Abstract

We propose a two fold approach towards modeling facial aging in adults. Firstly, we develop a shape transformation model that is formulated as a physically-based parametric muscle model that captures the subtle deformations facial features undergo with age. The model implicitly accounts for the physical properties and geometric orientations of the individual facial muscles. Next, we develop an image gradient based texture transformation function that characterizes facial wrinkles and other skin artifacts often observed during different ages. Facial growth statistics (both in terms of shape and texture) play a crucial role in developing the aforementioned transformation models. From a database that comprises of pairs of age separated face images of many individuals, we extract age-based facial measurements across key fiducial features and further, study textural variations across ages. We present experimental results that illustrate the applications of the proposed facial aging model in tasks such as face recognition and facial appearance prediction across aging.¹

1. Introduction

Developing computational models that help emulate humans in their remarkable ability in parsing faces, despite the many different facial appearance variations, has been one of the primary objectives of studies related to human facial analysis. Facial appearance variations are often influenced by factors such as facial aging, illumination variations, head pose variations, facial expressions etc. A comprehensive analysis on the recent advances in face recognition and face modeling is presented in [25].

Facial aging effects induce notable variations in one’s appearance across ages. During formative years, facial aging effects are typically observed in the form of pronounced variations in facial shape and during adulthood, they are observed in the form of subtle variations in facial shape and texture. Typically, individuals of the same gender and ethnic background exhibit similar facial aging traits across ages. Further, individuals undergoing weight gain/loss across years are observed to exhibit similar facial aging traits. Some of the factors that induce facial aging effects are (i) the prolonged effects of gravity (ii) loss in muscle elasticity (iii) facial fat atrophies etc. Drooping facial features, forehead wrinkles, nasolabial folds, broken jawline etc. are the most commonly observed manifestations of aging effects in adult faces.

1.1. Previous work

Most of the early insights into facial aging were provided by researchers from psychophysics and human perception. A series of experiments conducted by Pittenger and Shaw [16], Todd et al. [21], Mark et al. [11] helped identify certain geometric transformations that when applied on face profiles, result in growth related transformations. O’Toole et al. [12] observed that facial creases (wrinkles) often affected the perceived age of human faces. Typically, computational approaches towards facial aging address tasks such as (i) Age estimation from face images (ii) Appearance prediction across ages etc. Age estimation tasks are often performed by characterizing distances between key facial features and by studying the nature of facial wrinkles. Kwon et al. [7], Lanitis et al. [8], Gandhi [4], Geng et al. [5] etc. propose different methods to perform age estimation from face images. Table 1 summarizes the computational approaches that were proposed to characterize facial aging effects.

In this paper, we propose a computational model that characterizes the shape and textural variations adult faces undergo with age. Facial growth statistics derived from a database of age separated face images play a crucial role in developing the proposed model. The paper is organized as described below: Section II details the shape variation model. A physically based parametric muscle model for faces that helps characterize the subtle shape variations adult faces undergo, across different age groups is discussed in this section. Section III discusses the texture variation model that characterizes facial wrinkles across different age. Section IV illustrates the experimental results obtained

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Table 1. Computational approaches towards facial aging

<table>
<thead>
<tr>
<th>Reference</th>
<th>Approach: Overview</th>
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</thead>
<tbody>
<tr>
<td>Tiddeman et al. [20]</td>
<td>Used wavelets to model wrinkles on age-based face composites.</td>
</tr>
<tr>
<td>Lanitis et al. [9]</td>
<td>Characterized facial aging effects using regression functions</td>
</tr>
<tr>
<td>Ramanathan, Chellappa [18]</td>
<td>Proposed an anthropometry based facial growth model for young faces.</td>
</tr>
<tr>
<td>Suo et al. [19]</td>
<td>Built a high resolution grammatical face model to describe aging effects.</td>
</tr>
<tr>
<td>Patterson et al. [13]</td>
<td>Studied the effects of morphological changes in faces on biometric systems.</td>
</tr>
<tr>
<td>Haibin et al. [10]</td>
<td>Proposed a novel face descriptor to study facial aging effects.</td>
</tr>
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</table>

using the proposed facial aging model. We conclude the paper in Section V.

2. Shape variation model

Facial shape variations due to aging are often observed by means of subtle drifts in facial features and progressive variations in the shape of facial contours, across ages. We propose a facial shape variation model that represents facial feature deformations as that driven by the changing physical properties of the underlying facial muscles. The model is based on the assumption that the degrees of freedom associated with facial feature deformations are directly related to the physical properties and geometric orientations of the underlying facial muscles. Further, since factors such as weight-loss or weight-gain across ages can influence facial feature deformations, the proposed shape variation model has been formulated such that it implicitly accounts for such external factors.

Drawing inspirations from the ‘revised’ cardioidal strain transformation model [21] that was proposed to model the shape variations human faces (in profile views) undergo during formative years (0 to 18 yrs), we propose a shape variation model for adult faces that takes the following generic form:

\[
x^{(i)}_{t_1} = x^{(i)}_{t_0} + k^{(i)} [P^{(i)}_{t_0}]_x \\
y^{(i)}_{t_1} = y^{(i)}_{t_0} + k^{(i)} [P^{(i)}_{t_0}]_y
\]

where \((x^{(i)}_{t_0}, y^{(i)}_{t_0})\) and \((x^{(i)}_{t_1}, y^{(i)}_{t_1})\) correspond to the Cartesian coordinates of the \(i\)th facial feature at ages \(t_0\) and \(t_1\), \(k^{(i)}\) corresponds to a facial growth parameter and \([P^{(i)}_{t_0}]_x, [P^{(i)}_{t_0}]_y\) corresponds to the orthogonal components of the pressure applied on the \(i\)th facial feature at age \(t_0\). Developing the facial growth model using the above formulation amounts to:

- Identifying the growth related pressures applied on fiducial features \([P^{(i)}_{t_0}]_x, [P^{(i)}_{t_0}]_y\) : Attributing the facial feature drifts to the pressures applied by the underlying facial muscles, we develop a parametric muscle model for human faces that helps identify the pressure distribution.

- Identifying the Cartesian coordinates of facial features at ages \(t_0\) and \(t_1\) : Facial growth statistics collected in terms of facial measurements extracted across different fiducial features across ages, helps identify the feature coordinates across age transformation.

- Computing the facial growth parameters \(k^{(i)}\) across all fiducial features.

2.1. Parametric muscle model

We propose a physically based parametric muscle model for human faces that implicitly accounts for the physical properties, geometric orientations and functionalities of each of the individual facial muscles. Drawing inspiration from Waters’ muscle model [23], we identify three types of facial muscles namely (i) Linear muscles (ii) Sheet muscles (iii) Sphincter muscles, based on their functionalities. Further, we propose transformation models for each muscle type. The number of parameters needed to completely specify the muscle configurations are much fewer in the proposed model than that in Waters’ model [23] and its derived versions ([3], [24]). Fig. 1 illustrates the 18 facial muscles that were identified in developing the model and further illustrates the ‘point of origin’ and ‘point of insertion’ of each individual muscle.

Fig 2 illustrates the three types of facial muscles. The following factors are to be taken into consideration while developing the pressure models (i) Muscle functionality and gravitational forces: The proposed pressure models reflect the muscle functionalities such as the ‘stretch’ operation and the ‘contraction’ operation. The direction of applied pressure reflects the effects of gravitational forces. (ii) Points of origin and insertion for each muscle: The degrees of freedom associated with muscle deformations are minimum at their points of origin (fixed end) and maximum at their points of insertion (free end). Hence, the deformations induced over a facial feature directly depends on the distance of the facial feature from its point of origin of the underlying muscle. The transformation models proposed on each muscle type is illustrated below.
Figure 1. (i) Configuration of different facial muscles is illustrated (For clarity of presentation, the symmetric distribution of facial muscles are assumed implicit). M01, M02 . . . etc. correspond to the muscle tags and I, II and III correspond to the muscle types (explained in detail in section 2.1) (ii) The points of origin and insertion of different facial muscles are illustrated.

1. **Linear muscle** \((\alpha, \phi)\)

Linear muscles correspond to the ‘stretch operation’. As illustrated in fig. 2(i), linear muscles are described by their attributes namely, the muscle length \((\alpha)\) and the muscle orientation w.r.t to the facial axis \((\phi)\). The farther a feature is from the muscle’s point of origin, the greater the chances that the feature undergoes deformation. Hence, the pressure is modeled such that: \(P^{(i)} \propto \alpha^{(i)}\). \((\alpha^i)\) is the distance of the \(i^{th}\) from the point of origin). The corresponding shape transformation model is described below:

\[
x_{t_1}^{(i)} = x_{t_0}^{(i)} + k \left[ \alpha^{(i)} \sin \phi \right] \\
y_{t_1}^{(i)} = y_{t_0}^{(i)} + k \left[ \alpha^{(i)} \cos \phi \right]
\]

2. **Sheet muscle** \((\alpha, \phi, \theta, \omega)\)

Sheet muscles correspond to the ‘stretch operation’ as well. As described in fig. 2(ii), sheet muscles are described by four of their attributes (muscle length, angles subtended etc.). The pressure applied on a fiducial feature is modeled as \(P^{(i)} \propto \alpha^{(i)} \sec \theta^{(i)}\), the distance of the \(i^{th}\) feature from the point(s) of origin of the underlying muscles. The shape transformation model is described below:

\[
x_{t_1}^{(i)} = x_{t_0}^{(i)} + k \left[ \alpha^{(i)} \sin \theta \cos \phi \right] \\
y_{t_1}^{(i)} = y_{t_0}^{(i)} + k \left[ \alpha^{(i)} \sin \theta \sin \phi \right] \\
z_{t_1}^{(i)} = z_{t_0}^{(i)} + k \left[ \alpha^{(i)} \cos \phi \right]
\]

3. **Sphincter muscle** \((\alpha, \beta)\)

The sphincter muscle corresponds to the ‘contraction / expansion’ operation and is described by two attributes. The pressure modeled as a function of the distance from the point of origin, \(P^{(i)} \propto \rho^{(i)}(\phi^{(i)}) \cos \phi^{(i)}\), is directed radially inward / outward.

\[
x_{t_1}^{(i)} = x_{t_0}^{(i)} + k \left[ \rho^{(i)}(\phi^{(i)}) \cos \phi^{(i)} \right] \\
y_{t_1}^{(i)} = y_{t_0}^{(i)} + k \left[ \rho^{(i)}(\phi^{(i)}) \sin \phi^{(i)} \right]
\]

Since facial muscle configurations are very well studied [6], the parameters that define the muscle attributes such as the muscle size, its physical location, its geometric orientation etc. are known apriori and only the facial growth parameter needs to be estimated. Fig. 3 illustrates the pressure distribution as modeled on different types of facial muscles. Please refer to the supplemental material for...
additional analysis on the facial muscle models. Next, we discuss the acquisition of facial growth statistics that helps in computing the facial growth parameters for different age transformations.

2.2. Facial growth statistics

From a database that comprises of 1200 pairs of age separated face images (predominantly Caucasian), we selected 50 pairs of face images each undergoing the following age transformations (in years): 20 yrs $\rightarrow$ 30 yrs, 30 yrs $\rightarrow$ 40 yrs, 40 yrs $\rightarrow$ 50 yrs, 50 yrs $\rightarrow$ 60 yrs and 60 yrs $\rightarrow$ 70 yrs. The image pairs were compiled from the Passport image database [17]. We selected 48 facial features from each image pair and extracted 44 projective measurements (21 horizontal measurements and 23 vertical measurements) across the facial features. Dense facial measurements such as above extracted across age transformation, implicitly capture facial growth patterns and hence are crucial for the shape transformation model. Fig. 4 illustrates the 48 facial features that were used in our study. We analyze the intra-pair shape transformations from the perspective of weight-loss, weight-gain and weight-retention and select the appropriate training sets for each case.

2.3. Model computation

Consider the facial shape transformations from age $t_0$ years to $t_1$ years. Let the training set that was chosen for the experiment comprise of pairs of age separated face images of individuals (from $t_0$ years to $t_1$ years) who underwent either weight-gain or weight-loss across ages or who retained their weight across age transformation. Let $(x_{t_0}^{(i)}, y_{t_0}^{(i)})$ and $(\tilde{x}_{t_0}^{(i)}, \tilde{y}_{t_0}^{(i)})$, $1 \leq i \leq 48$ correspond to the Cartesian coordinates of the 48 facial features on the average faces at ages $t_0$ years and $t_1$ years. Let $K_{t_0,t_1} = [k_{t_0,t_1}(1), k_{t_0,t_1}(2), \ldots, k_{t_0,t_1}(18)]^T$ denote the growth parameter corresponding to the 18 facial muscles. Developing the shape transformation model amounts to computing $K_{t_0,t_1}$, given the average faces for $t_0$ years and $t_1$ years and the pressure configurations. Since facial muscles overlap heavily on different facial features, we model the deformations induced over a facial feature as a linear superposition of the deformations induced by the individual facial muscles that act on the facial feature. Reformulating the shape transformation model, the deformations induced over a facial feature ‘i’ from $t_0$ yrs to $t_1$ yrs, that is influenced by $n$ facial muscles, the indices of which are denoted as $(m_1, m_2, \ldots, m_n)$, is modeled as

$$
\tilde{x}_{t_1}^{(i)} = \tilde{x}_{t_0}^{(i)} + \sum_{j=1}^{n} [k_{t_0,t_1}(m_j) \xi_{t_0}(m_j)]
$$

$$
\tilde{y}_{t_1}^{(i)} = \tilde{y}_{t_0}^{(i)} + \sum_{j=1}^{n} [k_{t_0,t_1}(m_j) \psi_{t_0}(m_j)]
$$

where $1 \leq i \leq 48$ and $(\xi_{t_0}(m_j), \psi_{t_0}(m_j)) = (\{p_{t_0}^{(m_j)}(u), p_{t_0}^{(m_j)}(v)\}_{u,v})$ correspond to the orthogonal components of the pressure applied on facial feature ‘i’ by $m_j$'th facial muscle. Figure. 4(ii) illustrates the correspondences between the facial features and the underlying facial muscles.

Anthropometric studies often characterize facial growth by means of ratios of facial measurements (also addressed as proportion indices). An inherent advantage of using proportion indices to characterize facial growth is that the scale factors corresponding to face images are easily accounted for. In our study, a total of 946 proportion indices are selected from the 44 facial measurements. Studying the transformations corresponding to different proportion indices from $t_0$ yrs to $t_1$ yrs, we arrive at a set of linear equations the solution of which helps determine the growth parameters $K_{t_0,t_1}$.

Consider the transformations observed on the proportion index $d_{15-16}$ (the nasal index) from $t_0$ yrs to $t_1$ yrs,
that warps the fiducial features on the average face at age 

\[ t_0 \] to that on the test face. (The warping function is derived using the thin plate spline formulation for interpolation techniques).

\[ \mathbf{w} : (x_0^{(i)}, y_0^{(i)}) \rightarrow (x_0^{(i)}, y_0^{(i)})^J, \quad 1 \leq i \leq 48 \]

The estimated warping function \( \mathbf{w} \) is used to map the flow of facial features between average faces (eq. 4) to that corresponding to the test face \( I_{t_0} \), which can be subsequently used to induce shape variations in the test face.

\[ [\Delta \mathbf{x}_{t_0 t_1}, \Delta \mathbf{y}_{t_0 t_1}] \mapsto [\Delta \mathbf{x}_{t_0 t_1}^j, \Delta \mathbf{y}_{t_0 t_1}^j] \quad (\mathbf{x}_{t_0}^j, \mathbf{y}_{t_0}^j) = (\mathbf{x}_0^j + \Delta \mathbf{x}_{t_0 t_1}^j, \mathbf{y}_0^j + \Delta \mathbf{y}_{t_0 t_1}^j) \]

### 3. Texture variation model

Textural variations observed in human faces with increase in age are often perceived in the form of facial wrinkles, creases and other skin-artifacts. Often, facial wrinkles observed on individuals belonging to the same age group, gender and ethnicity tend to share structural similarities in aspects such as their locations, orientations etc. In spite of such similarities, the density of facial wrinkles tends to be highly subjective. From a modeling perspective, facial wrinkles and other forms of textural variations observed in aging faces can be characterized on the image domain by means of image gradients. In this subsection, we propose a texture variation model that characterizes facial wrinkles and other related facial aging effects, by means of image gradient transformation functions.

Let \((I_{t_0}^{(i)}, I_{t_2}^{(i)})\), \(1 \leq i \leq N\) correspond to pairs of age separated face images of \(N\) individuals undergoing similar age transformations \((t_1 \rightarrow t_2)\). In order to study the facial wrinkle variations across age transformation, we identify four facial regions which tend to have a high propensity towards developing wrinkles, namely (i) the forehead region \((W_1)\) (ii) the eye-burrrow region \((W_2)\) (iii) the nasal region \((W_3)\) (iv) the lower chin region \((W_4)\). \(W_n, 1 \leq n \leq 4\) corresponds to the facial mask that helps isolate the desired facial region. Next, we categorize the region-based facial wrinkle variations across age transformation into one of the following three classes: (i) subtle wrinkle change (ii) moderate wrinkle change and (iii) strong wrinkle change. This classification is performed by studying the pixel-based differences in gradient magnitudes and orientations.

Let \(\nabla I_{t_1}^{(i)}\) and \(\nabla I_{t_2}^{(i)}\) correspond to the image gradients of the \(i\)’th image at \(t_1\) and \(t_2\) years, \(1 \leq i \leq N\). Let us assume that all the \(N\) image pairs fall under the same class of wrinkle variations (subtle / moderate / strong) (ie) all the \(N\) image pairs underwent similar textural transformations from \(t_1\) years to \(t_2\) years. Given a test image \(J_{t_1}\) at \(t_1\) years, the image gradients of which is \(\nabla J_{t_1}\), we induce textural variations by incorporating the region-based gradient
differences that were learnt from the set of training images discussed above.

\[ \nabla J_{t2} = \nabla J_{t1} + \frac{1}{N} \sum_{i=1}^{N} \sum_{n=1}^{4} W_n \cdot (\nabla I_{t2}^{(i)} - \nabla I_{t1}^{(i)}) \]  

(6)

The transformed image \( J_{t2} \) is obtained by solving the Poisson equation corresponding to image reconstructions from gradient fields [14]. Figure 5 illustrates the subtle, moderate and strong wrinkle pattern changes that were learnt from individuals belonging to the age group 50 - 60 yrs. The illustration was obtained by adding the image gradient differences that were learnt for each of the three categories onto an image with zeros intensity and subsequently by using Poisson reconstruction [14].

4. Experimental Results

Fig. 6 provides an overview of the proposed facial aging model. The figure illustrates the muscle-model based facial feature drifts that induce shape transformations for the cases of weight-gain and weight-loss. Further, the figure illustrates the effects of image gradient transformations in inducing facial wrinkles. Fig 7 illustrates the facial shape variations (for the cases of weight-gain, weight-loss and weight-retention) across 6 individuals and further illustrates the three types of textural variations (subtle, moderate, strong) that were induced on the shape transformed face.

On a database that comprises of 260 age separated image pairs of adults, we perform face recognition across age progression. The image pairs were compiled from both the Passport database [17] and the FG-NET database [1]. We adopt a very simple recognition algorithm namely, Principal Component Analysis [22], to perform recognition across ages under the following three settings: (i) No transformation in shape and texture (ii) Performing shape transformation (ii) Performing shape and textural transformation. Table 2 reports the rank 1 recognition score under the three settings. The experimental results highlight the significance of transforming shape and texture, when performing face recognition across ages. The shape variations that were induced correspond to the ‘weight-gain’ category and the textural variations correspond to the ‘moderate wrinkle’ category.

<table>
<thead>
<tr>
<th>Experimental Setting</th>
<th>Rank 1 (%)</th>
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<tbody>
<tr>
<td>No transformations</td>
<td>38</td>
</tr>
<tr>
<td>Shape transformations</td>
<td>41</td>
</tr>
<tr>
<td>Shape and Texture transformations</td>
<td>51</td>
</tr>
</tbody>
</table>

5. Discussions and Conclusions

The proposed facial aging model poses some unique advantages over other similar methods.

- **Facial growth statistics**: Facial measurements extracted across different facial features across ages provide considerable evidences on facial growth. Computational models that are built using such ground-truth data on facial aging implicitly account for the different rates of growth observed across ages.

- **Gender, Ethnicity**: The facial measurements were extracted from men and women who were predominantly Caucasian. Hence, the model can account for gender-based and ethnicity-based facial growth patterns.

- **Weight loss/gain**: We compute facial growth parameters for each of the instances namely weight-loss / gain / retention separately and hence, account for this factor successfully.

- **Alternate wrinkle patterns**: The rates at which facial wrinkles are manifested on individuals across different ages is often subjective. The proposed texture variation model can be used to predict the different wrinkle patterns that could have been observed on the individual.

In future, we wish to reduce the redundancy in the required facial features. The proposed facial aging model cannot account for facial hair and hence cannot address hair loss. With the advent of 3D measurements of growing adult faces (by means of laser scans), the proposed shape transformation model can be adopted to characterize facial aging effects in 3D.

References


Figure 6. An overview of the proposed facial aging model: Facial shape variations induced for the cases of weight-gain and weight-loss are illustrated. Further, the effects of gradient transformations in inducing textural variations are illustrated as well.


Figure 7. Appearance prediction across ages: The 2nd column illustrates the shape transformation results for the three types of weight-change across ages. The 3rd, 4th and 5th columns illustrate the textural variations induced on the shape transformed image, using image gradient transformations that correspond to ‘subtle’, ‘moderate’ and ‘strong’ wrinkles. (The original images belong to the FG-NET aging database [1] and the FRGC dataset [15].)