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Human Face Aging based on Deep Learning: A survey

Ms. T. S. Deshmukh [1], Dr. M. D. Kokate[2]

[1]Research scholar, Matoshri COE & Research Centre, Eklhare, Nashik, 422105 India
[2]Principal SNJB's K. B. Jain College of Engineering, Chandwad, 423101 India.

Abstract

Face Age progression enables predicting the future appearance of a person. Facial aging affects human face in diverse forms from early stages to old age. Over few decades, researchers are working on development of various face progression techniques to meet the challenge of creating accurate aged face for smart systems applications. Here we present analysis of face age progression methods for child and adult face. Deep Learning has found vast applications in the fields of Computer vision. With the advent of deep generative networks success rate has increased in terms of aging accuracy and identity preservation. Here some databases regarding face aging are described in terms of the number of persons along with their age ranges. The goal of this survey is to know ongoing efforts used in age progression.

Keyword : Face age progression (FAP); Deep learning.

1. Introduction

Almost all countries are facing severe problem of human trafficking. Human trafficking victims are men, women, as well as children. According to National Crime Records Bureau around 3 to 4 lakhs of persons go missing every year [1]. Facial aging is a most important technology for finding out missing person, as parents or relatives are can have at least one photograph of missing person. Other applications where we can use face aging in human-computer interaction, entertainment, animation.

Every Indian must have a Aadhar card. No biometrics are captured of children below five years. On the basis of age information and facial photograph Children UID is processed and are linked with the UID of their parents. When they turn 5 and 15, they need to update their biometrics of fingers, iris and facial photograph. When they grow up intimation to this effect will be mentioned in the Aadhaar letter. Later on, once the child is grown into adult the photo in database is not update. With the help of the generated appearances the database can be updated.

Various progressive changes are observed in a human face, which include skin texture, weight, facial hair, etc. There is change in face and neck appearance with age. Face becomes flabby or we find dropping appearance due to deprivation of muscle tone and derma thinning. Face has no desirable smooth surface as dermis dries out and the underlying layer of fat reduce. Wrinkles cannot be avoided. They are likely to grow more quickly due to sun exposure and cigarette smoking. Dark spots increase on the face in terms of numbers and size. Due to sun exposure these pigment changes are largely.

Appearance of mouth may change due to missing teeth and lips may get smaller. Size of the lower face may lessen out due to loss of bone mass in the jaw and makes forehead, nose, and mouth more noticeable. Nose may also elongate to a slight extent.

Probably due to growth in cartilage the ears may look longer in some people. Greying of Eyebrows and eyelashes. Wrinkles would be seen in skin around the eyes. Eyes may look sunken because of fat from the eyelids settling into the cranial-orbit. The lower eyelids can slacken. The upper eyelid droop due to weakening in muscle. A greyish-white ring may develop at the outer layer of the eye. The colouring of the iris is reduced(pigmentation), hence very aged people eyes seem to be look like grey or light blue.

2. Related Work

Human face ageing is due to different factors such as genetic, environment and behavioural factors. Hence while predicting appearance, we have to take account on individual ageing rates instead of fixed once's, which is a big challenge.

In early days face age progression was divided into physical model based and prototype model based. Models which are based on physical model are built on the biological model and human aging mechanism of aging such as the muscle [2], wrinkles on face [3,4], facial shape [5,6]. Disadvantage of physical model based is that they are computational expensive. Prototype based approach divides face into groups from which average faces represent age pattern [7,8]. Disadvantage of the prototype approach is cannot preserve identity. Face age progression methods based on deep learning has gained more attention as they perform well in terms of identity retention and aging accuracy.

Conditional Adversarial Autoencoder (CAAE) [9] was delineated for face progression task to achieve face aging and rejuvenation, by using single sample. In CAAE, the face is charted to a latent vector, and then the values are imposed to the face manifold constraints on age. Personalized face features are preserved by the latent vector preserves (i.e., personality) and progression is controlled by the age condition. Using CAAE only rough wrinkles were generated. To overcome this problem, J. Zeng et.al. [10] created a generative model based on CAAE with some development: 1) A component that seek to improve the convergence of very deep networks called as an auxiliary classifier was additional inserted on the discriminator, and also categorizes them into the target age group; and 2) a pre-trained deep face recognition model is used to preserve identity and pre-trained age estimation model is used to preserve age similarity age. Wang et.al [11] introduced Identity Preservation generative adversarial networks which collectively had both, an identity preservation and an age estimator. IPCGANs can be put into different feature creation task, like hair colours, various facial expressions, no beard-to-beard etc without making any changes in IPCGAN. If condition is removed from the framework of IPCGAN, it can be used for image translation task.

An attention-based generative adversarial networks framework by Zhu *et al.* [12], who stated that without using a pixel-wise loss, distorting or ghosting effects can be reduced. To avoid these artefacts generator is trained to output an attention mask and a colour mask. The attention mask studies to spot the image zones related to the age synthesis; the colour mask studies how to adjust those areas. Hence background area and the unique identity of a person over time are well conserved. to produce enhanced vision of face image, Neha Sharma et.al. [13,14] used a fusion-based generative adversarial network approach. Cycle-GAN achieved the face aging, then Enhanced Super-resolution Generative Adversarial Network (ESRGAN) enhanced the aged look to improve the clarity of image.

As face is the utmost affected part of aging of looks there is a requirement to extract robust face feature based on this theory Boussaad et.al.[15] examined usefulness of deep-learning based methods as features extraction tool. AlexNet, Inception V3, GoogleNet, SqueezeNet and ResNet50 these popular pre-trained deep-convolutional neural network models' evaluation was carried out. Experiment was conducted on a commonly used face-aging database FG-NET. AlexNet seemed to be the finest to handle differences in age and the utmost capable for age invariant face recognition. Author in forthcoming research wants to test these pre-trained models on additional databases and combine them with other pre-processing approaches. A potent deep-featured encoding-based discriminative model was introduced by Shakeel et. al. [16] for age-invariant face recognition. To learn important deep features a pre-trained deep-CNN AlexNet model is being used, these values are encoded by learning a code book, and each feature is being converted into S-dimensional codeword for picture representation. Author has proposed feature-encoding structure based on locality constraint. Shakeel et. al. [16] wants to design a new convolutional layer to achieve optimization of feature representation and feature fusion at same time. Huang et. al [17] presented a recursive generative adversarial network-based face age progression architecture which is trained concurrently on the whole ageing span to reduce the generated errors as the authors is of the opinion that training each of the face age progression structure units separately causes artefacts for age progressions over long time spans since faults gather when being passed through the network chain.

With varying lifestyle human appearance will change a lot. As said face elderly look is due to diverse factors such as genetic, environment and behavioural factors. Anwaar et.al [18] introduced image synthesis using age and weight. For weight progressed face Constrained Local Model is used and then Conditional Adversarial Auto Encoder is used to generate age-progressed face image. Face morphing of weight progressed facial image and age-progressed facial images is carried out which creates future face image and keep natural looks.

Human face ageing takes place in two ways, from child to adult and then ageing process in adult is subjected to change by texture. For face age progression and regression on children appearance, Chandaliya et.al [19]. proposed an architecture based on generative adversarial network and Variational Autoencoder with Perceptual loss i.e., like the same photo but shifted by one pixel called as Conditional Perceptual Adversarial Variational Autoencoder. CPAVAE framework is robust against variation like illumination and pose. But authors planned to take together age and gender loss to preserve identity. In [20], child face aging and regression, gender is used as a constrain. Authors used Conditional Generative Adversarial Network (cGANs), a convolutional neural network that is 19 layers deep (VGG19) based perceptual loss and LightCNN29 age classifier to produce good results.

Table: Summary of FAP

Author	Year	Database	Note	Different loss & evaluation tool
Zhifei Zhang et.al [9]	2017	MORPH, CACD	Mapping of face to a latent vector. Then vector is extrapolated to the face manifold conditional on age. No paired samples	Tool: Qualitative and quantitative (Survey form) comparisons.
J. Zeng et.al [10]	2018	UTKFace , FGNET	A supplementary pretrained classifier is added on the discriminator. To preserve identity and age similarity, deep face recognition model and a pre-trained age estimation model are used	Losses: Image Adversarial loss, Age classification loss, Age preserving loss, Identity preservation loss.
Wang et.al [11]	2018	CACD	Identity and age similarity is conserved by using an age estimation model.	Inception score metric used for evaluating the quality of generated images. User Study evaluation. Losses included: adversarial loss, perceptual loss, Age classification loss.
Zhu *et al.* [12]	2020	MORPH	Pixel-wise loss is not used still obscuring or ghosting effects can be reduced.	Tool:To estimate the aging accuracy Face++API. to approximate the age distributions, i.e., mean value of both real and generated faces in each age group, Loss function used: Adversarial loss, Attention loss, Age classification loss.

Neha Sharma et.al. [13,14]	2020	IMDB-WIKI, CACD, UTKFace, FGNET,Celeb A	A combination-based Generative Adversarial Network used.	Tool: Face ++ toolkit, parameters confidence score number and age estimation value. Loss function: cycle consistency loss, Identity loss, GAN loss, perpetual loss ,content loss.
Boussaad et.al [15]	2020	FGNET	To extract robust face feature using pretrained pre-trained deep-convolutional neural network mode	Tools: Pretrained CNN models used Alexnet, GoogleNet, Inception V3, Squeeze Net, ResNet
Huang et.al [17]	2020	MORPH, CACD	Face image is produced by maintaining image quality, accurate aging, and identity preservation.	Tool: Face ++ is used for face aging accuracy and identity preservation. Inception score is used to assess quality and variety in created image. Loss function: adversarial loss,age estimation loss, Identity Consistency loss.
Anwaar et.al [18]	2020	MORPH, CACD, UTK	Future face image produced using age and weight.	Tools: Structural Similarity Index (SSIM)
Chandaliya et.al.[19]	2019	The children longitudinal Face (private).	Generative adversarial network and Variational adversarial network with Perceptual loss (CPAVAE), a model for face progression and regression on little one face.	Tools: Inception Score , Frechet Inception score, Eucledian Distance and Cosine similarity Score Loss function:Perceptual loss , adversarial loss ,Kullback-Leibler divergence loss
Chandaliya et.al [20]	2020	The children longitudinal Face (private).	Child face progression and regression. Using gender as constrain.	VGG19 based perceptual loss

3.Data Set

Performance of deep neural network depends on number of existing training information hence this segment introduces datasets often used in face age progression works. Most frequently chosen data set by researchers is (CACD) Cross Age celebrity dataset [21], and Academic MORPH [22] database. There are 160,000 plus images of 2,000 celebrities in the CACD dataset with age varying from 16 to 62, only associated with estimated age labels. The images in MORPH-II are taken in supervised scenario with neutral expression, uniform light, simple backgrounds and correct age labels.

Other datasets used in FAP are FGNET, which is a publicly available dataset also used for age progression. FGNET contains 1002 images of age ranging from 0 to 69. Images in FGNET are captured in uncontrolled situations. UTKFace database contains more than 20,000 images from age varying from 0 to 116 with labels of age, gender and ethnicity. It is subgroup of MORPH, CACD dataset and images taken from Google and Bing. The 524,230 face images were selected from IMDB and Wikipedia websites to form new IMDB-WIKI dataset [23]. CelebA dataset contains around 203 thousand [24] images with web crawled collection of celebrities with high level of difference of poses, light, expression and accessories.

LFW [25] datasets hold 13233 Metadata images web crawled with low resolution of 250*250. Adience datasets contains around 27,000 images with Age span from 0 to 60 plus and age and gender as labels. Images are web crawled from Flickr. FFHQ datasets contains 70,000 images with high quality Flickr images and high variation in ethnicity. Age span ranges from 0 to 70 plus. FFHQ Aging database is an extension of FFHQ datasets where more labels are added to images like age, gender, pose, glasses, eye occlusion.

ITWCC [26] datasets contain around 8000 images from age of 0 to 32 with age and gender as labels. These are web crawled images of child celebrities with high differences of poses, light and facial expression. AGFW dataset contains 19k of images with an age span of from 10 to 64 with age as labels. These images are web crawled and gathered from "The Productive Aging Laboratory [28]". AgeDB database [29] contains images of famous persons with manually labelled ages. It contains 17k of images with age span of 9 – 95 years. The Children Longitudinal Face [30] is a private dataset in which age ranges from 2 to 18 years. CLF dataset consist of 3682 Images. A resolution of 354×472 pixels for the captured face images. Challenging acquisitions with pose, light and expression, some images are also captured with occlusion like headscarves, cap, dressing on face, whiskers, specs, birth marks such as moles, cuts, different eye colour, and blemish in CLF dataset images.

4. Future Work

There are many challenges to be resolved by upcoming works. Literature survey shows that most FAP contributions is done on adult face ageing while less work is found on child face ageing. It is found that facial changes in adults are mostly texture-based, the changes in the craniofacial are much more difficult to produce while child is growing up, hence this is wide area for future work. It is seen that most research focus on progression very less is mentioned about rejuvenation, which also offers good area to research.

One major challenge is database of young children, as there is private dataset available for child Face Age progression. There is need to collect database for Indian ethnicity for all age ranges, as available datasets are of mix ethnicity. Human face aging also depends upon external factors as lifestyle, working condition etc. Face images with such labels should be collected.

While performing FAP this process also include some personalised facial characteristic for a sole person such as mole, birthmark, scars etc… which do not change with time. The 3D face aging is open problem. Dataset collection of 3D images, computing cost etc are some of the problems need to be addressed in 3D face aging.

5.Summary

In this paper, investigation of face age progression studies is been carried out. Face age progression is still an upcoming field for several application. The number of contributions in FAP are based on condition-based concepts. Challenges for deep face age progression are database. Elderly and children face images should be increased. Additional information such as profession or nutrition type etc. of the face images helps FAP methods to be tailored to the specific conditions of an individual.

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