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Face age progression and regression based on various types of GANS

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Abstract. Recently, there has been a surge of interest among scientists in the application of face age progression and regression, spanning various fields such as criminal investigation and archaeology. Simultaneously, the computer world has been buzzing with excitement over Generative Adversarial Networks (GANs), thanks to their remarkable efficiency and adaptability. Within this context, researchers have successfully harnessed the power of GANs to develop methods for face age progression and regression. Each of these approaches boasts its unique model and architecture, equipping them with distinct sets of limitations and advantages. This article provides a comprehensive review of the methods of implementing face age progression and regression by GANs. To be specific, this paper mainly talks about Wavelet-based GANs and Identity-Preserved cGANs. For each method, the author introduces its basic idea and explains its framework and special parts in detail. The outputs of each model and their characteristics and limitations are also concluded in the discussion. Besides, this paper also describes two real-life applications of this technology, including finding lost children and predicting results after cosmetic surgeries. The introduction of the practical applications provides possible directions for researchers to combine different types of GANS with face age progression and regression in the near future.

Keywords: Face Age Progression and Regression, Generative Adversarial Network, Deep Learning.

1. Introduction

Face age progression and regression, which means predict people's future look and estimate their previous appearances based on given images, tries to generate face photographs with or without the effect of "aging" while keeping customized elements of the face (i.e., personality) [1]. Undoubtedly, face age progression and regression have many different applications. Therefore, this topic has captured the attention of the scientific community in recent times. Undertaking additional research in this domain is both imperative and auspicious.

In the past in this field,there were many ways to implement face age progression and regression and two of them should highlighted due to their representatives. The former one is called Conditional Generative Adversarial Network(cGANS), a conditional version of the Generative Adversarial Network (GAN) that enhances the GAN with more data to ensure that the resulting image matches expectations [2]. The second method is called CycleGAN, which is developed for unpaired image-to-image translation when there is no one-to-one relationship between images in the source and target

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domains. Then a more advanced method called Conditional Adversarial Autoencoder (CAAE) was created. While creating synthetic face photos with rough aging effects, the personality data was preserved using the Conditional Adversarial Autoencoder (CAAE) framework [3]. By combining face age progression and regression with GANS, scientists have achieved many important results. For example, scientists have achieved a fine-grained modeling of the age transformation process by using StyleGANS [4]. Besides, with CycleGANS, image can be transformed to an intended age group while retaining the person's original identity, from a sample age group [5]. In the field of surgery, GANS models can be applied to predict the possible results of cosmetic surgery. With various kinds of applications mentioned above, it's important to do further research in the field of age progression and regression. Therefore, an overall review in this area is necessary.

The rest of the chapter is divided into the following sections. To begin with, this review will recapitulate the three typical methods of achieving age progression and regression as well as their advantages and limitations in Section 2. Then, in Section 3, what aspects of this technology can be applied will be shown and this paper will analyze and discuss potential improvement. Lastly, Section 4 concludes by summarizing the chapter and providing conclusions based on the techniques covered here.

2. Methods

2.1. Wavelet-based GANS

2.1.1. Brief introduction

Researchers put up with a face aging model that is attribute-aware by using wavelet-based GANs [6]. In order to make sure that each simulated old face image keeps the properties of its corresponding input, the authors specifically integrated attribute vectors of faces into the model's generator and discriminator. They also included a wavelet packet transform (WPT) module so that they could capture textural information linked to age across several scales in the frequency range, which improved the visual quality of the resulting images [6].

2.1.2. Framework

This GAN-based face aging model generates visually convincing old faces based on inputs of young-face photos and their semantic data. A wavelet-based discriminator D and a face attribute embedded generator G make up the network. The generator network creates aged faces by synthesizing young faces and embedding facial features into them. In order to make the generated results equal to the related input and indistinguishable from generic ones, the discriminator network is used. To reduce the matching uncertainty associated with unpaired training data, the generator and discriminator incorporate the p-dimensional attribute vector characterizing the input [6].

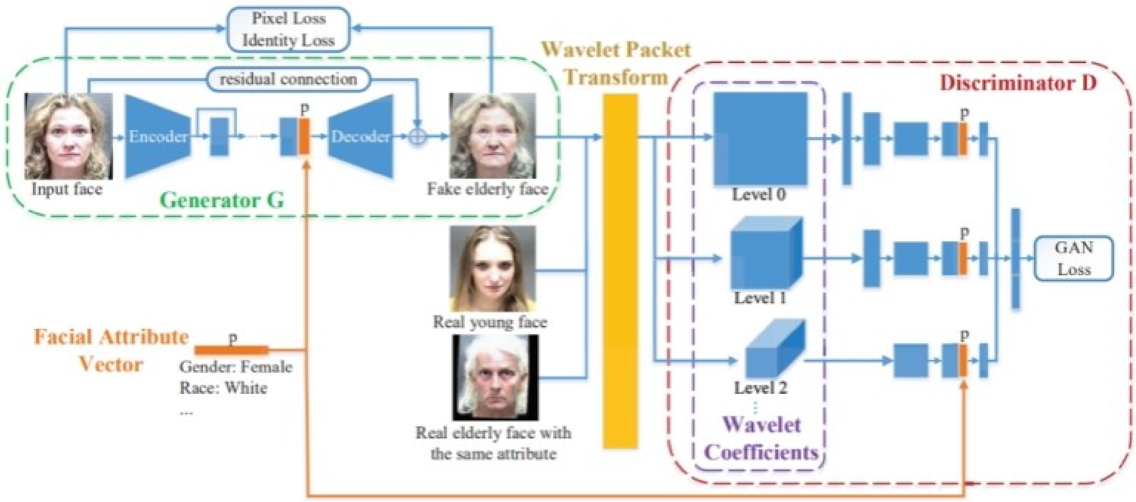

Figure 1. Framework of Wavelet-based GANS [6].

The framework of Wavelet-based GANS is shown in Figure 1. The special part of this model is that it has a Wavelet-based Discriminator. The discriminator serves two primary purposes: 1) separate generic from synthesized facial images; and 2) determine whether each generation's attribute is loyal to that of the matching input [6]. Wavelet-based Discriminators excel due to the efficiency inherent in wavelet transforms compared to other transforms like Fourier transforms. This efficiency stems from the fact that wavelet transforms are grounded in functions with localization in both spatial and frequency domains. Using a number of methods, such as selection based on frequency or spatial context, wavelet transforms can be applied to obtain precise information from an image, adding it to or replace it in another image. Additionally, it is possible to customize the wavelet function utilized in the transform to embody special characteristics that are beneficial in the specific applications of the transform [7]. The Wavelet-based Discriminator can infer specific information if traits are kept in generated images by repeating the input attribute vector and relating it to the outcomes of each intermediate convolutional block of each pathway. All routes' outputs of the same size are combined into a single tensor at the discriminator's conclusion. The label tensor is then used to compute an adversarial loss estimate [6].

2.1.3. Discussion

In-depth quantitative evaluation findings reveal that the approach mentioned above performs at the cutting edge on available datasets, while qualitative findings demonstrate that this method is capable of generating visually convincing face images.

2.2. Identity-Preserved cGANS

2.2.1. Introduction of idea

Everybody ages differently, so this technique to face aging plans to produce a face image whose goal age falls within a certain age range rather than producing a particular-age face image.

When face images with the same target age are grouped together, the purpose of face aging is akin to modifying the aging patterns of faces within the target age group to the face whose old face is to be synthesized. The synthesized face must exactly match the input face for identification. In order to overcome this, researchers put up with an Identity-Preserved Conditional Generative Adversarial Networks (IPCGANs) framework, where a cGANS module generates a face image that mimics the target age and appears realistic. According to both qualitative and quantitative evaluations, this technique can yield faces that are more realistic in different terms with human observations [8].

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2.2.2. Framework

The desired age label and input image are combined, while the generator G is then given this data. The label is 128 ×128 × 5.[8] To differentiate between synthetic faces and faces within the targeted age group, a discriminator, denoted as D, is employed. Researchers mandate that the characteristics of the input and the synthesized face match precisely to preserve identifiable information. In order to make the synthesized face match the desired age, an age classifier is applied in this model [8] shown in Figure 2.

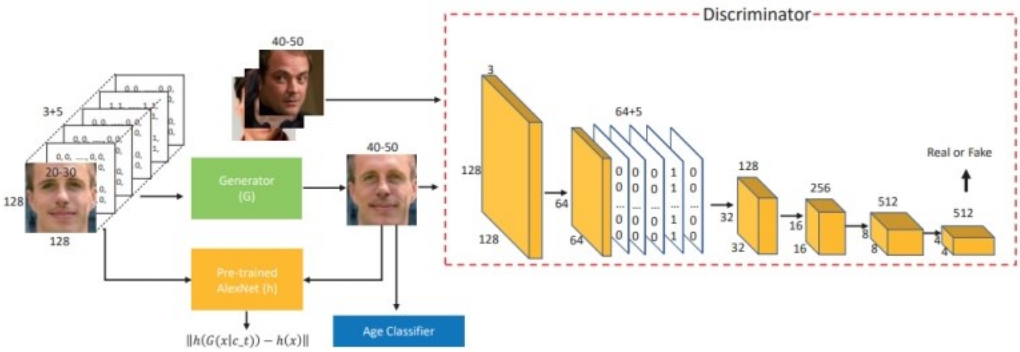

Figure 2. Framework of Identity-Preserved cGANS [8].

Researchers use cGANs for face image generation because face aging attempts to create a synthetic face with a target age. Researchers specifically specify y as actual face image from the desired age group and p_x(x) and p_y(y), respectively, to signify the distribution of x and y. With vGANs, the discriminator D shouldn't label the synthetic face with the target age C_t as a counterfeit sample. The likelihood that actual faces pertain to real face D(x|C_t) is supposed to be high for real faces. D is in charge of aligning the produced photos with the input label C_t[8].

However, adversarial loss cannot guarantee that the information being identified will be preserved in the generated samples. In order to maintain the identity information for the produced face images, researchers consequently add the perceptual loss to the face age objective:

$$L_{indentity}=\sum \|h(x) - h(G(x|C_t)\|^2 \quad (1)$$

In this case, the features received are represented by h(·).The elderly face no longer distinguishes itself from x. Because of this, pixel space does not use the mean square error (MSE) between x and its aged face G(x|C_t). G(x|C_t) will be forced to equal x in the event of an MSE loss [8].

2.2.3. Discussion

Researchers suggest a cGANs-based method to face aging. The goal age and the aged faces are consistent with the aid of the discriminator in cGANs.

In an effort to maintain the authenticity of the input photographs, researchers attempt to match the high-level properties of input faces and synthetic face images, ensuring that they closely resemble each other. This method enables the generation of high-quality faces that share both identity and the desired target age. Qualitative and quantitative studies support the efficacy of the strategy. Additionally, IPCGANs is a broad framework. It can be used for procedures involving a variety of features, such as changing black hair to brown, blonde, or golden hair, or a beard without sideburns or a mustache into a beard with a 5 o'clock shadow. This architecture can be used to the task of picture translation if the condition part is left out [8].

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3. Applications and discussion

3.1. Help find missing children in forensics

The application of face aging technology holds promise in the field of forensics, aiding in the search for missing children. Moreover, this technology is already in active use. [9]. Many children have been separated from their parents for many years after being lost or trafficked. Therefore, their appearance has changed greatly, which adds to the difficulty of finding lost children. Leveraging face aging progression, individuals can anticipate their future appearances by using past photos of their children as provided by their parents. When these GAN-generated images closely resemble the actual progression, they can significantly enhance the effectiveness of law enforcement and forensic efforts in locating missing children. However, the photos provided by parents may contain a lot of noise points due to the age, and if the GANS model cannot be denoised well, the feasibility of the generated photos will be low, and may even play a misleading role. Besides, many children are very young when they go missing or are trafficked, so all parents can provide are pictures of them as toddlers. Currently, the outcome of face aging progression applied to younger age photos diverges considerably from reality. Therefore, there is a necessity for the development of a more advanced GANs model to address this disparity.

3.2. Cosmetology

Plastic surgery has become a fashion in today's society. There is a great demand for accurate prediction of results after cosmetic surgery. The researchers discussed changes related to age in the features of skin, the effects of face aging on the faces of human, and prevention techniques (including measures like skin protection and skincare), together with cosmetic treatments for addressing facial aging. [10]. According to the aging databases that are partially dense, they constructed the dense long-term aging database using age progression [10]. Based on the above research, using face aging progression and regression to predict possible outcomes after cosmetic surgery is becoming a reality [11]. The application of facial aging progression and regression technology in the field of cosmetic surgery and cosmetology provides a more intuitive and visual way for patients to better understand and make decisions about whether to undergo relevant cosmetic surgery or treatment. They can provide cosmetic surgeons with a more precise preoperative assessment and surgical planning, and help patients anticipate and understand the effects and possible changes of surgery.

Regarding the precision of face aging progression and regression approaches, there is still potential for development in this area. To forecast and model face changes, these technologies currently rely mostly on algorithms and artificial intelligence, but the accuracy of these technologies can be impacted by a number of variables, such as individual variances, environmental circumstances, and non-predictive physiological changes. As a result, additional study and advancements are still required to boost the effectiveness and precision of these procedures.

4. Conclusion

This systematic review aims to comprehensively introduce different types of GANS researchers used to implement face age progression and regression. Two types of GANS, Wavelet-based GANS and Identity-Preserved cGANS, are mainly discussed. This review describes their specific structures, as well as their features and functionalities. Furthermore, their shortcomings and upgradable parts are also mentioned. Advances in science and technology are urgently needed in this area to solve potential problems. In addition to methods, this review introduces two popular applications of face age progression and regression, including finding lost children and predicting results after cosmetic surgeries. The author introduces how face age progression and regression is applied in these two fields, what benefits it brings, and what limitations and shortcomings currently exist. The review suggests that future work should seek to continuously improve and innovate the GANS model, so that it can achieve more accurate and efficient face age progression and regression, and provide results more

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interactive and visually. As a result, there is potential to broaden the usage of this technology in everyday situations.

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