Aging Faces : Learning Facial Growth Models

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1. Introduction

Developing computational models for human faces that account for different facial appearances due to factors such as illumination variations, head pose variations, varying facial expressions, occlusions etc. has long been of interest in the computer vision and psychophysics communities. Human faces convey significant information pertaining to individuals such as their identity, gender, age group, ethnicity etc and further facial expressions often help identify the emotional state of individuals. Hence perception studies suggest that human faces are associated with high psychosocial importance and identify attributes such as facial attractiveness, facial age etc. as factors that regulate interpersonal behavior. From a face recognition perspective, numerous algorithms have been developed to perform still-image based and video-based face recognition in the presence of illumination and head pose varitions [5]. In this paper, we develop computational models that characterize facial aging effects commonly observed during formative years (0 to 18 years) and in turn help perform face recognition across age progression.

During formative years, while shape variations in the cranium are prominent with increase in age, textural variations in the form of wrinkles and other skin artifacts are minimal. Hence, we address the proposed facial growth model as a craniofacial growth model : a shape transformation model that characterizes facial growth observed during formative years by means of drifts observed in facial features with age. While developing facial growth models, taking into consideration the following aspects is crucial to the success of the model in characterizing facial aging effects :

- Different facial features have different rates of growth, during different ages. Face anthropometric studies [1] show that certain facial features attain growth saturation earlier than other facial features.
- Facial growth rates are dependent on factors such as gender, ethinicity etc. Such attributes need to be taken into consideration while developing the facial growth models.
- Though certain growth patterns can be observed across individuals belonging to the same ethinic group, individual-specific facial geometries need to be accounted for while developing facial growth models.

2. Craniofacial growth model

Most of the early research pertaining to craniofacial growth dealt with identifying geometric transformations which when applied on face profiles of children result in growth like transformations. Cardioidal strain transformations, 'revised' cardioidal strain transformations, spiral strain transformations, affine shear transformations etc. were some of the transformation functions that were studied in relevance to craniofacial growth models [4], [2]. We propose a craniofacial growth model that draws inspiration from the 'revised' cardioidal strain transformation model expressed mathematically as

$$P_i^{t_0} \propto R_i^{t_0}(1-\cos(\theta_i^{t_0})) \quad (1)$$

$$R_i^{t_1} = R_i^{t_0}[1+k_i^{t_0 t_1}(1-\cos(\theta_i^{t_0}))]$$

$$\theta_i^{t_1} = \theta_i^{t_0} \quad (2)$$

Fig. **??** illustrates the effect of applying the 'revised' cardioidal strain transformations on the outer contour of profile faces. In the eq. 1, $k_i^{t_0 t_1}$ is analogous to the growth parameter corresponding to the i'th fiducial feature from ages t_0 yrs to t_1

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yrs. Estimating the facial growth parameters corresponding to different fiducial features for the desired age transformation is a crucial aspect in developing the proposed craniofacial growth model. Face anthropometric studies, such as [1], provide age-based facial measurements extracted across facial landmarks from individuals belonging to the same gender and ethinic background. Facial growth models that incorporate such evidences collected on facial growth, implicitly account for gender based and ethinicity based factors that affect facial growth. The following is an algorithmic overview of the proposed craniofacial growth model :

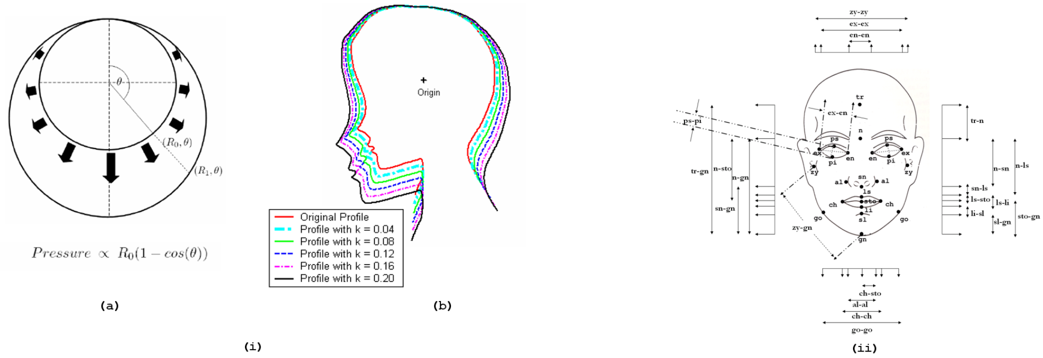

Figure 1. Craniofacial growth model

- Facial feature localization : Given a face image, 23 fiducial features often used in face anthropometric studies are localized in a semi automated process.
- Computing deviation parameters : It is often observed that individual faces tend to aspect ratios different from one another. Quantifying the subtle variations exhibited in facial aspect ratios amounts to quantifying attributes such as the 'ovalness' or 'flatness' of individual faces.
- Rescaling anthropometric data and localize origin of reference : The average anthropometric measurements provided in [1] are rescaled in accordance with the computed deviation parameters. The origin of reference for the 'revised' cardioidal strain transformation model is estimated.
- Computing growth parameters over fiducial features : 52 proportion indices result in a set of linear and nonlinear equations on facial growth parameters. Levernberg-Marquardt optimization procedure is used to compute the facial growth parameters corresponding to the 23 fiducial features.
- Computing growth parameters over entire face: Given the growth parameters over fiducial features, the thin plate spline formulation is used to interpolate facial growth parameters over the entire face.
- Appearance transformation : The forward transformation model is applied when $t_0 < t_1$ and the reverse transformation model is applied when $t_0 > t_1$. The forward transformation model typically results in missing textures on the transformed face. Thin plate spline interpolation techniques are used to compute missing textures.

The proposed craniofacial growth model is used to perform face recognition across age progression , prediction of one's appearances across ages etc [3].

References

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