Modeling Age Progression in Young Faces

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Abstract

We propose a craniofacial growth model that characterizes growth related shape variations observed in human faces during formative years. The model draws inspiration from the 'revised' cardioidal strain transformation model proposed in psychophysical studies related to craniofacial growth. The model takes into account anthropometric evidences collected on facial growth and hence is in accordance with the observed growth patterns in human faces across years. We characterize facial growth by means of growth parameters defined over facial landmarks often used in anthropometric studies. We illustrate how the age-based anthropometric constraints on facial proportions translate into linear and non-linear constraints on facial growth parameters and propose methods to compute the optimal growth parameters. The proposed craniofacial growth model can be used to predict one's appearance across years and to perform face recognition across age progression. This is demonstrated on a database of age separated face images of individuals under 18 *years of age.*

1. Introduction

Human faces comprise a special class of 3D objects that have long been of interest to computer vision and psychophysics communities. Apart from playing a crucial role in human identification, human faces convey a significant amount of information on one's age, gender, ethnicity etc. In addition, facial expressions and facial gestures often reveal the emotional state of an individual. Consequently, human facial analysis has received considerable attention and has led to the development of novel approaches to perform face recognition, facial expression characterization, face modeling etc. [14].

Psychophysical studies on human perception showed that changes in one's facial appearance often had a significant psychosocial impact on the individual [2]. For instance, facial attractiveness was attributed to affecting interpersonal relationships. It was observed that the perceived age of an individual often regulated the type and amount of behavior directed towards the individual. Further, growth related changes to human faces were observed to directly impact facial aesthetics. Studies related to the perception of growing faces have largely been inspired by D'arcy Thompson's study of morphogenesis [21]. Thompson pioneered the use of geometric transformations in the study of morphogenesis. Biological forms were embedded within coordinate systems and different morphogenetic events were described by means of global geometric transformations in the coordinate system. All through his study, he maintained that morphological changes were a result of the physical forces such as bio-mechanical stress and gravity that act on biological forms. Some of the initial studies related to craniofacial growth in humans were along similar lines.

1.1. Previous Work

Pittenger and Shaw [19] studied facial growth as a viscal-elastic event defined on the craniofacial complex. They applied strain, shear and radial transformations on facial profiles and studied the relative significance of each of the transformation in accounting for the global remodeling of human faces with age. They observed that shape changes in facial profiles induced by cardioidal strain transformations formed the primary source of perceptual information for relative age judgements. Further, Mark *et al*. [17] identified geometric invariants that are characteristic of cardioidal strain transformations and proposed that only transformations that preserve such geometric invariants in human faces would be perceived as growth-related transformations. By performing a hydrostatic analysis on the effects of internal forces (combination of biomechanical stress and gravitational forces) acting on a growing head, Todd *et al*. [23] proposed the 'revised' cardioidal strain transformation model to account for craniofacial growth. They treated the human head as a fluid filled spherical object that remodels in accordance with the direction and amount of pressure exerted on the surface. Mark *et al*. [16] extended the above model to

[1] This work was partly supported by a fellowship from Apptis, Inc.

three dimensions and simulated facial growth on 3D head scans of children.

In computer vision literature, age progression in human faces has been addressed from two perspectives: one towards automatic age estimation and age-based classification from face images and the other towards automatic age progression systems that could reliably predict one's appearance across age. Kwon and da Vitoria lobo [11] proposed methods to classify face images as that of babies, young adults and senior adults. They used face anthropometry based approaches to classify face images into images of babies and that of adults and proposed methods to analyze facial wrinkles to further classify adult faces as that of young adults and senior adults. Burt and Perrett [5] created composite faces for different age groups by computing the average shape and texture of human faces that belong to each age group. By incorporating the differences between such composite faces on regular faces, they observed a change in the perceived age of faces. Tiddeman *et al.* [22] further extended their work by using wavelet methods to prototype facial textures across age. Lanitis *et al.* [13] constructed an aging function based on a parametric model for human faces and performed automatic age progression, age estimation, face recognition across age etc. Further, Lanitis *et al.* [12] compared the above age estimation process with that of neural networks based approaches. Gandhi [9] designed a support vector machine based age estimation technique and extended the image based surface detail transfer approach to simulate aging effects on faces. Ramanathan and Chellappa [20] proposed a Bayesian age-difference classifier built on a probabilistic eigenspaces framework to perform face verification across age progression.

1.2. Motivation and Problem Statement

Some of the significant applications of studying age progression in human faces are face recognition across age (homeland security), automatic age estimation (parental control, age based Human-Computer interaction), prediction of one's appearance across age (finding missing individuals) etc. Developing models that characterize age progression in faces is a very challenging task. Facial aging effects are predominantly manifested in the form of shape variations during one's younger years and as wrinkles and other textural variations during one's older years [15]. Though the aforementioned approaches propose novel methods to address age progression in faces, in their formulation most approaches ignore the psychophysical evidences collected on age progression. Face anthropometric studies offer a good insight into craniofacial growth and hence have long been used by physicians in treating craniofacial disorders. Face recognition systems that were developed with the incorporation of such data would be better equipped in handling age progression in faces.

We propose a craniofacial growth model that characterizes the shape variations undergone by human faces during formative years. The craniofacial growth model draws inspiration from the 'revised' cardioidal strain transformation model proposed by Todd *et al.* [23] and further, accounts for the age based anthropometric constraints on human faces provided by Farkas [7]. The proposed craniofacial growth model can be used to predict one's appearance across age and to perform face recognition across age progression on individuals in the age range (0 yrs - 18 yrs). We perform experiments to demonstrate the same on a database of age separated face images of individuals in the age range (0 yrs - 18 yrs).

Section II gives an overview of the craniofacial growth model and highlights the importance of incorporating age-based anthropometric face measurements in developing the model. Section III discusses face anthropometry in relevance to studying age progression in human faces. Section IV provides a mathematical framework to the computation of the craniofacial growth model. Sections V discusses the experiments that were performed on age separated face images of individuals in the age range (0 - 18 years) using our model and section VI discusses the strengths and limitations of the proposed craniofacial growth model and offers insights into future work on this topic.

2. Craniofacial Growth Model

Studies related to craniofacial growth were largely based on the hypothesis that any recognizable style of change is uniquely specified by geometric invariants which form the basis for perceptual information. Mark *et al.* [17] identified three geometric invariants that are characteristic to cardioidal strain transformations. The geometric invariants can be described as follows : (i) angular coordinates of every point on an object in a polar coordinate system being preserved (ii) bilateral symmetry about the vertical axis being maintained (iii) continuity of object contours being preserved. Re-examining the analogy drawn between craniofacial growth and the remodeling of a fluid filled spherical object as proposed by Todd *et al.* [23], one can identify the following aspects that help preserve the aforementioned geometric invariants upon transformations : (i) pressure is directed radially outwards (ii) pressure distribution is bilaterally symmetric about the vertical axis (iii) pressure distribution is continuous throughout the object. Hence the proposed model satisfies the criteria based on geometric invariants observed in craniofacial growth. Fig. 1(a) illustrates the pressure distribution inside a fluid-filled spherical object. (A similar illustration appears in [2]).

Mathematically, the 'revised' cardioidal strain transformation model is expressed as follows [23]. Let P denote the pressure at the particular point on the object surface acting radially outward. Let (R_0, θ_0) and (R_1, θ_1) denote the

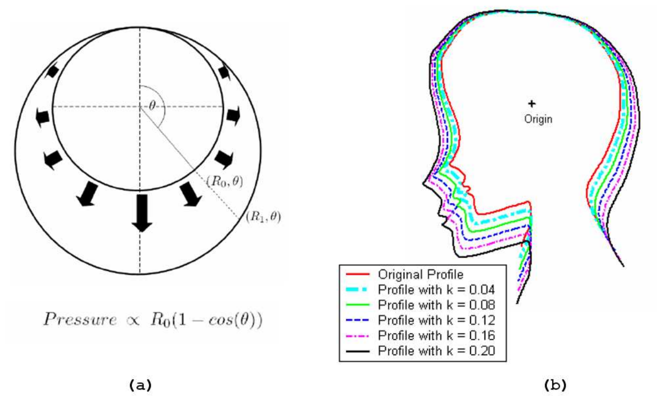

Figure 1. (a) Remodeling of a fluid filled spherical object (b) Facial growth simulated on the profile of a child's face using the 'revised' cardioidal strain transformations

angular co-ordinates of a point on the surface of the object, before and after the transformation. Let k denote a growth related constant.

$$\begin{aligned} P &\propto R_0(1 - cos(\theta_0)) \\ R_1 &= R_0 + k(R_0 - R_0\cos(\theta_0)) \\ \theta_1 &= \theta_0 \end{aligned} \quad (1)$$

We applied the 'revised' cardioidal strain transformation on the face profile of a child. Upon varying the growth parameter k, we observed that the transformation of face profiles closely resembled the one observed in actual facial growth. Further, the perceived age of each of the individual face profiles increased with increase in the growth parameter k. Fig. 1(b) illustrates the face profiles obtained by employing the above transformation. Next, we employed the age transformation model on frontal face images of children and observed that age transformed faces resembled real-life images taken across years better, for small age differences. For large values of k, which essentially implies larger age transformations, the aspect ratios between different regions of the transformed faces were less preserved. Fig. 2 illustrates the face images obtained by applying the 'revised' cardioidal strain transformation model. In each of the two instances illustrated in fig. 2, we observe that while the age transformation is perceivable in the initial few transformations, the aspect ratio of faces obtained for large age transformations seem unnatural.

Face anthropometric studies report that different facial regions reach maturation at different years and hence a few facial features change relatively less when compared to other facial features, as age increases. In relevance to the 'revised' cardioidal strain transformation model, this observation translates into the fact that different regions of human faces have different growth parameters across

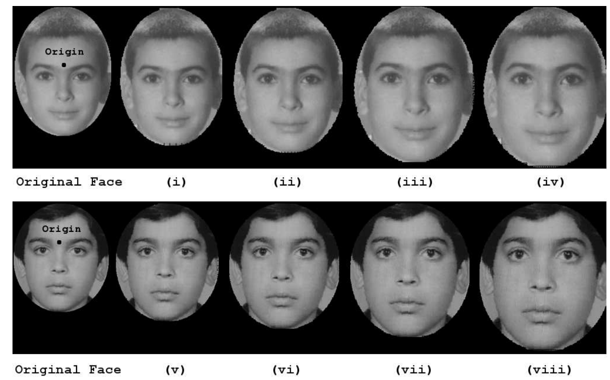

Figure 2. Age transformation results obtained by applying the 'revised' cardioidal strain transformation on real-life face images of two individuals (8 years and 13 years of age respectively). The growth parameters chosen for each of the 8 instances were (i) $k = 0.06$ (ii) $k = 0.12$ (iii) $k = 0.18$ (iv) $k = 0.21$ (v) $k = 0.06$ (vi) $k = 0.12$ (vii) $k = 0.18$ (viii) $k = 0.27$. The original images belong to the FG-Net aging database [1].

age. Hence, it is important to incorporate anthropometric evidences collected on facial growth while developing the model, whereby we can reliably estimate the growth parameters for different regions of the human face across age.

3. Face Anthropometry

Face anthropometry is the science of measuring sizes and proportions on human faces. Face anthropometric studies provide a quantitative description of the craniofacial complex by means of measurements taken between key landmarks on human faces across age and are often used in characterizing normal and abnormal facial growth. Farkas [7] provides a comprehensive overview of face anthropometry and its many significant applications. He defines face anthropometry in terms of measurements taken from 57 landmarks on human faces. The measurements taken on human faces are of three kinds : (i) projective measurements (shortest distance between two landmarks) (ii) tangential measurements (distance between two landmarks measured along the skin surface) (iii) angular measurements. By comparing real anthropometric measurements with that obtained through photogrammetry of human faces, Farkas identifies facial landmarks that can be reliably estimated from standard photographs of human faces (20%,25%,33%,50% or life size) for photogrammetric applications.

We use the age-based facial measurements and proportion indices (ratios of distances between facial landmarks) provided in [7] and [8] to build the craniofacial growth model. Since our study primarily involves frontal face images of individuals across age, we use only those facial landmarks that could be reliably located using photogram-

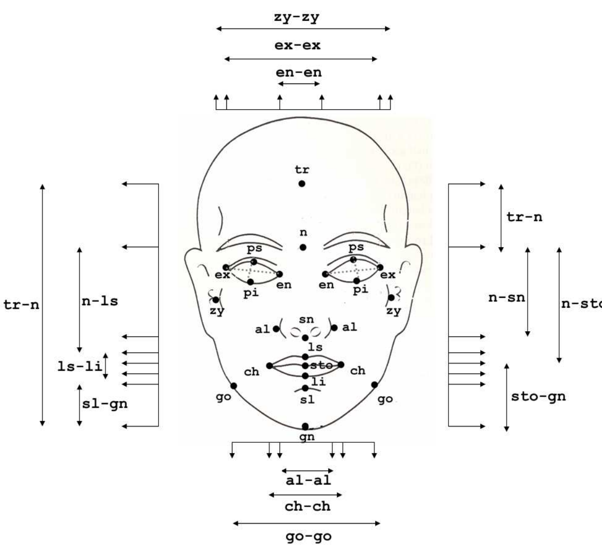

Figure 3. Face Anthropometry : Of the 57 facial landmarks defined in [7], we choose 24 landmarks illustrated above for our study. We further illustrate some of the key facial measurements that were used to develop the growth model.

metry. Further, we take into account only linear projective measurements taken on human faces across age, since angular measurements and tangential measurements on faces cannot be estimated accurately using photogrammetry of frontal face images. Fig. 3 illustrates the 24 facial landmarks and some of the important facial measurements that were used in our study.

Facial growth is often studied using proportion indices and hence we interpret facial measurements in terms of proportion indices while developing the craniofacial growth model. Some of the proportion indices that were used in our study were (i) Facial index ($\frac{n-gn}{zy-zy}$), (ii) Mandibular index ($\frac{sto-gn}{go-go}$), (iii) Intercanthal index ($\frac{en-en}{ex-ex}$), (iv) Orbital width index ($\frac{ex-en}{en-en}$), (v) Eye fissure index ($\frac{ps-pi}{ex-en}$), (vi) Nasal index ($\frac{al-al}{n-sn}$), (vii) Vermilion height index ($\frac{ls-sto}{sto-li}$), (viii) Mouth-Face width index ($\frac{ch-ch}{zy-zy}$) etc. Table 1 compiled from various anthropometric studies from [7] illustrates the different growth patterns observed in different parts of faces in men and women. RTI (Relative Total Increment) is defined as $\frac{l_{18}-l_1}{l_1} \times 100$ where l_1 and l_{18} correspond to mean value of the measurements obtained at ages 1 and 18 respectively. The age of maturation and the period of growth spurt are estimated by analyzing relative changes in facial measurements across years. Face anthropometry has been successfully used in computer graphics applications by DeCarlo *et al.* [6] in developing geometric models for human faces and by Kahler [10] in simulating growth on human head models.

Table 1. Growth pattern in different facial regions

Feature	RTI (%)		Growth Spurt (yrs)		Maturation age (yrs)	
	M	F	M	F	M	F
n-gn	50.5	44.8	1-4	1-5	15	13
zy-zy	38.7	35.9	3-4	3-4	15	13
en-en	20.5	17.5	3-4	3-4	11	8
al-al	30.9	21.2	3-4	3-4	14	12
n-sn	71.5	67.5	1-2	3-4	15	12

4. Computational Aspects

This section details the computational aspects involved in using face anthropometric data to develop the proposed craniofacial growth model that concurs with psychophysical studies related to the growth of human faces.

4.1. Feature localization

Of the 57 landmarks identified by face anthropometric studies, we chose 24 landmarks that can be reliably located on frontal faces as illustrated in fig. 3. To automatically detect facial landmarks on frontal faces, we use the face detection and feature localization method proposed by Moon *et al.* [18]. We detect facial features such as the eyes, the mouth and the outer contour of the face by fitting ellipses of different sizes and orientations. This operation enables the location of the following facial landmarks (tr, gn - forehead and chin), (en, ex, ps, pi - eyes) and (ch, sto, ls, li - mouth). Using proportion indices obtained through distances between the detected landmarks such as the *intercanthal index* ($\frac{en-en}{ex-ex}$), the *biocular width-total face height index* ($\frac{ex-ex}{tr-gn}$), the *intercanthal-mouth width index* ($\frac{en-en}{ch-ch}$) etc. we estimate the age group to which the face image belongs to and detect other facial landmarks using anthropometric data available on faces belonging to the particular age group. Minor errors in feature localization, do not affect the proposed method to compute facial growth parameters much.

Under the craniofacial growth model defined in eq. 1, we observe that facial features with angular coordinates $\theta = 0$ remain static and that features with angular co-ordinates θ such that $|\theta| \leq \epsilon$ where ϵ is a small number, grow minimally. Hence reliably estimating the origin of reference for the 'revised' cardioidal strain transformation model is crucial to the success of this model in characterizing facial growth. RTI defined in the previous section is a quantitative measure on the extent of growth observed in facial features across age. The RTI of the forehead length $tr - n$ is observed to be a low 11.8% in men and 2.25% in women when compared to that of other facial measurements. If the origin of reference is located between tr and n along the

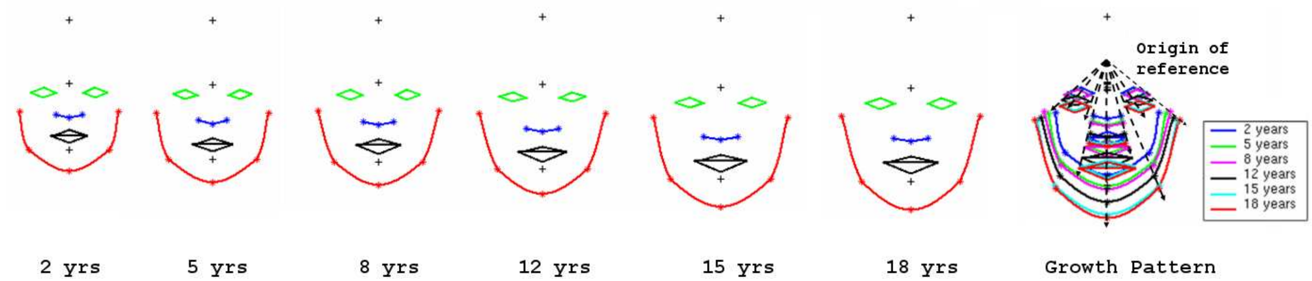

Figure 4. Prototype faces created for different ages using anthropometric measurements from [7] are illustrated. The flow of facial features across age illustrated separately, validates the constraints imposed by the craniofacial growth model proposed in eq. 1.

facial mid-line axis, one could appreciate the effectiveness of the radial and angular constraints defined by the craniofacial growth model in eq. 1 in characterizing facial growth. Fig. 4, further strengthens this notion. Prototype faces for different ages were created using the mean value of measurements taken across different facial landmarks. Fig. 4 illustrates the prototype faces for ages (in years) 2, 5, 8, 12, 15, 18 and illustrates the flow of facial features across age which is used in determining the optimal origin of reference for the craniofacial growth model.

4.2. Model computation : An Optimization problem

Let the facial growth parameters of the 'revised' cardioidal strain transformation model, that correspond to facial landmarks designated by $[n, sn, ls, sto, li, sl, gn, en, ex, ps, pi, zy, al, ch, go]$ be $[k_1,\ k_2,\ \cdots\ k_{15}]$ respectively. The facial growth parameters for different age transformations can be computed using anthropometric constraints on facial proportions. The computation of facial growth parameters is formulated as a non-linear optimization problem. We identified 52 facial proportions that can be reliably estimated using the photogrammetry of frontal face images. Anthropometric constraints based on proportion indices translate into linear and non-linear constraints on selected facial growth parameters. While constraints based on proportion indices such as the *intercanthal index*, *nasal index* etc. result in linear constraints on the growth parameters, constraints based on proportion indices such as *eye fissure index*, *orbital width index* etc. result in non-linear constraints on the growth parameters.

Let the constraints derived using proportion indices be denoted as $r_1(\mathbf{k}) = \beta_1, r_2(\mathbf{k}) = \beta_2, \cdots, r_N(\mathbf{k}) = \beta_N$. The objective function $f(\mathbf{k})$ that needs to be minimized w.r.t $\mathbf{k}$ is defined as

$$f(\mathbf{k}) = \frac{1}{2}\sum_{i=1}^{N}(r_i(\mathbf{k}) - \beta_i)^2 \qquad (2)$$

The following equations illustrate the constraints that were derived using different facial proportion indices. (α_j^i and

$$r_1 : \left[\tfrac{n-gn}{zy-zy} = c_1\right] \equiv\ \alpha_1^{(1)}k_1 + \alpha_2^{(1)}k_7 + \alpha_3^{(1)}k_{12} = \beta_1$$

$$r_2 : \left[\tfrac{al-al}{ch-ch} = c_2\right] \equiv\ \alpha_1^{(2)}k_{13} + \alpha_2^{(2)}k_{14} = \beta_2$$

$$r_3 : \left[\tfrac{li-sl}{sto-sl} = c_3\right] \equiv\ \alpha_1^{(3)}k_4 + \alpha_2^{(3)}k_5 + \alpha_3^{(3)}k_6 = \beta_3$$

$$r_4 : \left[\tfrac{sto-gn}{gn-zy} = c_4\right] \equiv \alpha_1^{(4)}k_5 + \alpha_2^{(4)}k_7 + \alpha_3^{(4)}k_{12} + \alpha_4^{(4)}k_4^2 + \alpha_5^{(4)}k_7^2 + \alpha_6^{(4)}k_{12}^2 + \alpha_7^{(4)}k_4\ k_7 + \alpha_8^{(4)}k_7\ k_{12} = \beta_4$$

β_i are constants. c_i is age-based proportion index obtained from [7].)

We use the Levenberg-Marquardt non-linear optimization algorithm [3] to compute the growth parameters that minimize the objective function in an iterative fashion. We use the craniofacial growth model defined in Eq. 1 to compute the initial estimate of the facial growth parameters. The initial estimates are obtained using the age-based facial measurements provided for each facial landmark, individually. The iterative step involved in the optimization process is defined as

$$\mathbf{k}_{i+1} = \mathbf{k}_i - (\mathbf{H} + \lambda diag[\mathbf{H}])^{-1}\nabla f(\mathbf{k}_i) \qquad (3)$$

where $\nabla f(\mathbf{k}_i) = \sum_{i=1}^{N} r_i(\mathbf{k})\nabla r_i(\mathbf{k})$ and $\mathbf{H}$ corresponds to the Hessian matrix evaluated at $\mathbf{k}_i$. At the end of each iteration, λ is updated as illustrated in [3].

Next, using the growth parameters computed over selected facial landmarks, we compute the growth parameters over the entire face region. This is formulated as a scattered data interpolation problem [4]. On a cartesian coordinate system defined over the face region, the growth parameters $\mathbf{k} = [k_1, k_2, \cdots, k_n]$ correspond to parameters obtained at facial landmarks located in $(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)$. Our objective is to find an interpolating function $f : R^2 \rightarrow R$ such that

$$f(\mathbf{x}_i) = k_i \qquad i = 1, \ldots, n \qquad (4)$$

where $\mathbf{x}_i = (x_i, y_i)$ and the thin-plate energy functional $\mathbf{E}$ defined as

$$\mathbf{E} = \int\int_{\Omega} f_{xx}^2(\mathbf{x}) + 2f_{xy}^2(\mathbf{x}) + f_{xx}^2(\mathbf{x}) d\mathbf{x} \quad (5)$$

is minimized. E is a measure of the amount of bending in the surface. In eq. **??**, Ω is the region of interest (face region, in our case). Using the method of radial basis function, the interpolating function that minimizes the energy functional can be shown to take the form

$$f(\mathbf{x}) = p(\mathbf{x}) + \sum_{i=1}^{n} \lambda_i \phi(|\mathbf{x} - \mathbf{x}_i|) \quad (6)$$

where $p(\mathbf{x})$ is a linear polynomial, λ_i are real numbers and $|.|$ is the Euclidean norm in R^2. The linear polynomial $p(\mathbf{x})$ accounts for affine deformations in the system. We adopt the thin plate splines functions defined as $\phi(\mathbf{x}) = |\mathbf{x}|^2 \log(|\mathbf{x}|)$ to comprise the basis functions. As illustrated in [4], to remove affine contributions from the basis functions, we introduce additional constraints $\sum_{i=1}^{n} \lambda_i = \sum_{i=1}^{n} \lambda_i x_i = \sum_{i=1}^{n} \lambda_i y_i = 0$. Eqs. 4 and 6 coupled with the constraints above, results in the following linear system of equations solving which we compute the interpolating function f. The linear system of equations is

$$\begin{pmatrix} \mathbf{A} & \mathbf{P} \\ \mathbf{P}^T & \mathbf{0} \end{pmatrix} \begin{pmatrix} \lambda \\ \mathbf{c} \end{pmatrix} = \begin{pmatrix} \mathbf{k} \\ \mathbf{0} \end{pmatrix} \quad (7)$$

where $\mathbf{A}$ is a matrix with entries $A_{i,j} = \phi(|\mathbf{x}_i - \mathbf{x}_j|)$ $i, j = 1, \ldots, n$, $\mathbf{P}$ is a matrix with rows $(1, x_i, y_i)$, $\lambda = (\lambda_1, \cdots, \lambda_n)$ and $c = (c_1, c_2, c_3)$ the coefficients of the polynomial function. Thus the growth parameters computed at selected facial features using face anthropometry is used to compute the growth parameters over the entire facial region. Upon computing the growth parameters, the proposed craniofacial growth model can be applied to automatically age the face image. For an age transformation from ‘p’ years to ‘q’ years $(q > p)$, the model takes the form similar to the one defined in eq. 1. On a polar coordinate framework, the transformation is defined as

$$\begin{aligned} R_q^i &= R_p^i(1 + k_{pq}^i(1 - \cos(\theta_p^i))) \\ \theta_q^i &= \theta_p^i \end{aligned}$$

where i corresponds to the i’th facial feature and k_{pq}, the growth parameters for a transformation from ‘p’ years to ‘q’ years. The model can also be used to lower the age of face images. For an age transformation from ‘p’ years to ‘q’ years $(p > q)$, we define the following inverse transformation.

$$\begin{aligned} R_q^i &= \frac{R_p^i}{1 + k_{qp}^i(1 - \cos(\theta_q^i))} \\ \theta_q^i &= \theta_p^i \end{aligned}$$

5. Experimental Results

Here, we describe two experiments that were conducted on a database of age separated face images of individuals under 18 years of age. The proposed craniofacial growth model was used to predict one’s appearance across age and to perform face recognition across age progression. The database comprises of a set of images from the FG-Net aging database[1] and a set of age separated face images that we collected for our research. Our database comprises a total of 233 images of 109 individuals.

Fig. 5 shows some of the age transformation results obtained using the proposed model. In fig. 5 we illustrate the original and the age transformed face images along with the facial growth parameters for different age transformations on different individuals. The facial growth parameters help observe the different growth patterns on individuals across age. For instance, one can observe that while facial features along the outer contour of the face grow rapidly in the initial few years, they grow relatively lesser when compared to other facial features, beyond 15 years of age.

Next, for the face recognition experiment, we create the gallery and the probe sets from the database such that the gallery set comprises of a single image per individual and the probe set comprises of either single or multiple images per individual. One of the challenges involved in recognizing face images of children across age progression is to account for growth related shape variations in children’s faces. Most face recognition systems process face images as 2D vectors of fixed dimensions $M \times N$. Such a constraint if imposed on pairs of age separated face image of children, would result in the face recognition system comparing pairs of face images with misaligned facial features that were scaled without due considerations on facial growth. Hence, to perform recognition across age separated face images of children, a better approach to handle the differences in the size of faces would be to employ an age transformation such that pairs of images that are to be compared are transformed to the same ages and hence presumably have comparable sizes.

To highlight the importance of performing an age transformation on pairs of age separated face images before performing face recognition across age progression, we designed the following experiment. Let the images comprising the gallery set and probe set be designated as $\mathbf{G} : \{G_1^{x_1}, G_2^{x_2}, \cdots, G_m^{x_m}\}$ and $\mathbf{P} : \{P_1^{y_1}, P_2^{y_2}, \cdots, P_n^{y_n}\}$ respectively. Let $(x_1, \cdots, x_m, y_1, \cdots, y_n)$ correspond to the different ages of individuals present in the gallery and the probe sets. Under the first setting, the images in the gallery and the probe sets are scaled and cropped such that they are all of dimensions $M \times N$ and the eyes are aligned across all images. Under the second setting, given a probe image $P_i^{y_i}$, we perform an age transformation operation on all the gallery images and generate the gallery images for age

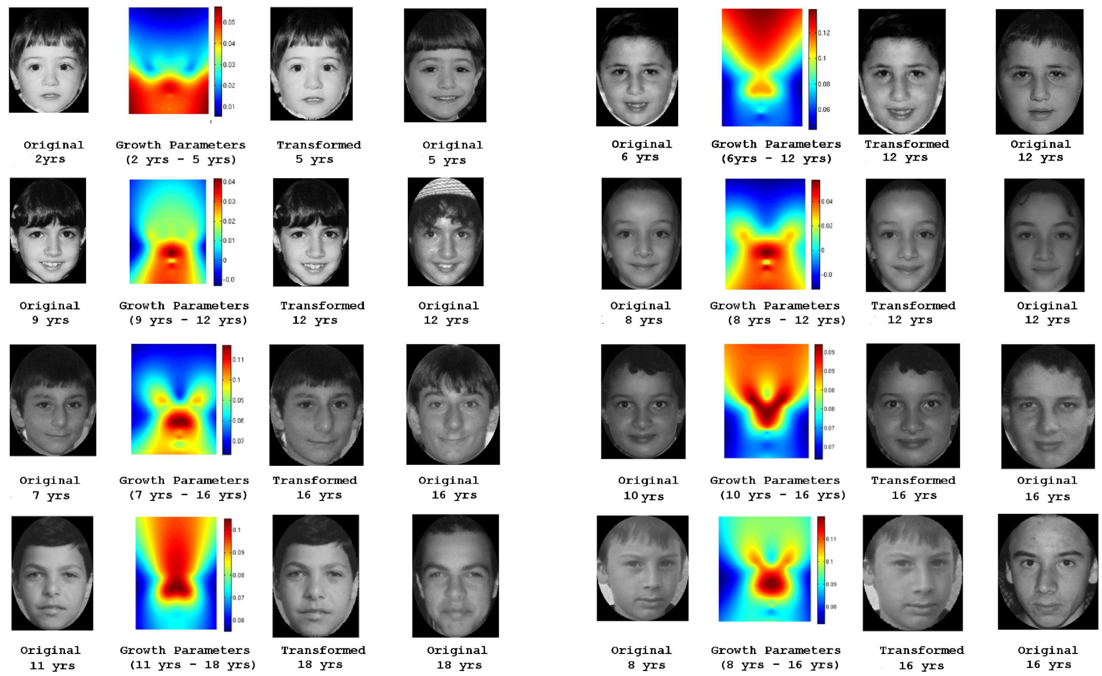

Figure 5. Age transformation results on different individual. (The original images shown above were taken from the FG-Net database [1].)

y_i years. Such an operation is repeated for all the probe images $P_i^{y_i}$, $i = 1 \ldots n$. Fig. 6 illustrates the gallery images that were generated for different ages from the images of two subjects in the original gallery. Using eigenfaces [24], we perform face recognition under both the settings. The recognition results tabulated in Table 2 show that better recognition rates can be achieved when age transformation operations are performed on pairs of age separated face images of individuals before performing recognition. The recognition results reported in 2 were obtained without accounting for differences in illumination, head pose, facial experssions etc. between pairs of age separated face images. Hence, the rank 1 recognition scores are low.

Table 2. Recognition results (%) before and after age transformation

Approach	Rank 1	Rank 5	Rank 10
No transformation	8	28	44
Age transformed	15	37	58

6. Discussions and Conclusions

We have proposed a craniofacial growth model that takes into account both psychophysical evidences on how humans perceive age progression in faces and anthropometric evidences on facial growth. We have demonstrated the effectiveness of the proposed model in predicting one's appearance across age and in improving recognition results across age separated face images of individuals. To discuss some of the strengths and weaknesses of the proposed method :

- The craniofacial growth model that we propose is unique for each individual. Though growth patterns are often observed in humans across age, there might be subtle differences in facial growth between different individuals. Under the same age transformation, though the facial growth parameters computed at facial landmarks are identical across individuals, the facial growth parameters computed over the entire face region is adapted to each individual differently and hence is different for different individuals.

- The model accounts for gender based differences in facial growth as it was developed using anthropometric data pertaining to men and women, separately.

- Further, the craniofacial growth model can be adapted to characterize facial growth on people from different origins by using anthropometric data pertaining to people from those origins. In this work, the anthropometric data used to develop the model was obtained from facial measurements taken on Caucasian faces and hence, we expect our model to work better on Caucasian faces.

- But, the proposed approach lacks a textural model and does not account for textural variations across age. Hence facial hair and other commonly observed textu-

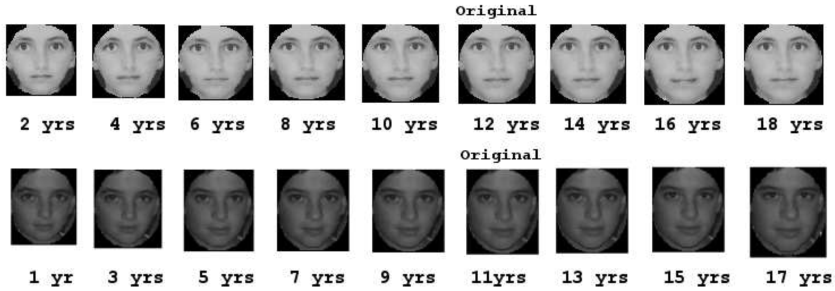

Figure 6. Generated gallery images at different ages for two subjects from the original gallery set

ral variations in teenagers are not accounted for. Further, it does not account for changes in the amount of fat tissue in the face. The model retains 'baby fat' and hence the age transformation results obtained on toddlers were poor.

In future, we wish to take a closer look at textural variations in human faces with age (both during formative years and during old age).

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