Effects of Aging over Facial Feature Analysis and Face Recognition

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Abstract While finding our way in using human faces as a biometric measure, it's common to tackle with significant problems such as illumination, pose variation and facial hair. But, dealing with the aging process of an individual had been generally overlooked until recently. This relatively untouched playground may enable us more insight while tackling with the problems. This article puts the phenomenon of "aging of face" into the proper place in computer vision studies, outlines what has been done up to this point and draws out some new directions for future research.

Keywords face recognition, biometrics, aging, age estimation, modeling the aging process

1 Introduction

If we ignore some early implementations, by some medieval Chinese merchants who had used fingerprints to settle serious business transactions, or some forgetful Chinese parents using fingerprints and footprints to differentiate children from one another, for hundreds of thousands years, **face recognition** had always been the only tool for mankind for authentication and authorization purposes.

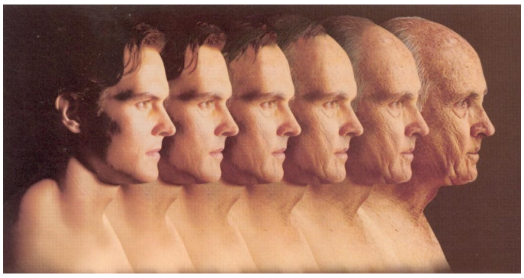

Figure [1] : Dealing with age related issues in computer vision may also give us some insight about the **perception of age** in human brain

Nowadays, maybe not singled out among abundant biometric identifiers, such as **fingerprints**, **retina** or **DNA**; **face** is still one of the most useful biometric tools we use in 21st century's sophisticated authentication and authorization problems.

Face recognition has already its own bag full of challenges and recently we're in the progress of discovering yet another problem, and a tough one indeed: **aging of a person**.

2 Age Dilemma : An Obstacle, or New Horizons?

Depending on what side you are, **aging** may be a threat to your algorithm or an interesting research opportunity. Looking from the **face recognition** point of view, aging brings havoc to the algorithms. In fact, in order to call a biological measurement qualify to be a **biometric**, it should satisfy the **permanence** requirement *(among others)* [8].

> ***permanence****: the characteristic should be sufficiently invariant (with respect to the matching criterion) over a period of time.*

The face recognition algorithms should be robust enough to fulfill this requirement.

Figure [2] : Face images displaying aging variation. Each row shows images of the same individual [10][11]

On the other hand, aging itself is the ultimate fact that each human experience continuously and we have lots of applications waiting to be implemented around the concept of aging.

Here, we have 3 different research activity around human aging:

- Age invariant face recognition
- Age estimation
- Modeling / simulating aging process

2.1 Age Invariant Face Recognition

The performance of face recognition and/or authentication systems is greatly affected by within-person variations encountered in human faces [10]. Among these "within-person" variations, aging is one of the most significant ones.

In most studies in face recognition, aging factor is generally overlooked. This is most relevant because, the effects of aging is observed over a long time and until recently, most real-life problems demanded a short time-span around "present time".

The face recognition methods that overcome aging fall into two main categories : **generative** and **non-generative**. [1]

Generative approaches apply a computational model to simulate the aging and then apply subsequent recognition algorithms. On the other hand, **non-generative** approaches concentrate on deriving "**age-invariant signatures**" from faces.

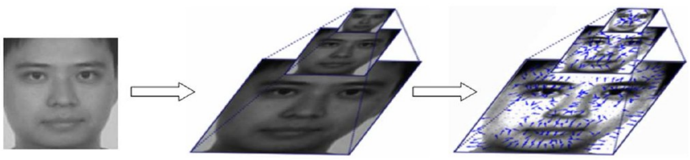

Figure [3] : Computation of a Gradient Orientation Pyramid from an input image [4]. It is proposed that, by discarding the gradient magnitude and utilizing some hierarchical techniques, the new descriptor yields a robust and discriminative representation.

2.1.1 Non-Generative Approaches

For example, in [4], Ling *et. al.* uses a face operator based on image gradient orientations taken from multiple resolutions. Thus they obtain parameters for an **SVM** *(Support Vector Machine)* which is used as a classifier for face verification across ages *(see Figure[3])*.

In this work also, it is stated that that, although the aging process adds difficulty to the recognition task, it does not surpass **illumination** or **expression** as a confounding factor.

Figure [4] : Drifts in facial features for a few age-separated face images from the FG-Net aging database. The drifts across images of same individuals appear coherent *(top two rows);* while they are somewhat incoherent *(third row)* when the images belong to different individuals [5]

Another team that handles the problem in similar approach is Biswas et. al., and they utilize location drift of facial features across ages [5]. The main point is to look forward **coherencies** in facial feature drifts across ages.

They claim that the coherency of some selected facial features is larger on two different images of the same person with different ages *(see Figure[4])*. Of course, in this work, only the most frontal fiducial features are selected, because the features on the outer boundaries of the face tend to change swiftly with head pose variations and facial actions *(laughing, even smiling)*.

The method is quite intuitive and simple. When we define the incoherency as:

$$U_{ij} = \frac{|a_i - a_j|}{r_{ij}}$$

where $|\mathbf{a}_i - \mathbf{a}_j|$ is the magnitude of the vector difference between the two feature drifts $\mathbf{a}_i$ and $\mathbf{a}_j$ while $\mathbf{r}_{ij}$ is the distance between the corresponding feature locations.

The combined potential energy of the drift map characterized by **K** feature drifts is given by:

$$C = \sum_{i=1}^{K} \sum_{j=i+1}^{K} U_{ij}$$

The lover the potential energy **C**, it's more likely that the images belong to the same person.

2.1.2 Generative Approaches

This approach is mostly related to Modeling / Simulating Aging Process, which is explained in Section[2.3]. There are variety of tools to build a computational model for facial aging. For example in two different works of Ramanathan and Chellappa [6][7].

The first one focuses on childhood growth modeling, whereas the latter addresses the adult aging simulation.

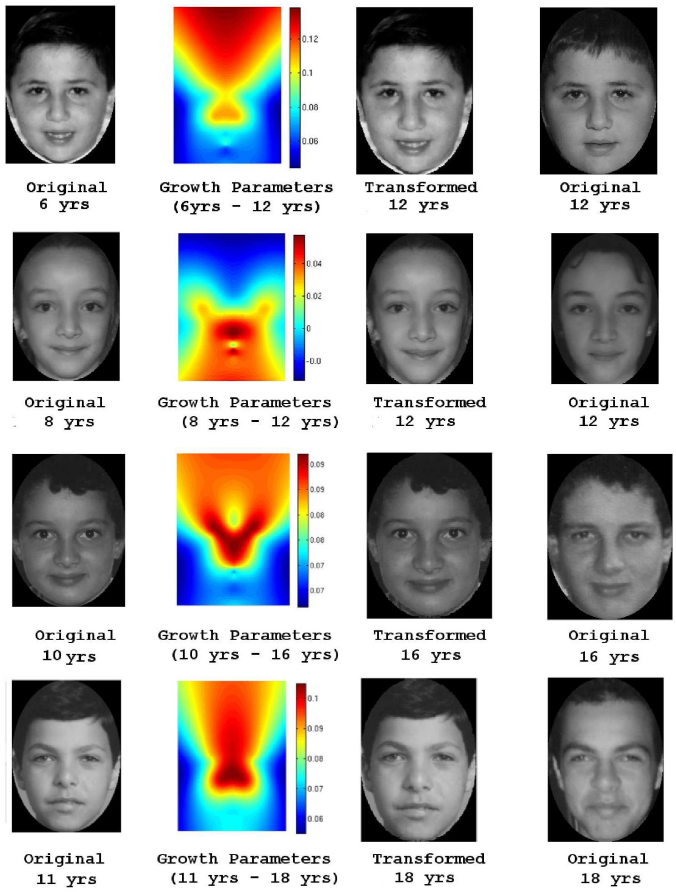

Figure [5] : Age transformation results on different individual (from the work of Ramanathan and Chellappa [6] which focuses on aging in childhood)

The facial transformation is very much different in formative years *(childhood)*, so in [6], the authors try to build a model based on "*craniofacial*" growth *(the growth of skull and face)*.

The key point here is to model the facial growth by means of **growth parameters** defined over facial landmarks. These landmarks are also most common ones used in anthropometric studies. The age-based anthropometric constraints on facial proportions translate into linear and non-linear constraints on facial growth parameters. The problem then reduces to implement methods for computing the optimal growth parameters.

This approach only addresses the geometrical growth of the face, and does not take into account other facial attributes, such as **texture**. This means that a lot of future work is left to be done.

In the team's other work [7], for modeling the aging process in adulthood, they present a twofold method:

- Build a muscle-based geometrical change model that captures the subtle changes through adulthood
- Develop an image gradient based texture transformation function that characterizes facial wrinkles and other skin artifacts often observed during different ages

The bottom-line is: the two approaches have their own strengths and weaknesses. The key studies are carried through on completely different target areas and solutions are created generally on specific purpose. Currently, we lack a comparative figure on the performances of these two approaches.

2.2 Age Estimation

The human brain can analyze the face and estimate the approximate age of the subject, though this estimation is not accurate. The perception of age in human brain is still a subject of research.

Researcher	Database	Training Data	Testing Data	Age Prediction Accuracy
Kwon and Lobo [18]	47 images, classified by babies, young adults and senior adults	-	15 images	100 %
Horng et al. [15]	230 images, classified by babies, young adults and senior adults	-	230 images	81.6%
Hayashi et al. [13]	300 images ranging from 15 – 64 years	-	300 images	27%
Lanitis [22]	330 images ranging from 0 to 35 years old	250 images	80 images	Mean Error: 3.83 years

Figure [6] : Age prediction performances for different approaches

The motivation behind age estimation can be [9]:

- Age specific human computer interaction
- Age-based indexing of face images
- Development of automatic age progression systems
- Understanding the process of age perception by humans

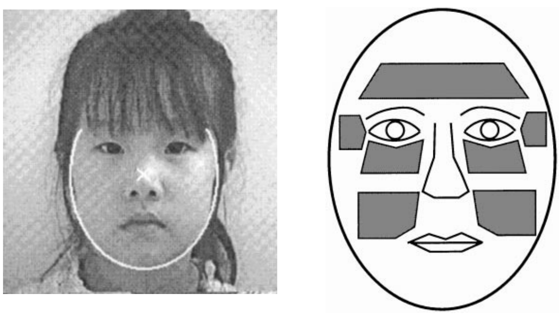

Figure [7] : *(left)* Oval template fitting in [3] , *(right)* wrinkle geography, which shows the regions that are searched for facial wrinkles

All methodologies in age estimation apply different approaches for different epochs in human life: **infants**, **young adults** and **senior adults** [9].

In infant years, the body develops very fast and the algorithms focus on changes on skull size and ratios among facial features. In young adults, there's no change in skull size or ratios and wrinkles start to appear. In the senior adulthood, wrinkles mostly determine the age

2.3 Modeling / Simulating Aging Process

Another aspect of age considerations is simulating the aging process over a human face. Our challenge may be, for instance, taking a still image of a person around his/her thirties and apply an artificial aging process over this subject. Then we may obtain the subject's estimated state in forties, fifties or more.

This tool may be used in problems such as:

- Guessing the present state of a missing person
- Automatic update of a face database at security check points, such as airports

Figure [8] : *(up)* Original image of Quentin Tarantino – Age 41 years *(down)* Artificially aged Tarantino 50, 60, 70 and 80 years respectively [13]

Also, modeling the aging process is a common tool in face recognition tasks as mentioned in Section[2.1.2].

3 Database Available

Among many available face databases around the world [14], three of them includes significant sets for aging individuals.

- MORPH Database
- FG-NET
- FERET Database

MORPH Database [15] is composed of more than 17,000 images of over 4,000 individuals, between ages 15-68. These individuals are chosen from males and females *(not homogeneously)* and from three different ethnicity *(very much skewed)*.

FG-NET (Face and Gesture Recognition Research Network) database is composed of over 1000 images of 82 subjects between the ages of -069 years. This database also includes some additional information such as:

- Some 68 landmark features that were identified manually, on all face images
- Some meta information or informative tags such as image size, age, gender, spectacles, etc.

The database was constructed by using real life album images, so the content is uncontrolled and has quite a variation of facial expressions *(probably mostly skewed towards smiling, as is usual when taking photos)*.

FERET Database is also a large database not specialized only on aging but also has variations on illumination, pose and facial expressions. The images are well tagged and classified for age differences and for other attributes. The age separation between the instances is 18 months or more. The database contains over 2,000 images

4 Discussions and Conclusions

Human aging is an important aspect for biometrics and also for all face processing applications and not studied in depth yet.

The studies on this field may yield some insight for the Age Conception in human beings.

Collecting database is not easy but fortunately, there are various sources to start with.

The subject has various aspects and various impacts on different disciplines. For example, aging is an obstacle in face recognition (beside others such as beard, glasses etc.). On the other hand, aging is a natural process in humans' life and there might be thousands of computer vision applications regarding this process.

Age estimation is one of the major issues in those applications. Another one is modeling the aging process. This latter may be useful in security applications (such as in passport control), or finding lost children.

The bottom line is: “aging” is an important aspect that has various impacts on different disciplines and a fertile ground for future research.

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