e.g. [12]). Also, we follow the approach proposed in [9], i.e., incorporating the self-critical way of training into the soft policy gradient updates. More concretely, the empirical estimate $\hat{Q}_{\pi_\theta}(s_t, a_t)$’s are replaced with Monte Carlo estimations over single trajectories. These estimations correspond to the final five aesthetics scores given by the aesthetics score network. This exposes the need for estimations via separate neural networks for predicting $Q_{\pi_\theta}(s_t, a_t)$’s. State-dependent baseline is set as the average of the five scores. This baseline deviates slightly from [9] (which uses the baseline score got by the greedy policy under current policy $\pi_\theta$) but experimentally it is more effective as shown in [7]. In a word, the main difference from conventional self-critical training is applying the way of self-critical on the soft (not the vanilla) policy gradient.

2.5 Aesthetics score network
In this paper, we designed a network dedicated to scoring the aesthetics of human faces. We use the lightweight module Efficient Channel Attention (ECA) [11], and we adopt EfficientNet-B4 [10] as a pre-trained model to extract features of the image. Then a convolution operation is performed with a kernel size of 3. We normalize the features before using the ReLU activation function. Next, it is input to the ECA module, and we flatten it into a 1-dimensional vector after activation and adaptive average pooling. After this, it is input into the regression network, which returns the aesthetics score. We trained this aesthetic face scoring model above using the SCUT-FBP5500 dataset [5].

2.6 Face attribute selection
We use Spearman’s rank correlation coefficient or Spearman’s $\rho$ measures the dependence between facial semantic attributes and aesthetic quality as in [6]. We have to choose the dimensions with better decoupling effects, i.e., one only observes continuous changes of a single semantic attribute when traversing the coefficients of those dimensions. To further narrow the scope, only the attributes with strong correlation ($|\rho| > 0.3$) and also being significant ($p$-value < 0.01) are selected. After this step, we choose only five semantics, including body pose, bangs, lighting, gaze, and lipstick color.

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REFERENCES

[1] Xi Chen, Yan Duan, Rein Houthooft, John Schulman, Ilya Sutskever, and Pieter Abbeel. 2016. Infogan: Interpretable representation learning by information maximizing generative adversarial nets. In Proceedings of the 30th International Conference on Neural Information Processing Systems. Curran Associates Inc., Red Hook, NY, USA, 2180–2188.

[2] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative Adversarial Nets. In Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 2 (Montreal, Canada) (NIPS’14). MIT Press, Cambridge, MA, USA, 2672–2680.

[3] Zhenliang He, Meina Kan, and Shiguang Shan. 2021. EigenGAN: Layer-Wise Eigen-Learning for GANs. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV). IEEE, Montreal, QC, Canada, 14408–14417.

[4] Tero Karras, Samuli Laine, and Timo Aila. 2019. A style-based generator architecture for generative adversarial networks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. IEEE, Long Beach, CA, USA, 4401–4410.

[5] Lingyu Liang, Luejun Lin, Lianwen Jin, Daurui Xie, and Mengru Li. 2018. Scut-ffp5500: A diverse benchmark dataset for multi-paradigm facial beauty prediction. In 2018 24th International Conference on Pattern Recognition (ICPR). IEEE, Beijing, China, 1598–1603.

[6] Xudong Liu, Tao Li, Hao Peng, Iris Chuoying Ouyang, Taehwan Kim, and Ruizhe Wang. 2019. Understanding Beauty via Deep Facial Features. In 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). IEEE, Long Beach, CA, USA, 246–256. https://doi.org/10.1109/CVPRW.2019.00034

[7] Ruotian Luo. 2020. A Better Variant of Self-Critical Sequence Training. CoRR abs/2003.09971 (2020). arXiv:2003.09971 https://arxiv.org/abs/2003.09971

[8] MindSpore. 2022. https://www.mindspore.cn/

[9] Steven J. Rennie, Etienne Marcheret, Youssef Mroueh, Jerret Ross, and Vaibhava Goel. 2017. Self-Critical Sequence Training for Image Captioning. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR). IEEE, Honolulu, HI, USA, 1179–1195.

[10] Mingxing Tan and Quoc Le. 2019. EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. In Proceedings of the 36th International Conference on Machine Learning (Proceedings of Machine Learning Research, Vol. 97). Kamalika Chaudhuri and Ruslan Salakhutdinov (Eds.). PMLR, Long Beach, California, USA, 6105–6114. https://proceedings.mlr.press/v97/tan19a.html

[11] Qilong Wang, Banggu Wu, Pengfei Zhu, Peihua Li, Wangmeng Zuo, and Qinghua Hu. 2020. ECA-Net: Efficient Channel Attention for Deep Convolutional Neural Networks. In IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). IEEE, Seattle, WA, USA, 11531–11539. https://doi.org/10.1109/CVPR42600.2020.01155

[12] Brian D Ziebart. 2010. Modeling purposeful adaptive behavior with the principle of maximum causal entropy. Carnegie Mellon University, Pittsburgh, PA 15213.