A Survey on Face Age Progression Using Deep learning

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***Abstract*–Face aging progression (FAP) refers to synthesizing facial images while simulating aging to predict a person's future appearance. The generation of age-related facial images benefits a wide range of applications, including facial recognition systems, forensic investigations, and digital entertainment. In particular, recent successes achieved with deep generative networks have significantly improved the quality of age-synthesized facial images in terms of visual fidelity, aging accuracy, and identity preservation. However, a large number of recent contributions require systematic structuring of new discoveries and ideas to identify common taxonomies, speed up future research, and reduce redundancy. FAP is translation-based, conditional-based, and sequence-based. In addition, we provide a comprehensive overview of the most common performance assessment techniques to steer future research in the right direction.**

***Keywords* - Divide and conquer, image translation, Face aging, Generative adversarial networks and progressive neural networks**

I.INTRODUCTION

Facial aging is the process of rendering a specific younger face in such a way that it retains its individual characteristics while predicting future appearance with natural aging effects. Applications range from digital entertainment to information forensics and security. For example, in law enforcement, facial age history can help find missing children and missing persons using previous photos in facial analytics such as facial recognition and e-commerce platforms. This is also used in biometric systems to identify individuals based on certain characteristics.

Aging is limited for several reasons. First, we cannot control the effects of aging because we cannot remove aging during face image acquisition. Aging also affects people in different ways. External factors such as smoking, alcohol consumption, extreme weather, emotional stress, and dramatic weight changes can have an effect, accelerating the aging process. Therefore, the sophistication of age-invariant face recognition systems can help identify each person accurately even with age differences and avoid updating large face databases with new images. Before the advent of deep learning, the two main approaches to aging were the physical model approach and the prototyping approach. Physical modeling approaches focused on changes in physical factors such as wrinkles, hair, etc.) over time. The prototype approach learns about the features by averaging the faces of people that belong to the same age group. Age characteristics can be presented differently for different groups. However, this method results in smoother facial images and loss of identifying information.

Today, deep convolutional networks are widely used in image processing. Since GANs often produce realistic images, many studies have attempted to apply his GANs to facial aging. The basic GAN includes his two networks of generators and discriminators, which learn and mimic real-world data distributions. During training, the discriminator distinguishes whether the input image is from the real data or the output of the generator, but the generator produces an image that tricks the discriminator into predicting the real image. It tries to confuse the discriminator by many improvements in recent years to make the training process more stable and produce higher quality images. On the other hand, conditional GAN, a variation of GAN, is more useful than the original GAN. Conditional GANs produce images from specific labels or images rather than from random noise. For frame-to-frame conversion tasks like style transfer, super-resolution, and colorization, conditional GANs are appropriate. As a result, conditional GANs were frequently used in studies to create generic faces.

II.LITERATURE SURVEY

Neha Sharma et al used AttentionGAN and super-resolution GAN to obtain super-resolution images of aged faces. Their research converts an input face image into a desired aged face image and employs a filtering process to generate a high-resolution image with less computing time and storage. Image sharpening with enhanced edges is also used to improve the input quality of SRGAN. For this purpose, a three-step learning framework is proposed. In the first stage, preprocessed images are fed to the AttentionGAN generator G that performs facial age progression using an image-to-image transformation AttentionGAN. The generator captures both background and foreground attention to produce high-quality, identity-preserving face images. A unique property of AttentionGAN is that it efficiently maintains the background of the input image using attention and content masks while the generator focuses on the foreground of the desired image. Various attention and content masks are available to help generate the output of elderly facial images.

In the second stage, the output of AttentionGAN is input to the conditional block to decide whether to apply the regular expression filter. The regex filter selects the synthesized elderly face image from her AttentionGAN if the conditional block output is yes. This is because the output of AttentionGAN consists of a synthesized face image, an attention mask, and a content mask image. Therefore, using a regular expression filter process aid can reduce the computational time required for further SRGAN training. If the conditional block's output is 'no', the entire AttentionGAN's output feeds directly into the SRGAN training. However, with this method, full training of the model took about 26 hours due to the presence of unnecessary images in the model training. Training is performed in the final stage to get the final output image. The output of image sharpening is fed into SRGAN training. SRGAN training is performed on high-quality synthetic images. The test then produces a super-resolution image at the output. This process reduces computational complexity and training time.

Image details are highly preserved during processing time. The work thus produces high-resolution aged facial images that contain a wealth of information in a single image. The effectiveness of the proposed method is evaluated based on a number of publicly available datasets named UTKFace, CACD and cross-dataset analysis of IMDB-WIKI, CelebA and the FGNET datasets. Verification of the proposed work is confirmed by various attacks such as poses, facial expressions, makeup and lighting. Furthermore, simulation results are compared with existing approaches. The model's reliability and efficiency are demonstrated through qualitative and quantitative comparisons using age estimation and identity preservation evaluations.[1]

Zhizhong Huang and et al proposed a framework that can be continuously trained to eliminate cumulative artifacts and ambiguities. Furthermore, in this paper, we introduce age estimation loss to describe the age distribution to improve aging accuracy, and use Pearson's correlation coefficient as an evaluation metric to assess the smoothness of the aging procedure on the face. Extensive experimental results show superior performance over existing (c)GAN-based methods on two benchmark datasets.The difference between the age distributions of generic and synthetic faces in each age group, also known as age estimation error was used as an evaluation metric to assess the aging accuracy of various face aging methods. Face++ API first estimates the ages of both original and fake faces in each age group for a fair comparison. Second, the age estimation error is used to find the difference between the mean ages of real and fake faces in the same age group. Lower values simulate aging effects more accurately. Only young faces under the age of 30 are considered test samples by convention, while aged faces in the other three age groups are created using a different process. Even with larger age differences, the PFA-GAN consistently outperforms other baseline methods in these three age groups. CAAE does not produce strong enough aging effects, so even small changes in the synthesized face are overly smooth, leading to large errors in age estimates. Compared to IPCGAN, PAG-GAN has improved details due to its pyramid architecture and performs better on aged faces. By stepwise modeling the facial age progression, PFA-GAN achieves the highest aging accuracy among all methods, significantly overcoming the difficulty of learning multiple aging transformation patterns in cGAN-based methods. [2]

Quang T.M. Pham and et al introduced a novel semi-supervised learning method for age regression and progression that included two GAN models. To overcome the limitations of real datasets, they have used an additional generative adversarial network to train the model using a semi-supervised approach with integrated paired images. Introduced a new training method that separates aging and identity traits in order to better train the model. The proposed method allows Unet-based models to be used as generators, overcoming the bottleneck limitations of autoencoders. This helps the model create a more detailed image. The UTKFace dataset was used for training. This dataset contains over 20,000 face images as well as age (ranging from 0 to 116), gender, and ethnicity details. For fair comparison, only age information was used for training, ignoring gender and ethnicity designations.

The base mesh comes from a Conditional Adversarial Autoencoder (CAAE) model.A generator and two discriminators are included in the CAAE model. An autoencoder is a generator. Given an input image I1, the encoding section extracts features and generates encoded z.The encoded z and target age information t2 are fed into the decoder, which generates an output image I2 corresponding to age group t2. The main discriminator Dimg discriminates between real and false images based on the generator output and the age grade information t2. An additional discriminator Dz constrains the distribution of the encoded z to the previous distribution (e.g. uniform distribution). In addition to the usual loss function of GANs, the objective functions include the loss function of the discriminator Dz, the reconstruction loss L2 norm between the input and output images (to maintain identity), and the total variation loss (to remove artifact ghosts).To solve the problem of image quality degradation on output, we apply the Unet architecture to replace the autoencoder. The Unet architecture includes skip connections that help produce a more detailed output image. Additionally, jump connections also improve gradient flow, allowing the model to learn better than autoencoders.

cStyleGAN is used to create the synthesized data set. It takes a random vector z and age information t as input and generates face images for the corresponding age group t.Once the cStyleGAN model is trained, by simply changing the fixed z-age input, it generates synthetic facial images of the same person at different ages.These images are then used as input for training FaceGAN. In this phase, only FaceGAN is trained and cStyleGAN is frozen. Both qualitative and quantitative experiments have shown it to outperform the other methods considered, especially for the age regression task. Confidence scores indicate the model's ability to generate realistic human faces. This model also works well when preserving identity information and representing aging factors with low cosine similarity values. One of the limitations of this paper is that models for the age progression task do not perform well in learning local aging characteristics such as skin defects and wrinkles in the oldest groups.[3]

Mukesh Chauhan and et al proposed a system to develop a fully automated framework for facial recognition and progression. The study of facial features is known as "facial recognition", one of the major biometric authentication methods used in current scenarios. Compared to traditional authentication strategies, biometric authentication methods are considered highly meaningful and advantageous because biometric features are unique to each individual. This personal verification and identification problem is a vast area for researchers using verification strategies such as face, voice, fingerprint, ear, iris, and retina, and research in these areas has continued for the past two decades. rice field. Investigation of human face recognition and its progress towards real world application and practical use in life. We are not bound by existing databases limited to single human ethnic groups or well-annotated faces. All methods and algorithms should consider a more general database containing different cultivars with different image qualities and conditions. Traditionally, facial recognition is used specifically for resolution. An architecture with three models is proposed:

1.Core system module

2.Enhancement module

3.Application module

A key component of the human facial recognition system. We introduced a new face rendering scheme that uses K-Means grouping computations and face trimming with Active Shape Models (ASM) and wrinkle topography features that crop the face image to regions that cover the boundaries of the face.[4]

Sasikumar Gurumurthy and et al introduced a framework for identifying the resemblance of facial images based on age group and identifying the gender of a person, the image quality is improved by the image processing system and face identification in the face recognition system. The first step is image processing, which uses histogram equalization methods to improve the quality of face images. Use the Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE) method to improve brightness and contrast and convert color images to grayscale for accurate results. Histogram equalization is primarily useful for images with dark foregrounds and dark backgrounds, or both. In particular, this method may result in a better view of bone structure in radiographs and better detail in overexposed or underexposed photographs. There are many facial recognition technologies. Used image segmentation and image blending methods to detect faces. The introduced model detects faces from a database using eigenfaces with the PCA (principal component analysis) method. Eigen Surfaces are a group of eigenvectors primarily used in computer vision. This approach Sirovitch and Kirby. Used Eigenface in order to estimate the age and Fisherface algorithm for gender classification. Uses the principle method of linear discriminant analysis. This ensures that the specified image is female or male. K-cross-fold validation and leave-one-out classifiers are used to test the algorithm's efficiency. The classifier highlights results when used with several public databases.[5]

There are some studies that directly use GANs to model aging trajectories among any two age groups. Yang et al., for example, created a discriminator with a pyramid architecture that enables pre-trained neural networks to estimate higher level age-related details. In addition to retaining identity information, Liu et al. Moreover, facial attribute discrepancies still exist in previous studies, in which facial attribute vectors are fed to both generators and discriminators to suppress unnatural changes in facial attributes.

cGAN-based methods typically target age groups. On the other hand, GAN-based methods train multiple models separately for each age assignment. The difference between these two different types of methods is that cGAN-based methods are more flexible than the GAN-based methods, whereas GAN-based methods can achieve better facial aging results.

III.CONCLUSION

The Face age progression based on Generative Adversarial Networks uses progressive neural networks to model aging progression. This framework gradually aged the input young face to mimic human facial aging and also introduces a new estimated age of loss and aging smoothness index. This framework can be optimized to remove cumulative errors. Experimental results substantiated by the two datasets compared superiority of PFA-GANs over other cGAN-based methods with regard to identity preservation, image quality, aging accuracy, and smooth aging.

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