Facial Aging Databases, Techniques and Effects of Aging: A Survey

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Abstract: *The facial aging databases promises results are shown on face recognition researches. Nevertheless, face recognition and retrieval across age remains tough and is still challenging. Facial aging represents the accumulation of changes over time Cross-Age Reference Coding (CARC) and a brand new big-scale dataset for face recognition and retrieval throughout age called Cross-Age Celebrity Dataset (CARD). One of the challenges in computerized face recognition is to achieve temporal invariance. In this Paper, we present a comprehensive evaluation of literature on cross age face recognition starting with the biological consequences of aging , it provides a survey of techniques, effects of aging on overall performance evaluation and facial aging databases. Evaluation of the impact of aging on the performance of age-invariant face recognition system is an vital measurement. We also study a 3D aging modelling technique for Face Recognition. It also presents a unique and efficient facial image representation primarily based on Local Binary Pattern (LBP) texture features.*

Keywords: *Face Recognition, Age invariant face recognition, 3D aging, Facial aging, Local binary pattern.*

I. INTRODUCTION

Face related issues (e.g., face detection, face recognition) are significant but challenging, and that they have drawn several computer vision researchers' attention for many years. For matching faces, there are four key factors that negotiate the accuracy: pose, illumination, expression, and aging[9]. By taking advantage of widely existing celebrity images on the web, a new approach is to deal with this problem with a distinct angle from prior works. Rather than modelling the aging process with sturdy constant assumptions, we have tendency to adopt a data driven approach and introduce a novel coding method known as CARC. Our assumption is that if two people look alike when they are young, they may conjointly look similar when they both grow older. Since images downloaded from web could be noisy, CARC is intended to be vigorous against such noise. Note that although the thought of employing a reference set for face recognition was proposed in other literatures such as[10] they did not take into account the age variation. The proposed method is basically dissimilar because we have a tendency to incorporate the age information of the reference set into the coding framework.

The challenges are mainly due to huge facial appearance variations in a subject and similarities among subjects. A few of the face recognition applications where age compensation is needed embody deals with identifying missing people screening and problems for multiple enrolment detection. These three situations have two common characteristics: i) significant age difference between probe and gallery images and ii) inability to obtain a user's face image to update the template. Face recognition accuracy is sometimes restricted by massive intra class variations caused by factor like pose, lighting, expression, and age[15]. Due to the increasing effects of both biological and environmental factors, facial aging affects every individual differently.

II. RELATED WORK

Face recognition has been investigated for several years by many researchers. The facial aging process has received a substantial amount of attention with relation to automatic methods for age estimation, age simulation/progression, and age invariant face recognition[14] .In this work, we are primarily involved with how facial aging, namely elapsed time, affects the performance of face recognition systems. All of the previous studies on this topic follow an analogous approach: (i) partition the database (face pairs) depending on age group or time lapse, (ii) report summary performance measures (*e.g*. TAR at fixed FAR) for every partition independently, and then (iii) draw conclusions from the differences in performance across the partitions. Supported this procedure, the subsequent conclusions are reported[24] : (i) Face recognition performance decreases as the time elapsed between two images of the same person will increase. (ii) Faces of younger individuals are harder to identify than faces of older individuals. Face recognition has been investigated for several years by many researchers; Ahonen et al.[11] with success apply texture descriptor, local binary pattern (LBP), on the face recognition problem. Wright et al.[18] propose to use thin illustration derived from training images for face recognition. The tactic is established to be sturdy against occlusions for face recognition. Recently, Chen et al.[4] use a high dimensional version of LBP and accomplish near-human performance on the LFW dataset. Compared with the other published approaches, the proposed method for aging modeling has the subsequent features:

- 3D aging modeling: We tend to use a pose correction stage and model the aging pattern more logically in the 3D domain. Taking into consideration that the aging may be a 3D process, 3D modeling is best suited to capture the aging patterns. We've given away a way to build a 3D aging model given a 2D face aging database. The proposed method is our solely viable substitute to structure a 3D aging model directly as no 3D aging database is presently out there.
- Separate modelling of shape and texture changes: We've compared three different modelling methods, namely, shape modelling only, separate shape and texture modelling, and combined shape and texture modelling. We have shown that the separate modelling is better than combined modelling method, given the FG-NET database as the training data.
- Evaluation by means of a state-of-the-art commercial face matcher, FaceVACS: All of the preceding studies on facial aging have used PCA-based matchers. We have used a state of- the-art face matcher to approximation of our aging model. The proposed method can thus be helpful in practical applications requiring age correction process. Despite the fact that we have evaluated the proposed method only on one specific face matcher, it can be used directly in conjunction with any other 2D face matcher.
- Diverse Databases: We have used FG-NET for aging modelling and evaluated the aging model on three distinct databases, FG-NET , MORPH, and BROWNS. We have determined substantial performance enhancements on all the three databases. This depicts the effectiveness of the proposed aging modeling method.

III. TYPES OF DATABASES

Databases play a fundamental role in research for benchmarking the face recognition algorithms. Several face datasets are presented, but only some of them are particularly designed to address the Aging problem.

- ***FERET***

Previously released face databases such as FERET comprise slight age variations. The database have a total of 1199 subjects that includes 14,126 images and 365 duplicate sets of images.

- ***FG-NET aging database***

The FG-NET aging database have a total of 82 different subjects (6–18 images per subject) that includes 1002 images collected by mainly scanning photographs of the subjects by means of ages ranging between newborns to 69 years old subjects.

- ***MORPH***

MORPH is much larger database than FG-NET. It comprises two sets; Album 1 and Album 2. Album 1 is relatively smaller than Album 2, and have a total of 1690 face images of 625 individuals in the age range 15–68 years. The images in MORPH stand for an adverse population regarding age, gender, and ethnicity.

- ***Cross-age celebrity database (CACD)***

An additional publicly accessible large scale face aging dataset is collected[4] Named CACD. It has a total of 163,446 images of 2000 subjects. This dataset consist of celebrity images across 10 years from 2004 to 2013. The images are collected from Google Image Search with celebrity name and year as keywords.

IV. FACTORS INFLUENCING FACIAL AGING

The aging adult face is influenced by several environmental perturbations such as solar radiations, smoking, drug use and psychological stress.

Table 1- Factors affecting aging

SL.No.	Factors	Caused by	Affected Area
1)	Environmental Influences	i. Age changes ii. General exposure to the elements, such as wind and arid air. iii. Smoking iv. Dehydration	• Facial aging • Skin • Facial wrinkles • Grayish cast to the complexion.
2)	Innate Changes	i. Changes in the bony support structure of the face and subsequent changes in the musculature. ii. Gravity iii. Hyperdynamic facial expressions.	• Upper lip, Nose and Ear.
3)	Hard tissue facial age changes	***Morphological changes*** i. Remodelling of bone ii. Morphological modifications iii. Photoaging (i.e., skin aging due to solar radiations) ***Horizontal changes*** i. Craniofacial skeletal change. ii. Cranial horizontal changes. ***Vertical changes*** i. Increase in age	• Head and Face • Head, Face and Neck. • Skin • Human variation due to sex, ancestry and environmental influences. • Head circumference and head length. • Lower and upper face.

The critical review of the discussed topic "Facial Aging Databases, Techniques and Effects of Aging" in different papers are shown in the table.

Table 2- Facial Aging using different techniques in different papers from [1] to [7]

SL No.	Title	Author and Year	Learning Method	Database (#subject,#image)	Pros	Cons
1)	Toward automatic simulation of aging effects on face images.	Lanitis et al. (2002)	PCA	Private Database (12,85)	Demonstrated the potential in designing face recognition systems robust to aging variations.	Intra-person variations degrade the system performance.
2)	Modeling age progression	Ramanathan et al. (2006)	PCA	FG-NET+ Private Database (233,109)	The craniofacial growth model that we propose	The proposed approach

	in young faces				is unique for each individual.	lacks textural model and does not account for textural variations.
3)	Automatic Face Estimation Based on Facial Aging Pattern	X.Geng et al. (2007)	PCA	FG-NET (10,10)	Proposes an automatic age estimation method named AGES.	Face images under all possible pose and illumination conditions are not always available in reality.
4)	Cross-Age Reference Coding for Age-Invariant Face Recognition and Retrieval	Chen et al. (2014)	Linear Projection And cosine	FG-NET (82,1002) MORPH (13618,55134)	Achieve high accuracy in face recognition across age.	Performance is not improved.
5)	A Longitudinal Study of Automatic Face Recognition	Anil K. Jain Et al. (2015)	COTS matcher	FG-NET (82,1002) MORPH (317,1585	Multilevel statistical models were used to estimate populationmean trends in genuine scores, particularly with respect to increasing elapsed time between two face images.	Studying the stability of the impostor distribution over time

6)	Aging face recognition: a hierarchical learning model based on local patterns selection	Li et al. (2016)	Universal subspace analysis	MORPH Album 2	A two-level hierarchical learning model for aging face recognition.	facial appearance is subject to significant change during the aging process.
7)	Age invariant face recognition and retrieval by coupled auto-encoder networks	Xu et al. (2017)	Non linear Factor analisis	FG-NET (82,1002)	Through CAN, we can nonlinearly separate identity feature to be age-invariant from one given face image	face recognition problems with other variations like expression, illumination and pose

V. CONCLUSION

In this paper, we have a tendency to propose a replacement approach for age-invariant face recognition and retrieval known as Cross-Age Reference Coding. After surveying certain papers, we can map low-level feature into an age-invariant reference space. Experimental results show that the proposed method can outperform state-of-the-art methods on each MORPH and CACD datasets and attain high accuracy in face recognition across age. We also additionally bring in a large-scale face dataset, Cross-Age Celebrity Dataset, for the aim of face recognition with age variation. This study showed that there are certain obvious, generally agreed upon skeletal and soft tissue age-related shape, size, and configuration changes in individuals in excess of the course of the adult lifespan. We've also a 3D facial aging model and simulation method for age-invariant face recognition. The extension of shape modelling from 2D to 3D domain offers extra capability of compensating for pose and, potentially, lighting variations. Our results clearly show that facial images are often seen as a composition of micro patterns such as flat areas, spots, lines, and edges which can be well described by LBP.

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