What shall I look like after N years ?

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ABSTRACT

—*"What shall I look like after N years?"*
In this paper, we present an Auto Age Progression system, which automatically renders a series of aging faces in the future age ranges and generates an aging sequence (aging video) covering the entire life for an individual input. In the offline stage, a set of age-range specific dictionaries are learned from the constructed database, where the dictionary bases corresponding to the same index yet from different dictionaries form a particular aging process pattern across different age groups, and a linear combination of these patterns expresses a particular personalized aging process. In the online stage, for an input face of an individual, our system renders the aging faces corresponding to different age ranges through the aging dictionaries, and then generates an age progression by the presented face morphing technology.

Categories and Subject Descriptors

J.5 [**Arts and humanities**]: Arts, fine and performing

Keywords

Age progression system, face aging, face morhping

1. INTRODUCTION

Age progression has found application in some domains such as authentication systems, finding lost children, and entertainment. Recently, some demos/Apps related to face aging have been developed. For example, Face Transformer[1] and AgingBooth[2] are receiving great interest. However, these demos/Apps require some manually operations, which are not very convenient. Besides, the generated aging faces for different inputs are very similar, and not many personalized characteristics are preserved. Furthermore, the aging faces correspond to the coarse age periods, i.e., Teenager, Adulthood, Older.

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[1]http://cherry.dcs.aber.ac.uk/Transformer/

[2]http://www.piviandco.com/apps/agingbooth/

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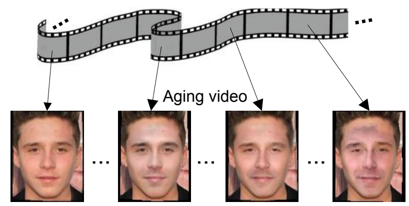

Figure 1. The unfold frames of aging video generated by our demo. An face photo of individual (on the left top) is shot or loaded, then our presented demo automatically generates an aging sequence (aging video) covering one's whole life.

Therefore, we develop an Auto Age Progression system, which can render a series of aging faces in the future age ranges (one age range spans no more than 10 years) and generate a whole aging sequence covering the entire life for an individual input. Figure 1 shows the unfold frames of an aging video for an input face. Compared to the previous Apps, our system has two advantages: (1) **Automatic** & **Personalized**: our system can automatically render the aging face in a personalized way by the proposed aging bases; (2) **More Visualized**: our system can generate a whole aging video densely covering the entire life.

Technically, we firstly collect the intra-person aging pairs from the Web and the available databases, and then we design a corresponding aging dictionary to represent the aging characteristics in one age group. Finally, all aging dictionaries are simultaneously trained by a personality-aware dictionary learning model on the collected data. Above steps are offline operation.

In our system, we load or photograph an input face. The face is first aligned by the face alignment technology. Then its gender and age will be estimated by the gender and age estimators. The aging face in one age range will be rendered by calling the aging dictionary, which is saved in the backstage. After rendering all aging faces, we generate more dense aging faces between the aging faces of the two nearest age ranges by the face morph technology. A loop-play video is made by stringing all the aging faces. Figure 2 shows the interface of our auto age progression system.

2. TECHNOLOGY

2.1 Data Collection

We download a large number of intra-person face photos covering different ages from Bing, and two other databases, CACD database [1] and MORPH aging database [3]. We select the photos with approximately frontal faces and relatively natural illumi-

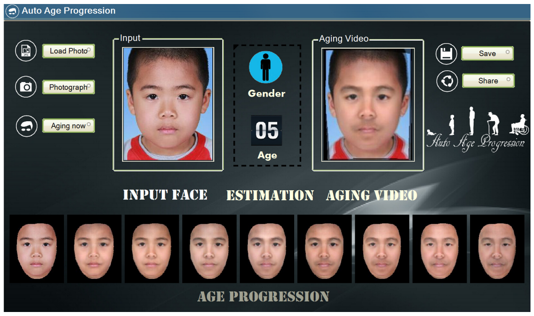

Figure 2. Interface of the presented system. When an input face photo is loaded/photographed, the system first estimates his/her age and gender, and shows aging faces in different age ranges, as well as an aging video from now to future playing in the loop.

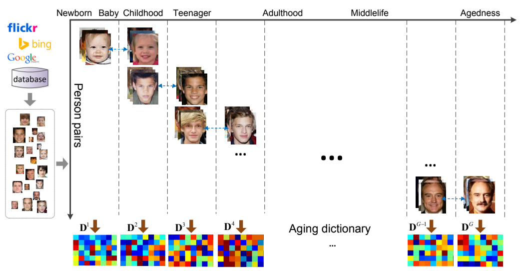

Figure 3. Data collection and aging dictionary learning. $\mathbf{D}^g$ denotes an aging dictionary of the age group g. We collect short-term aging face pairs and then train the aging dictionary.

nation, and then use collection flow [2] to correct all the faces to common neutral expressions. We divide all images into 18 age groups (i.e., $G = 9$): 0-5, 6-10, 11-15, 16-20, 21-30, 31-40, 41-50, 51-60, 61-80 of two genders. Actually, the aging faces of most subjects fall into only one or two age groups (i.e. most persons have face photos covering no more than 20 years). Therefore, we further select those intra-person face photos which densely fall into two neighboring age groups. Finally, As shown in Figure 3, the training database contains 3,200 face aging pairs.

2.2 Aging Dictionary Learning

Let $\{\mathbf{x}_i^g, \mathbf{y}_i^g\}$ denote a face aging pair of the person i in the age group g. Assuming m face aging pairs covering two neighboring age groups, we train two aging dictionaries for male and female, respectively. For the age group g and $g+1$ ($g = 1, 2, \cdots, G-1$), we define their aging dictionaries $\mathbf{D}^g$ and $\mathbf{D}^{g+1}$ to capture the corresponding aging characteristics, which will be learned in the following.

$$\begin{aligned}
&\min_{\mathbf{D}^g,\mathbf{D}^{g+1}} \sum_{i=1}^{m} \{\left\|\mathbf{x}_i^g - \mathbf{H}^g\mathbf{D}^g\mathbf{a}_i^g - \mathbf{p}_i^g\right\|_2^2 \\
&\qquad + \left\|\mathbf{y}_i^g - \mathbf{H}^{g+1}\mathbf{D}^{g+1}\mathbf{a}_i^g - \mathbf{p}_i^g\right\|_2^2\} \\
&s.t.\ \mathbf{a}_i^g = \arg\min_{\mathbf{z}_i^g} \left\|\mathbf{x}_i^g - \mathbf{H}^g\mathbf{D}^g\mathbf{z}_i^g - \mathbf{p}_i^g\right\|_2^2 + \lambda_1\left\|\mathbf{z}_i^g\right\|_1 + \lambda_2\left\|\mathbf{z}_i^g\right\|_2^2 \\
&\quad \mathbf{p}_i^g = \arg\min_{\mathbf{q}_i^g} \left\|\mathbf{x}_i^g - \mathbf{H}^g\mathbf{D}^g\mathbf{a}_i^g - \mathbf{q}_i^g\right\|_2^2 + \gamma\left\|\mathbf{q}_i^g\right\|_1 \\
&\quad \left\|\mathbf{D}^c(:,l)\right\|_2 \leq 1,\ i = 1, ..., m,\ l = 1, ..., k,\ and\ c = \{g, g+1\},
\end{aligned} \tag{1}$$

where $\mathbf{a}_i^g$ and $\mathbf{p}_i^g$ are the representation coefficient and personalized layer respectively, and the latter is invariant in the aging process, i.e., mole. λ_1, λ_2 and γ are the parameters to control the corresponding terms. The optimizing of Eq. (1) can be solved by referring to bi-level optimization in the paper [4].

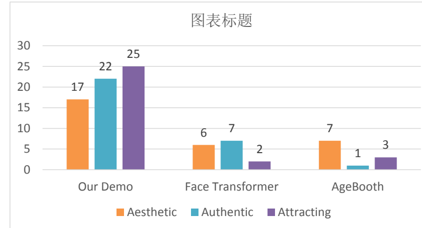

Figure 4. Evaluation of the aging show from the 30 volunteers. The vertical axis is the number of persons.

2.3 Age Progression and Aging video

For a given face $\mathbf{x}$ belonging to the age group g[3], we can render its aging faces $\{\mathbf{x}^{g+1}, ..., \mathbf{x}^G\}$. The coefficient and personalized layer are optimized by solving the following optimization:

$$\begin{cases}
\mathbf{a}^g = \arg\min_{\mathbf{z}^g} \|\mathbf{x}^g - \mathbf{H}^g\mathbf{D}^g\mathbf{z}^g - \mathbf{p}^g\|_2^2 + \lambda_1\|\mathbf{z}^g\|_1 + \lambda_2\|\mathbf{z}^g\|_2^2 \\
\mathbf{p}^g = \arg\min_{\mathbf{q}^g} \|\mathbf{x}^g - \mathbf{H}^g\mathbf{D}^g\mathbf{a}^g - \mathbf{q}^g\|_2^2 + \gamma\,\|\mathbf{q}^g\|_1
\end{cases}. \tag{2}$$

Then the aging face is $\mathbf{x}^{g+1} = \mathbf{x}^g - \mathbf{H}^{g+1}\mathbf{D}^{g+1}\mathbf{z}^g - \mathbf{p}^g$. For one aging face, we blend into the original face to obtain the blending face; for two arbitrary aging faces $\mathbf{x}^{g+j}$ and $\mathbf{x}^{g+j+1}$ in the neighboring age ranges, we morph their blending faces with different weights by the face morphing technology. Finally, we make a video by stringing all aging faces and view the played faces according to the age axis. An age progression example is shown in Figure 1.

3. EVALUATIONS

We compare our aging system with two other Apps: Face Transformer and AgeBooth. The properties of the aging system are evaluated in three aspects: aesthetic, authentic, attracting. 30 volunteers (12 females and 28 males who are students, staffs and businessmen ranged from 18 to 50 years old) participate in the user study. We conduct user study by making participants vote for some aging results of two apps and our system on 20 input faces: 10 females and 10 males. The average voting results of three aspects are shown in Figure 4. We can see that our system has gained the highest voting support in all the three aspects. The Face Transfer and AgeBooth are comparable with each other.

4. CONCLUSION

In this paper, we proposed an auto age progression system. This system can automatically render a series of aging faces in the future age ranges and generates a whole aging sequence covering the entire life for an individual input. The supplementary slides can be found at http://t.cn/R2Ja5kO.

5. ACKNOWLEDGEMENTS

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[3] The age and gender are estimated by age and gender estimators.