Face Aging Simulation

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ABSTRACT
Face aging is one of the most challenging task in image processing and is commonly used in many areas. This paper consists of compositional method which will represent faces of different age groups. The representation of faces in different age group is done hierarchically i.e. using And-Or graph, in which the And nodes will decompose the face into different components (e.g. wrinkle, hair) for crucial age perception and the Or node will represent the diversities of faces. The graph is then represented using Markov chain.

The diversities or the uncertainties of the faces are learnt from the large database which consists of large number of images. There are two criteria for evaluating the result the aging simulation and one of them is the accuracy of the simulation i.e. whether the perceived image belongs to a particular age group, and second is the preservation of the identity i.e. whether the face, that is retrieved after simulation process is preserving the identity of the person or not. The statistical analysis of these two above mentioned criteria will decide the performance of the aging simulation.

Keywords
And-Or Graph, Aging modeling, ANOVA.

1. INTRODUCTION
Face aging is a challenging issue in image processing and in digital media field. Aging is an unavoidable process for all the people. As and when time passes by and the age of the person increases different types of changes starts taking place on a person's face, such as wrinkles, hair whitens. This change on face depends on factors such as smoking, survival press and lifestyle. It can also be a genetic reason behind the changes on the person's face. There are two criteria for evaluating the results of simulation. One is the accuracy of the simulation that is whether the retrieved images are perceived of the intended age group, and the second is the preservation of the person's identity that is whether the aged face is perceived as the same person. The age of the person is usually judged from their non-facial factors such as hair color and style, the boldness of the forehead, while these non-facial factors are not taken into consideration while modelling the face. There are large variations of perceived age within each biological face group due to external factors, like health, life style, etc. They lack the quantitative measures for evaluating the aging results in the literature. Hence all these characteristics demand a typical face modelling system to account for face details related to age perception, intrinsic uncertainty in aging process.

In previous work, the aging process was divided into two categories, child growth and adult aging. In modelling child's growth, the main factor considered was the face, i.e. in child's growth, there is change in face, no other factors are considered like hair for aging process. Many researchers has defined some landmarks on the faces [7] [14] [15], where some transformation needs to be applied for modelling the shape change on a child's face. Ramanathan and Challepa [15] these are the two people who have defined the growth parameter over the defined landmarks to build the crania facial growth parameters, and anthropometric evidences are included to make the model consistent with the actual data. Lanitis et al. [13] has built three aging functions that is describing the relationships between the facial age and the AAM parameters, by which the age of the child can be estimated from its image, and others has worked on texture parameters in the facial growth.

2. RELATED WORK
Compositional and dynamic model are used in face aging. The faces in each age group are grouped using the hierarchical And-Or graph using the compositional model. And node decomposes the facial parts to describe the facial details whereas the Or node represent a large diversity of faces using alternative selections. Markov process on parse tree representation is modeled in face aging. In dynamic model a large annotated face dataset and the uncertainty of face aging is modeled explicitly. This model is used construct long term face aging patterns from impure, partially dense aging database.

In image warping, face aging is done with the help of comparing two images- a young age picture and an old age picture. This comparison is done with the help of AAM and warping methods. Due to intrinsic uncertainty two criteria are used to evaluate the face aging results: 1. Accuracy of simulation in which for 4each group of age 80 real images from dataset and 80 simulated images are used. Using ANOVA (Analysis of Variance) the difference in the age estimation performance is calculated between the real and simulated image. 2. Preservation of Identity in which the aging sequences for an individual is collected from family and relatives and synthesizes one aging sequence from images of initial age group. Initially the image is preprocessed as the image may contain various noise, diversity of tones and position. Warping is important part of face aging. The image is delineated with 68 points located along the outline of major facial features (such as nose, eyes, mouth, eyebrows, etc.) and the facial borders. Then the feature points' triangulation is done in which the human face is divided into small number of triangles. Now the information such as wrinkles, beard, shape and color changes are easy to detect by subtracting the two images.

3. PROPOSED METHODOLOGY

The paper is using the compositional dynamic model for face aging simulation, in which And-Or graph is used. Where the And nodes is representing the decomposition of the face, which divides the face into different parts. Or node represents the alternatives or the other possibilities of the wrinkled face. There are different possibilities of the changes on the person's face i.e. there is a large amount of uncertainty of the aging process. So these changes are learnt from a large dataset of faces. Based on the And-Or graph, the dynamics of the face aging process is represented as the first order Markov chain on the parse graph.

This generative process works in three steps, the first step is to generate face and hair image, second is to refine the different face components with landmarks and appearance. And last is to generate wrinkles and marks in the wrinkling zones of the face.

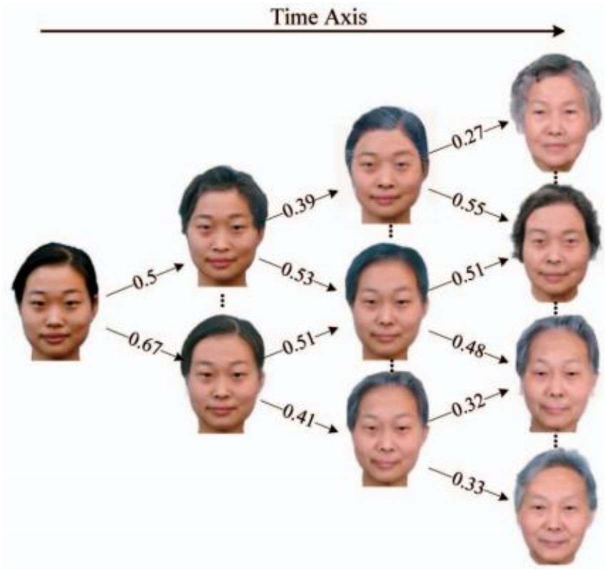

Fig 1: Uncertainty of Aging

The three steps are given as follows:

1. A. Hair aging

From a large dataset hair images are collected for each age group. The hair image in aging process is selected on the basis of criteria, first is the geometric similarity and second is the texture similarity. Thin Plate Spline (TPS) is used for computing the geometric similarity between the hair contours, while the texture similarity is computed by KL distance between vector flow histograms of the two hair textures. Then the selected hair of a particular age group is warped to fit the face shape on the basis of the skull structure.

B. Face aging

With aging of hair, some changes do appear on face like darkening of skin, dropping of muscles. Selection of the aging pattern for it is based on geometric and photometric similarities. There are 90 facial points that describes the facial geometry, TPS warping energy measures the cost for aligning two face geometries, is used as a natural shape distance. The difference between mean face shapes of different age groups and the adopted mean shape, changes the soft constraint during warping of face shape.

2. Facial Component Aging

Aging has adverse effects on facial components such as eyes, mouth, and forehead, here variations include changes in both geometry and photometry. Here the geometric distance is been measured with the help of TPS bending energy between any two facial components which are having the same topological characteristics, whereas the photometric distance is calculated with the help of squared intensity difference that are summed together in the Gaussian window around the matched points.

3. Wrinkle Addition

In wrinkle addition, wrinkles are added in various wrinkle zones. Aging effects 6 wrinkle zone on face. The wrinkle addition is done in 2 steps:

A. The curves are generated in various wrinkle zone. The number of curves and their positioning is dependent on the prior probability densities

B. The intensity profile is added using the dictionary. Poisson image editing technique is used to render the realistic wrinkle images.

3.1 EQUATIONS

The face is divided into 6 zones, where the wrinkles will appear. So for the wrinkle zone 'z', the Poisson distribution will provide with the number of wrinkles on 'm' zone.

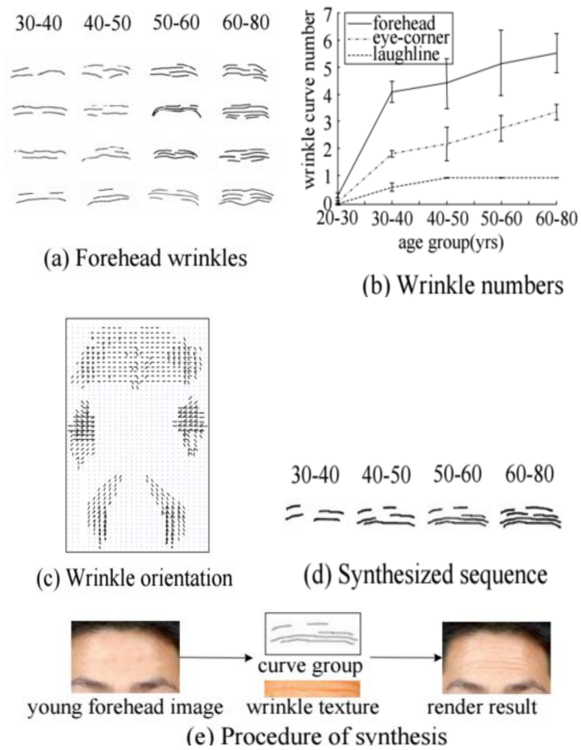

Fig 2: Wrinkle synthesis in different skin zone

$$p(n_t(z) = k; t) = \frac{\boldsymbol{exp}\left(-\boldsymbol{\lambda_t(z)}\right)(\boldsymbol{\lambda_t(z)})^{\boldsymbol{k}}}{\boldsymbol{k}!}$$

Where, nt(z) = total number of wrinkles in z zone, t =age group,

$$\boldsymbol{\lambda_t(z)} = \frac{\boldsymbol{1}}{\boldsymbol{M}} \sum (N_t^l(z)) \qquad \textbf{for k=1 to } \mathbf{M_t}$$

Where, M_t = training images at age group t, $N_t^l(z)$ =wrinkle in zone z of the lth sample at the age group t, $\boldsymbol{\lambda_t(z)}$=mean value.

Generating wrinkle curves

The geometric parameters of wrinkle curves are computed. The number of wrinkles is calculated using bigram model.

$$p(n_t(z) = k | n_{t-1}(z) = j) = \begin{cases} 0\,, & k < j \\ \frac{1}{2} p(n_t(m) = k; t)\,, & k \geq j \end{cases}$$

The formula, $p(n_t(z) < n_{t-1}(m) = 0$, forces to ensure that the wrinkle number increases as time goes and z is normalization factor.

The FG-Net database was referred and images were taken from the database for the algorithm. Divide the age range into five age groups: 20-29, 30- 39, 40-49, 50-59, and 60-79.Use images from the first group i.e,20-29 and age them using the dynamic compositional model into the other four groups respectively. The synthesis of a series of aging results from MORPH database was performed to test the generality of the algorithm. The features considered in the experiment include both the internal factors (e.g., brow, eyes, nose, mouth, skin zones) and the external factor (mainly the hair). Multivariate Regression Analysis (MRA) was applied to measure the contribution of each component for aging of the face. From the rank of contributions, one can see that for adult age estimation, wrinkles in laugh line, forehead, and around-eye region provide plenty of information. Two criteria's are used to evaluate the goodness of the aging model: 1) the accuracy of simulation, and 2) preservation of the identity. Test the synthesized image using various face recognition algorithms. Using ANOVA conclusion was drawn that the difference between the synthetic images generated using the face aging and the real images taken from the database FG-Net is minimal. These variations also differ between data sets done with hair as a component and without using hair as a component for face aging.

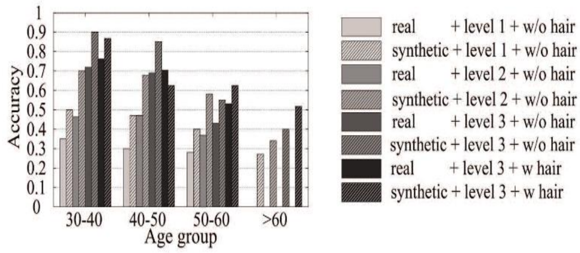

Fig 3: Results

4. RESULTS

The aging on face features are obtained using the difference between the old and the young face of the person. The aging information is obtained by the subtraction of the old and the young image of face using AAM face feature detection which helps in the simulation of aging for the image. The difference restricted to the area of face between old and young image restrict the experiment because the forehead and hair is not considered in AAM. Unfortunately, the feature points that are retrieved using the AAM model are quite limited and also there is a measurement error. This plays an undesirable effect on the transformation of the face in order to avoid this interpolation method is adopted. The interpolation method improves the number of feature points by triangulating the face image, the vertices of each triangle are made up at feature points and the midpoint of these form the new feature points The feature points are increased by a big number (approximately 118 after removing the repetitive ones) using this method and it also improves the quality of triangles so that more detailed transformation can be made. The aging result improves in 2 aspects after using interpolation method, one is the light area gets reduced and the other is deformation of eyes gets improved. Another approach is to achieve this is by manually adding feature points on the edge of face, eyebrows, hair, eyes, forehead, etc. Because these points are added by hand their positions are all accurate. This simulates the face aging as a whole. Using compositional model the results are mainly dependent on the large training dataset and the compositional model which includes the external and high resolution factors.

Subjective estimation	Facial part	face	eye	hair	forehead	laughline
	β	0.357	0.205	0.179	0.09	0.083
Objective estimation	Facial part	laughline	hair	forehead	face	eye
	β	0.480	0.408	0.373	0.257	0.181

Fig 4: Cumulative scores of automatic age estimation algorithm

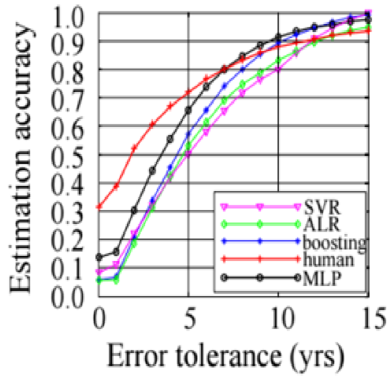

Fig 5: Performance of proposed regressors on assumed dataset

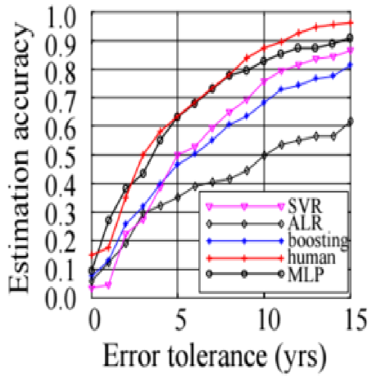

Fig 6: Performance of proposed regressors on FG-NET dataset

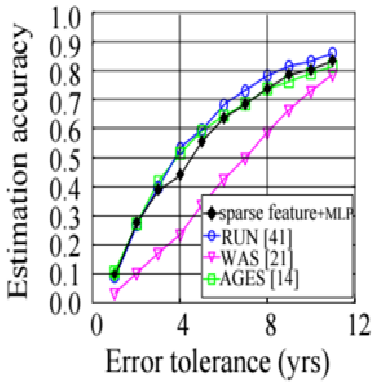

Fig 7: Comparison between the performances of the estimated algorithm and the-state-of-art algorithm on FG-NET dataset.

The cumulative scores for dynamic and compositional model for the different datasets are given in below figure 4. Figure 5 and figure 6 shows the performance of the algorithm on different datasets, and the comparison of the performances is shown in figure 7.

5. CONCLUSION

Compositional and dynamic model is used for modeling the algorithms for face aging simulation. The results synthesized by the algorithm will be evaluated for the accuracy of age simulation the results are attributed to the power of compositional model and the large training data sets. When more images of an individual are obtained the model can be extended by assigning more weights to the model and achieving applications other than entertainment ones. Objective evaluation on identity preservation can be conducted later on if more and more aging data becomes available as well as face recognition technology progresses. Here the feasibility of application of piece wise affine warping on simulating face is tested. More research remains in the field of age simulation. Detailed and in depth research can be done in selection of feature points and improvement in transformation. The improvement is done in two ways either by using interpolation technique or by assigning the points manually. The future focus includes introducing novel algorithms to support better transformation and training a larger database to get more accurate results. Also different aging models need to be researched and applied to find which one can yield a more accurate result.

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