An Overview on Face Aging Graphical Models: Compositional Dynamic Model and Concatenational Graph Evolution Model

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Abstract

In this paper, basically we focused on two models of the Face Aging graphical models. The models discussed in this paper are compositional dynamic model and concatenational graph evolution model. The compositional dynamic model represents face details(hair, wrinkles, etc.,) in each age group by hierarchical And-Or graph, Parse graph. CONcatenational Graph Evolution (CONGRE) aging model, that uses decomposition strategy in spatial and temporal aspects to learn long-term aging patterns from partially dense aging databases(MORPH, FG-NET).

1. Introduction

FACE aging is attracting increasing interest from researchers due to its grand challenge in real-world applications(e.g., looking for lost children or wanted fugitives, recognizing age-separated faces [13], facial template renewal). The objective of this paper is to synthesize aging effects that are visually plausible while preserving identity. In recent years, a lot of effort has been devoted to face aging modelling building face aging databases and aging model evaluation.

2. Related Work

2.1 Compositional Dynamic Model:

Compositional dynamic model for face aging consists of 3 levels which are represents all face images by a hierarchical And-Or graph and parse graph methods[3].

2.1.1 Levels In Compositional Dynamic Model:

The first level includes the low resolution face image(i.e. hair-style and face appearance). The second level refines the first level by modelling shape, intensity and other variability of facial components. The third level describes for the skin marks and wrinkles in different facial locations[6].

2.1.2 Methods For Compositional Dynamic Model:

And-Or Graph For Face Modelling

In compositional and dynamic model to the face aging process is represented by *And-Or graph[17]*. *And-Or graph* consists of And-nodes, Or-nodes and Leaf nodes[7].
The And nodes represents the decomposition , which divides a face into parts and primitives at three levels from coarse to fine. Or nodes represents the diversity of face appearance at each age group. leaf nodes are basic primitives.

Parse Graph

It implements by using multi-level face aging algorithm, which consists of computing the parse graph representation (by choosing the or-nodes)from an input young face by Bayesian inference(based on Bayesian rules which derivates the statistical methods).Sampling the parse graphs of other age groups from the dynamic model. Generating the aging image sequence by the generative model[10].

2.2 Implementation

Implementation details consists of representation and aging of each part i.e, hair, face, components, wrinkles[16] in the dynamic model. MORPH database , FG-Net aging database are used to develop in this model.

2.2.1 *Level 1:* ***Hair Aging***

For each group a large set of hair images are collected. For an observation select a similar hair image according to two metrics:

a)geometric similarity - the hair contours is computed using a Thin Plate Spine(TPS) warping energy between two hair contours.

b) texture similarity - it is computed by KL distance between vector flow histograms of two hair textures. Then the selected hair of group is warped to fit the face shape.

Based on geometric and photometric similarities the aging patterns are determined. For each face, 90 facial points are taken to calculate the mean and variance of various histograms. It is notice that bony and soft tissue changes are in shape, size and configuration during adult aging, and the shape changes in muscular regions is larger than in bony regions. Compute the differences between mean face shapes of different age groups and adopt the mean shape changes as soft constraints during warping of face shape as age increases.

2.2.2 Level *2*: ***Facial Component Aging***

In the facial component aging – eye aging is an best example .The transition probability (thickness of arrows) is computed from the dataset of eye patches across age groups and the geometric distance (energy between two eye Shapes) and the photometric distance (summing over the intensity differences) are computed. An aging result of eye is determined by using *Poisson* image editing techniques, the high frequency information is transfer in to skin region and perform color histogram specification to the non-skin area texture..

2.2.3 *Level 3*: ***Wrinkle Addition***

In this model the aging effects are determined by the wrinkle zones for each age group are selected randomly from the dataset. Generally the parameters of wrinkles (position, length and orientation)can be calculated by the simulation of age group algorithms. After the aging process at all the three levels, we integrate them together to Generate the final results.

3. A Concatenational Graph Evolution Aging Model

Great efforts made by the researchers on face aging modelling has proposed a variety of approaches[5]. Generally, these approaches are classified into two groups: the physical model-based approach and example based approach. Earlier researchers has built a face aging model to simulate physical aging mechanisms, while the later seeks to fit available real aging sequences and can be further classified into two types: prototyping method, and function-based method. In the spatial aspect, we construct a graphical face representation, in which a human face is degrade into mutually interrelated sub regions under the guidance of anatomical experts. In the temporal aspect, the long-term evolution of the above built graphical representation is modelled by connecting sequential short-term patterns.

3.1 Approaches In Graph Evolution Aging Model

3.1.1 Physical Model-Based Approach

Physical model-based approach simulates the face aging by modelling the structure and aging mechanisms of the muscles or facial skin[2] ,etc. Due to the ingeniousness of both facial structure and face aging mechanisms, physical model-based methods are often complicated and expensive. Due to these disadvantages it is difficult to obtain pragmatic results from physical modelling.

3.1.2 Prototyping Approach

Prototyping approach first divides age range into discontinuous age groups and define the average face of each group as its prototype, and then the dissimilarity between prototypes is defined as an axis of aging transmutation [4]. Some other researchers specially work on providing high-resolution aging results or introducing originality of face aging [8], lack of peculiarity is still the biggest disadvantage of prototyping approaches.

3.1.3 Function-Based Approach

Function-based approach relates the relationship between facial variables and corresponding age marker with an explicit or indirect function. In the process of child growth, the shape reform due to cranium growth is eminent; therefore, researchers proposed various methods to reproduce this change. So, most researchers study shape and texture changes simultaneously in adult aging modelling. Large varieties of functions are suggested, including quadratic function, support vector regression , kernel smoothing method or an implicit function [12][14].

3.2 Basic Ideas

The aging mechanism is intricate both spatially and temporally, but presently available face aging databases contain mostly partially dense data sets since collecting long-term dense face aging sequences is long-delayed.

To handle this problem, we initiate a concatenational graph evolution face aging model, which take advantage of spatial and temporal environs of face aging to know long-term aging patterns from partially dense databases.

From the spatial viewpoint, the face is a highly compound structure of collection of hard and soft tissues, both of which go through large changes during aging process. First, face aging of a definite sub region is mostly disciplined by the behaviours of a subgroup of muscles, i.e., face aging is partially local; second, the human face is a global structure even though of the spatial domain, so the aging of one face region is related to those of the other ones to some what, i.e., the aging patterns of different regions are not exactly independent.

From the temporal viewpoint, the long-term face aging process (i.e., across 3-4 decades) is highly nonaligned because a face withstand different changes in different stages and the aging rate is also time variant. Hence, learning long term aging patterns probably demands long-term aging sequences, and thus due to extensive faces, difficulties occur.

With the above assay, the proposed CONGRE aging model first builds a graphical face illustration, then learns long-term aging templates from partially dense data sets. Specifically, the model learning is composed of the following two steps.

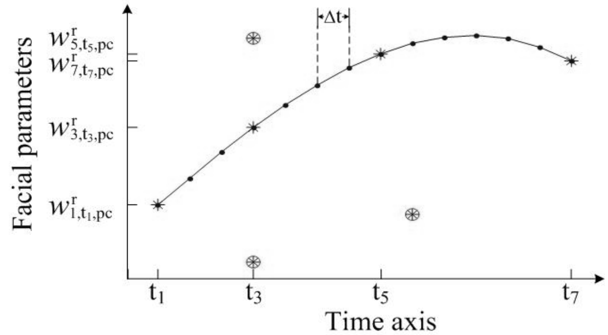
Step 1. Learning short-term face aging patterns: From openly available face aging databases such as FG-NET and MORPH, our model fetches short-term aging patterns from the real aging sequences. A function-based approach is used for this purpose since the short-term appearance changes of facial sub regions are comparably small.

Step 2. Concatenating learned short-term aging patterns into long-term patterns: By developing long-term aging process, we concatenate partially overlapping short-term aging patterns regularly into long term ones based on predefined principle[18].

3.3 Aging Models

3.3.1 Short-Term Aging Model

As quoted previously, short-term aging modelling directs to generate functions that can approximate the progress of aging parameters within a shorter age range for each face sub region [22].



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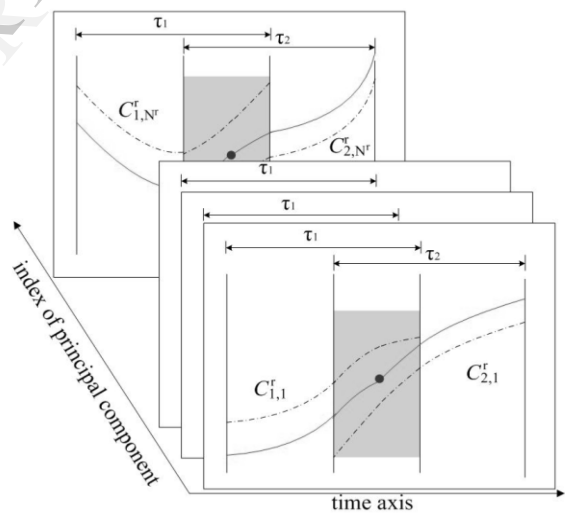
3.3.2 Long-Term Aging Model

As reviewed above, a long-term aging pattern is composed of some continuous short-term aging patterns. In this paper, we define the long-term face aging as a Markov process in the granularity of age intervals, based on which we can assume a sequence of temporally overlaying short-term aging patterns in latter ages for the input face. After the assumption, a long-term aging pattern is estimated by concatenating short-term aging patterns under constraints[22].



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3.4 Long-Term Aging Prediction By Concatenating Short-Term Aging Patterns

From the basic characteristics of the face aging process, pattern concatenation should adapt two constraints: smoothness constraints and consistency constraints. The earlier means that face aging should be a smooth process to avoid blunt changes. The latter indicate that aging pattern of different regions should be kept persistent, as the face is an organic structure; thus, the aging of different regions is associated with the others. In this division, we first properly defined measurements for these two constraints, based on which a tentative chance of concatenating two short term aging patterns is defined. Finally, an algorithm is proposed to anticipate long-term aging patterns by sampling with the described concatenating probability.

3.5 Real Aging Data

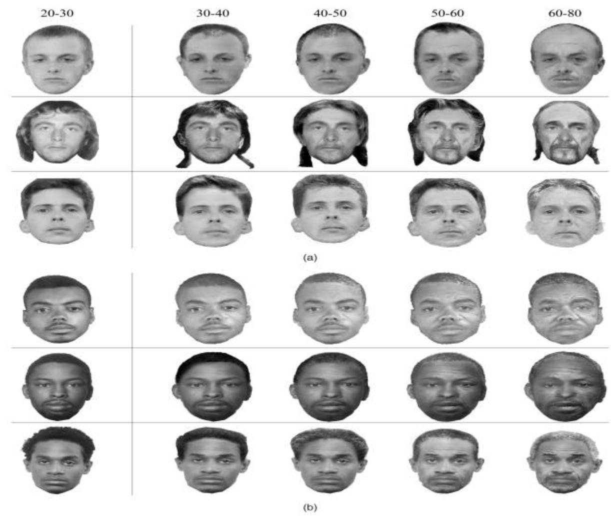
We use two openly available face aging databases: FG-NET [1] and MORPH [15]. We use images from FG-NET to design child growth models. In consideration that there exist possible differences between the growth patterns of boys and girls, two gender distinct growth models are built individually. We avail faces in the MORPH database for adult aging modelling. One of its extended versions includes 16,894 face pictures from 4,664 adults. To determine the long-term aging model, we use image sequences comprising of photos snapped at more than two different ages between 18 and 54 years. The maximum and average age periods are, appropriately, 33 and 6.52 years. Since a child's face appearance changes much faster than an adult's with age increasing, we show solid prediction results (every other year) for children, while for adult aging we give results about every 10 years.

3.5.1 Fg-Net Aging Database

The FG-NET[1] Aging Database is an image database comprising of face images showing a number of subjects at different ages. The database has been refined in an attempt to help researchers who explore the effects of aging on facial appearance. The database has been set up as part of the European Union project FG-NET (Face and Gesture Recognition Research Network).

3.5.2 Morph Database

MORPH[15] database is the biggest publicly available longitudinal face database. The MORPH database consist of 55,000 images of more than 13,000 people not beyond the age ranges of 16 to 77. There are averages of 4 images per individual with the time period between each image being an moderate of 164 days. This data set was made up for research on facial analytics and facial recognition. The MORPH database (non-commercial) was collected over a span of 5 years with abundant images of the same subject. This is not a controlled collection (i.e., it was collected in real-world conditions). The dataset also comprises of metadata in the fashion of age, gender, race, height, weight, and eye coordinates. *Fig 2.* Shows a sample data set



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3.6 Synthetic Aging Data

In this part, we conduct aging prediction by using the learned aging models. For child growth, since shape change is the most eminent feature while texture is probably stable and the format of training data is highly corrupted by non-aging variations, we reviews only shape growth models in this analysis. A likely face with age and gender labels known can be transformed to target ages by the equivalent growth model.

4. Conclusion

We present a compositional dynamic face aging model, based on simulation and age estimation as well as a concatenational graph evolution face aging model to construct long-term face aging patterns from impure, partially dense aging databases. With more and more aging databases become available as well as the progress of face recognition technologies, this kind of assessment will be accompanied on time.

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