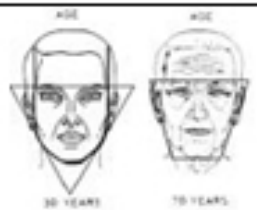
Facial texture variations ?



Face contour variations ?

Face images from passports

Face Recognition across Age Progression

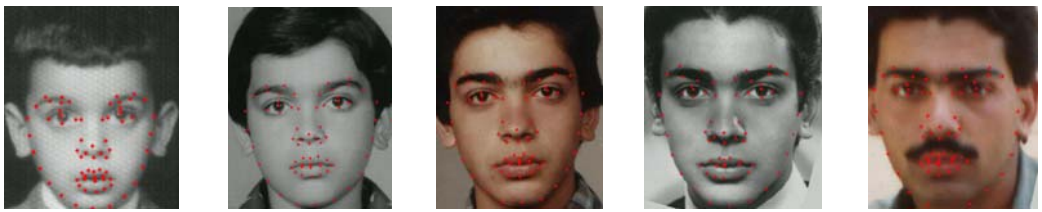
Dr. Rama Chellappa

Narayanan Ramanathan

Age Progression in Human Faces :

Facial aging effects are manifested in different forms in different ages :

- Changes in the shape of the cranium from infancy to teenage



7 yrs **13 yrs** **14 yrs** **17 yrs** **20 yrs**

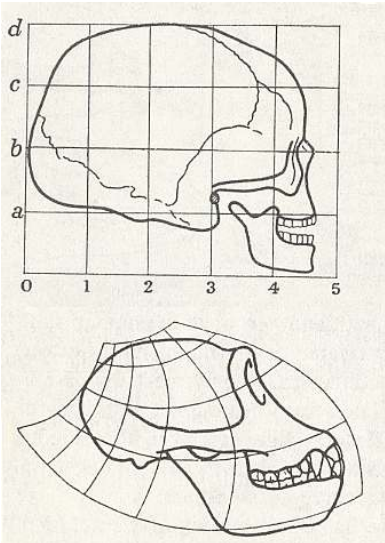
- Changes in the skin texture during adulthood

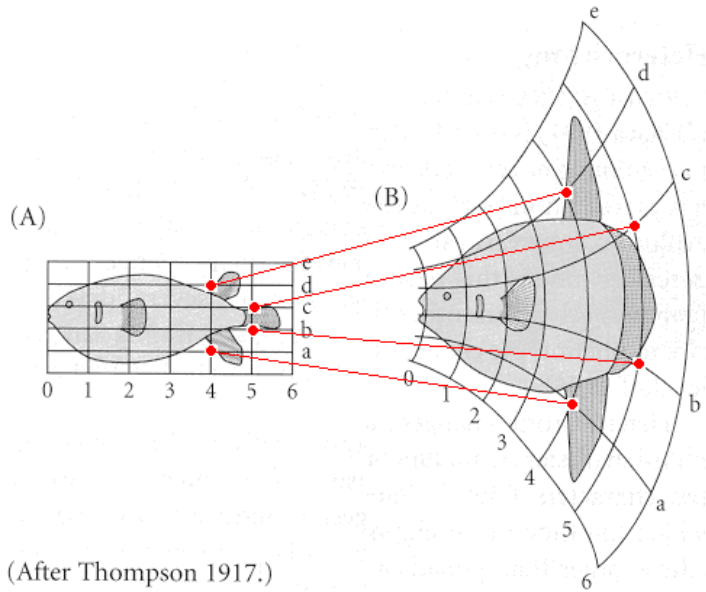
Outline

- Previous work on facial aging
- **Craniofacial growth model** (Modeling age progression in young faces)
- **Bayesian Age-Difference classifier** (Face verification across age progression)
- Experimental results
- Conclusions & Future work

Previous Work

- D'Arcy Thompson pioneered the use of geometric transformations in the study of morphogenesis :

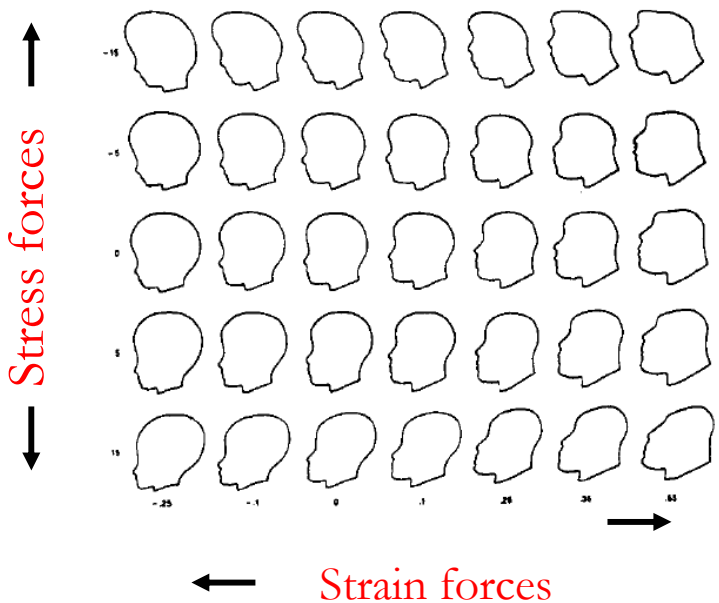


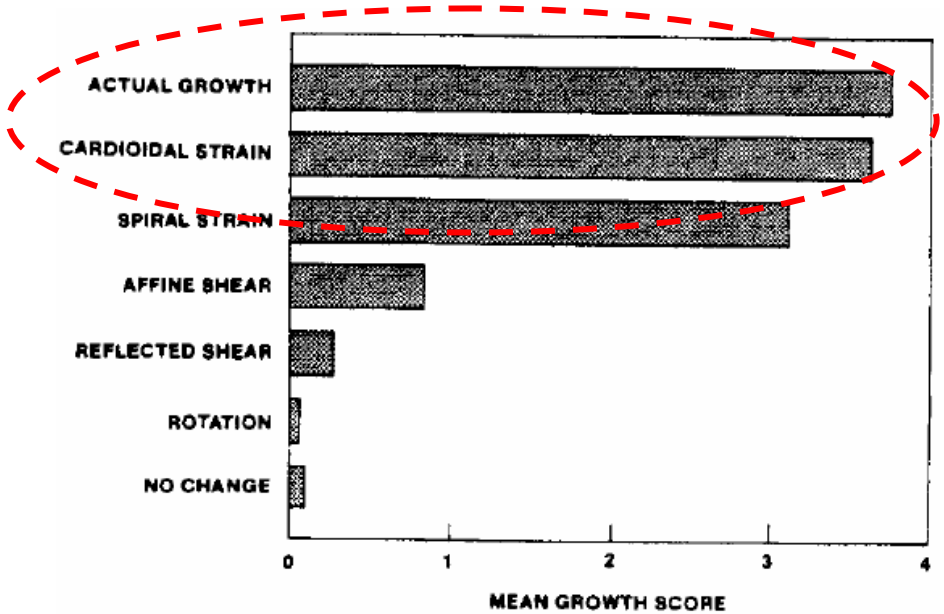


D'Arcy Thompson proposed that " **Geometric distortions associated with morphogenetic changes are a result of physical forces acting on the animal's environment.** "

Previous Work (contd.)

- J. B. Pittenger & Robert E. Shaw apply different transformations to the profile views of human heads : **Which transformation models facial growth best ?**





Mark et al. (1981) observed that cardioidal strain transformation was effective in modeling facial growth

Previous Work (contd)

- Ho Kwon et al. (1994) :

  Age classification from face images – young / old using face anthropometry

- Alice O'Toole (1997) :

  Age perception using 3D head caricature : exaggeration of wrinkles increased perceived age

- Tidderman et al. (2001) :

  Prototyping and transforming facial texture : Age perception

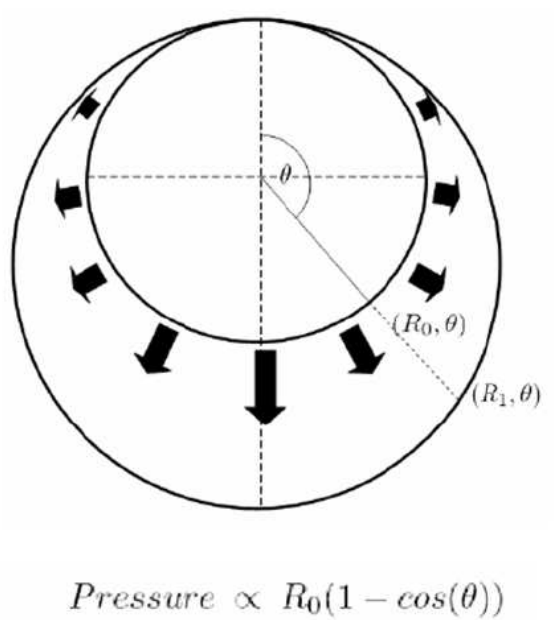
- Lanitis et al. (2002) :

  Builds aging functions using PCA coefficients of shape & texture of faces

Craniofacial Growth Model (contd.)

Wolf's law : Stress is a direct stimulant to growth

Remodeling of Human head with growth is considered analogous to the remodeling a fluid-filled spherical tank with pressure (Mark et al 1980)



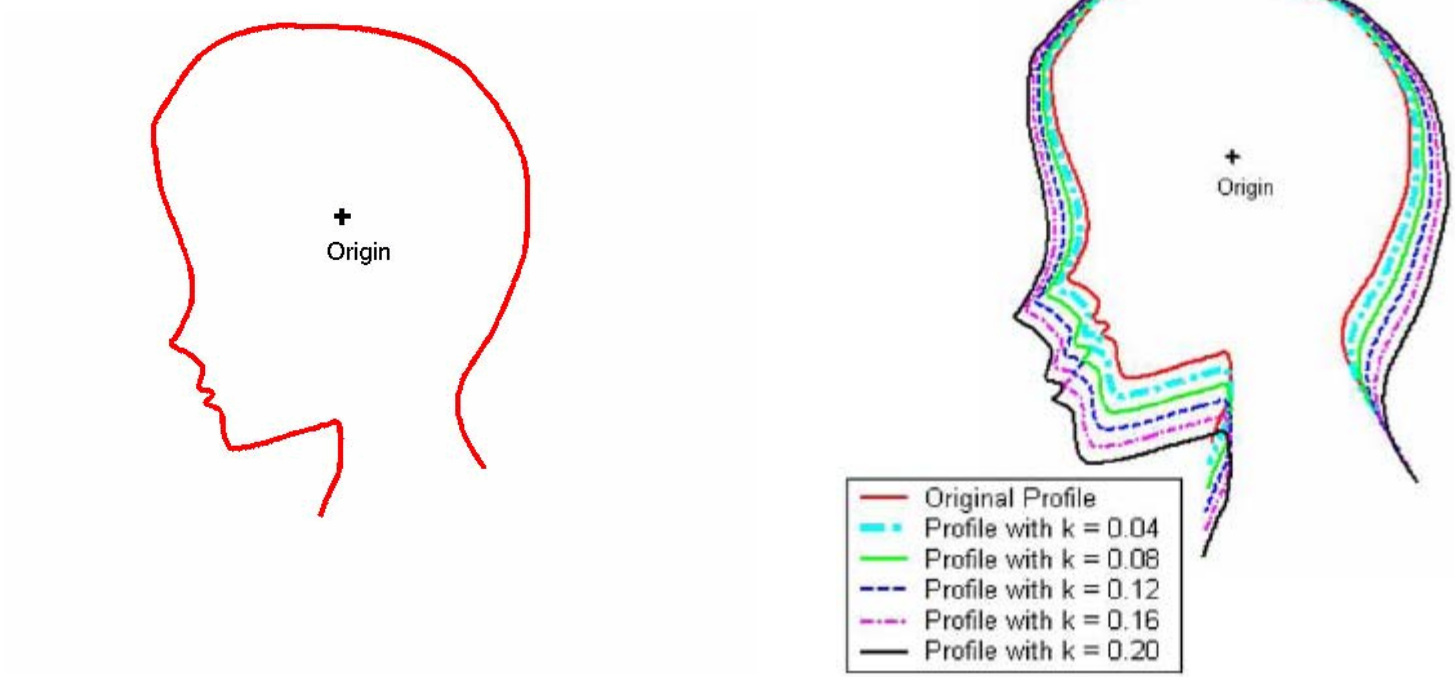
$$
\begin{aligned}
P &\propto R_0(1 - cos(\theta_0)) \\
R_1 &= R_0 + k(R_0 - R_0 \cos(\theta_0)) \\
\theta_1 &= \theta_0
\end{aligned}
$$

k : analogous to the growth parameter

Craniofacial Growth Model (contd.)

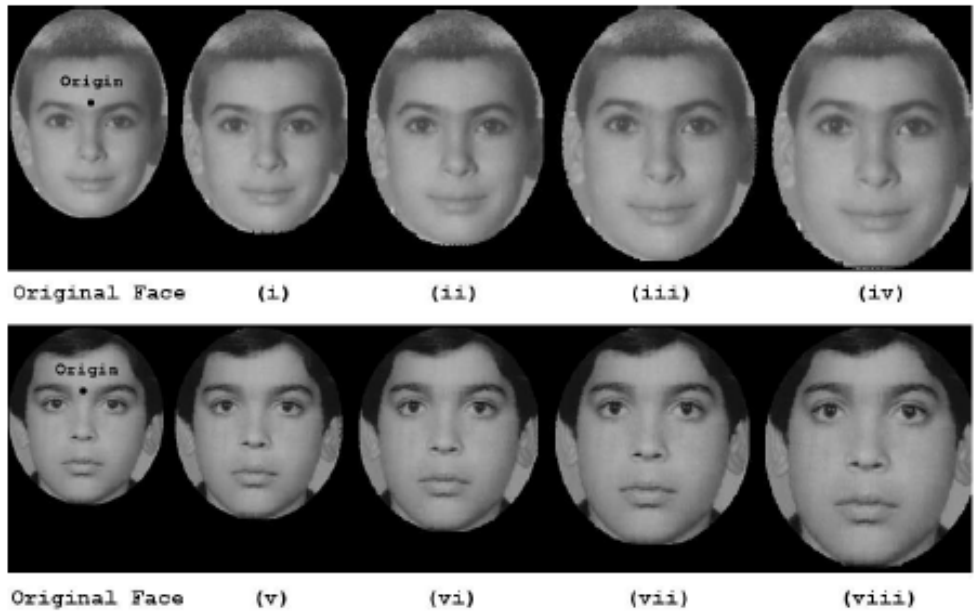
Applying the revised-cardioidal strain transformation model on profile views of human heads : the resulting transformation is perceived as that of facial growth

Resulting transformation



Craniofacial Growth Model (contd.)

Applying the transformation on real face images : we observe that the prediction is good for small age transformations and poor for large age transformations

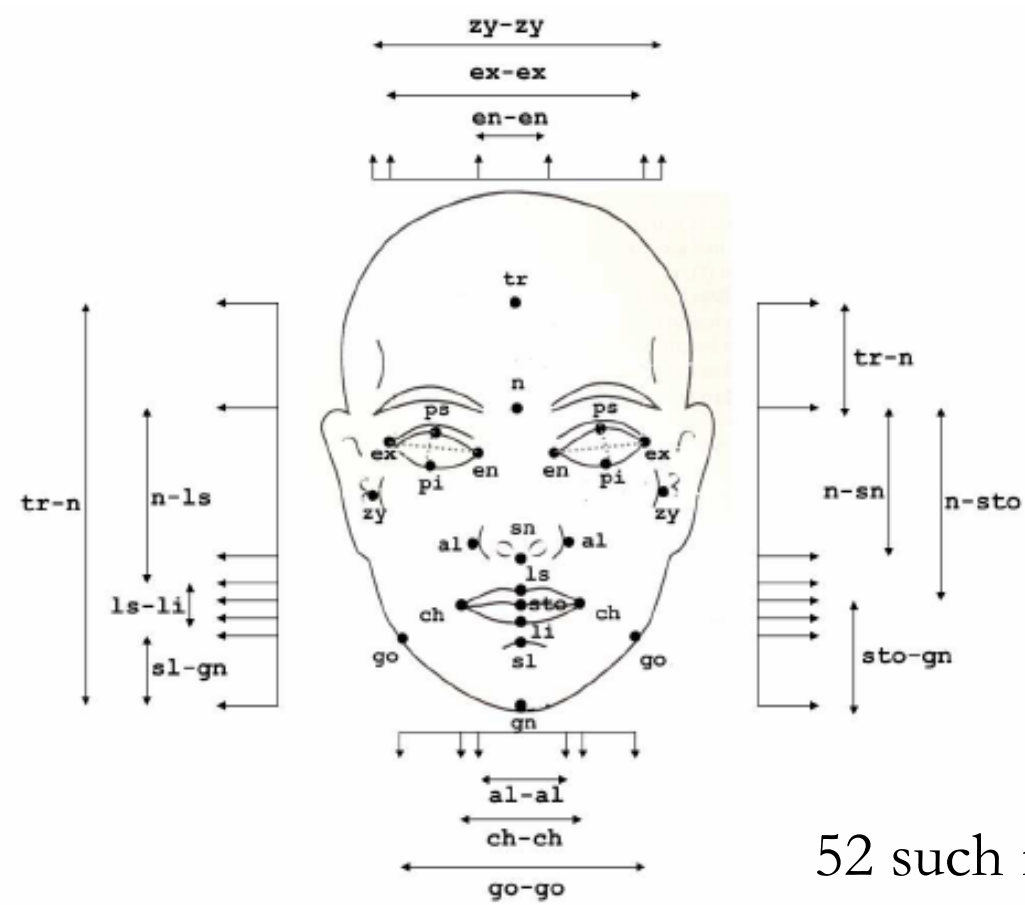


$$
\begin{aligned}
P &\propto R_0(1 - cos(\theta_0)) \\
R_1 &= R_0 + k(R_0 - R_0 \cos(\theta_0)) \\
\theta_1 &= \theta_0
\end{aligned}
$$

Growth parameters in different facial regions change with age

Hence, age-based anthropometric measurements are used to estimate facial growth parameters

Face Anthropometry

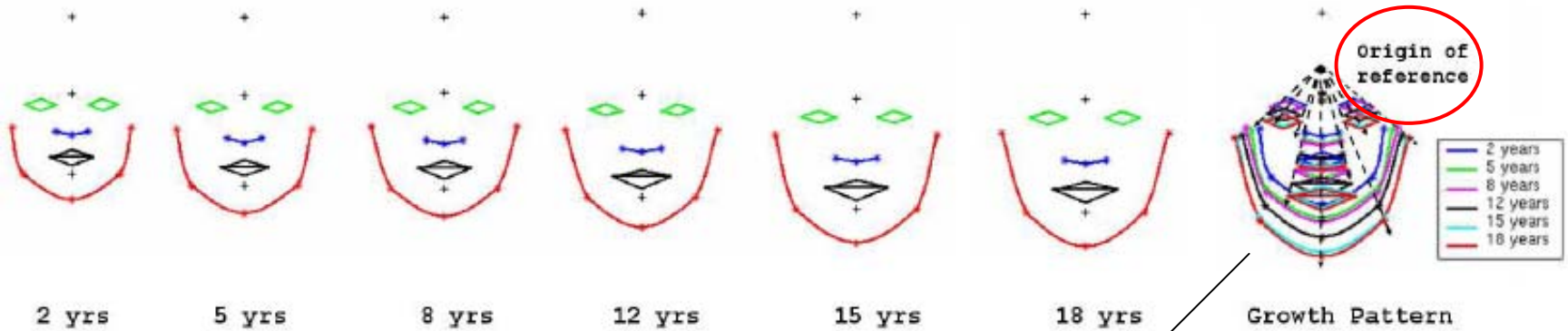


Leslie Farkas (1994) provides anthropometric measurements extracted from faces from different ages (0 – 18 yrs)

52 such facial measurements are used in our study.

Face Anthropometry (contd.)

Facial prototypes for different ages are created using anthropometric measurements.



The 'Origin of reference' for the revised-cardioidal strain model is estimated using the growth patterns observed across ages

Computing Growth parameters

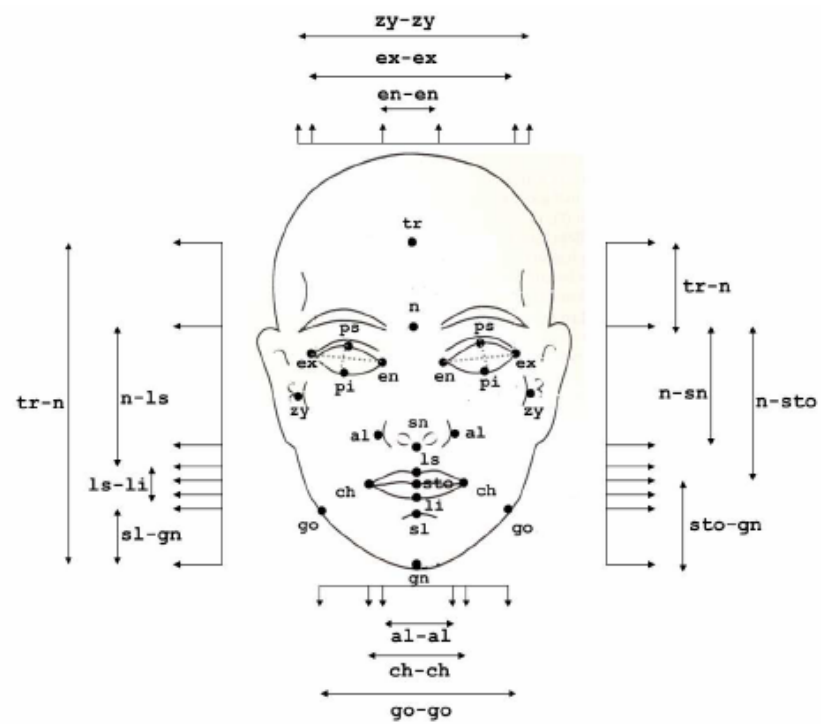
Linear and Non-linear constraints on growth parameters

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

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

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

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



Glossary

$[k_1,\ k_2,\ \cdots\ k_{15}]$ ⟶ Age-based growth parameters defined on 15 facial landmarks

c_i ⟶ Ratios of age-based facial measurements

Computing Growth parameters (contd.)

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

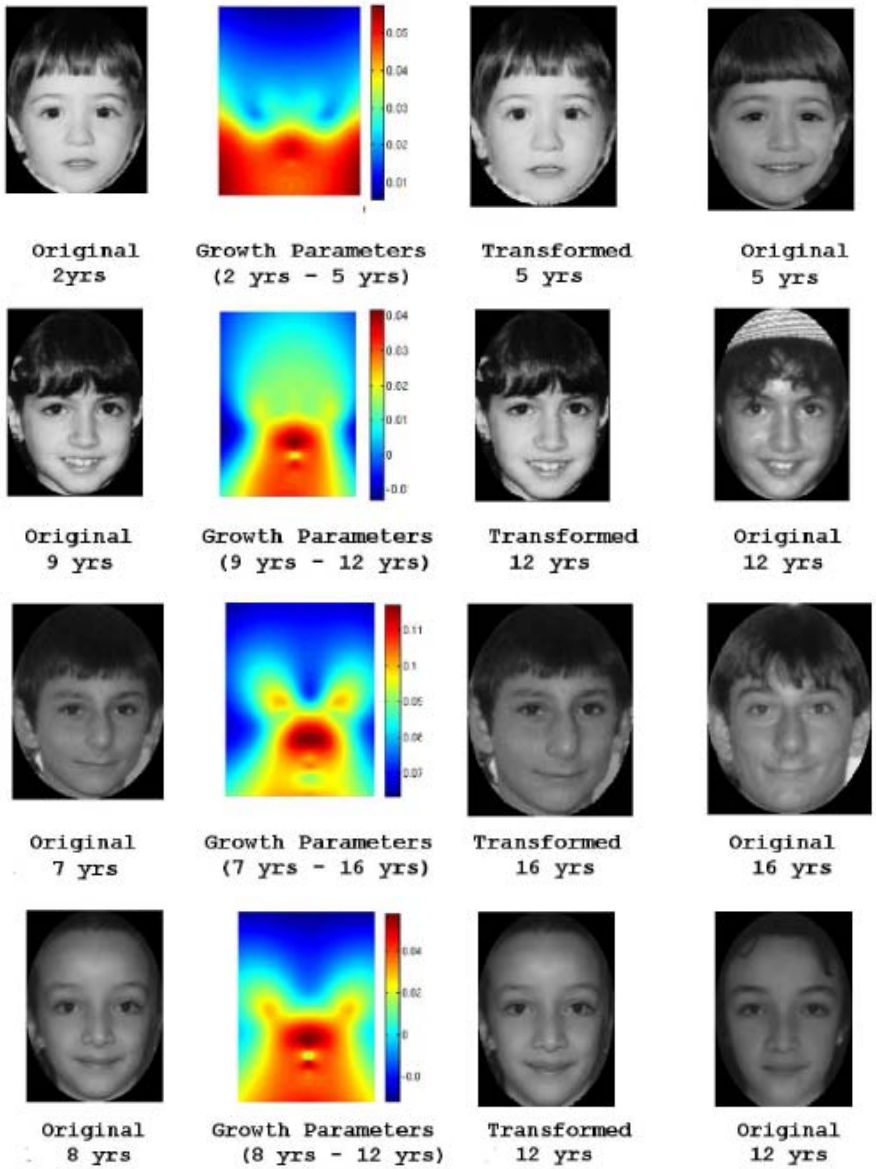
$$\mathbf{k}_{i+1} = \mathbf{k}_i - (\mathbf{H} + \lambda diag[\mathbf{H}])^{-1}\nabla f(\mathbf{k}_i)$$

The computation of the growth parameters is formulated as that of solving a non-linear optimization.

We use Levenberg Marquartd optimization to solve for the age-based growth parameters defined over facial landmarks

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

Using thin-plate spline formulations, we compute growth parameters over other facial regions



Results :

Prediction of appearance across age progression

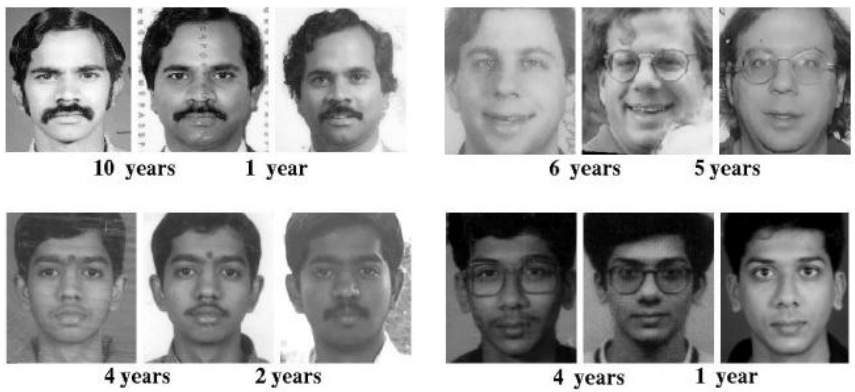
The proposed facial growth model can be used to perform face recognition across age progression on images of children

Face Verification across Age progression:

Problem Statement :

- Given a pair of age separated face images of an individual, what is the confidence measure in verifying the identity ?
- How does age progression affect facial similarity ?

Passport Image database

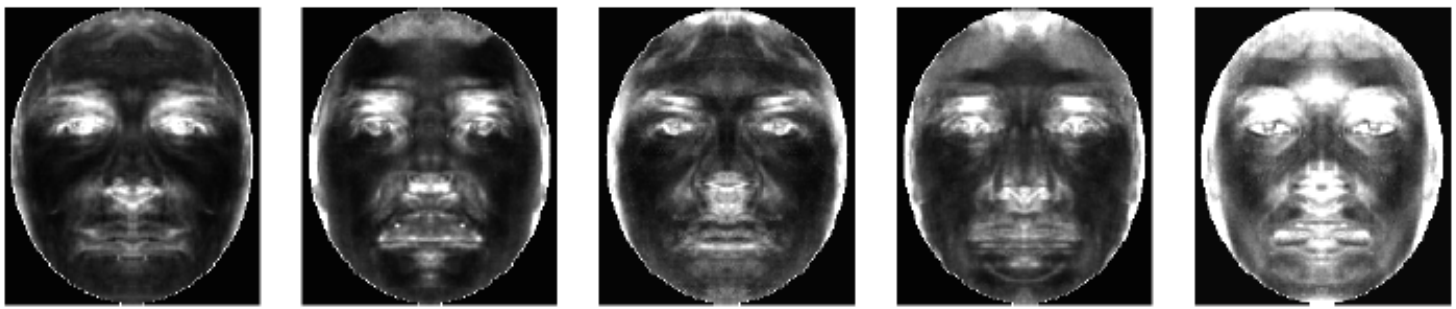


- 465 pairs of passport images
- Age range : 20 yrs to 70 yrs
- Pair-wise age difference
  - ✓ 1 - 2 yrs : 165
  - ✓ 3 - 4 yrs : 104
  - ✓ 5 - 7 yrs : 81
  - ✓ 8 - 9 yrs : 115

Bayesian Age difference classifier :

- Given a pair of age separated face images
  - Establish identity : intrapersonal / extrapersonal
  - Classify intrapersonal age separated samples based on age difference : 1-2 yrs , 3-4 yrs, 5-7 yrs, 8-9 yrs.

Textural variations due to aging observed in intra-personal images are captured in the difference images



1-2 years 3-4 years 5-7 years 8-9 years extra-personal

Age difference classifier : Overview

<u>First stage of classification</u>

- Create an intra-personal and extra-personal space using differences of PointFive faces
- Given a pair of face images, compute their difference image and estimate its likelihood from each class & classify the image pairs as intra-personal or extra-personal (MAP)

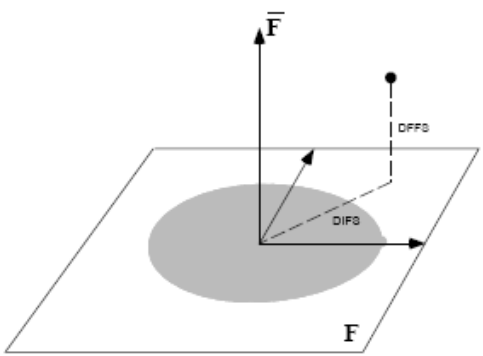
<u>Second stage of classification</u>

- Create age-difference based intra-personal spaces for each of four age-differences (1-2 yrs, 3-4 yrs, 5-7 yrs, 8-9 yrs).
- Estimate likelihood of intra-personal difference images from each of four classes & classify each pair using a MAP rule.

Age Difference Classifier (contd)

Subspace Density Estimation : Intra Personal class

Assume Gaussian distribution of Intra – personal image differences



(Courtesy : Moghaddam 1997)

$$
\begin{aligned}
P(\mathbf{x}|\Omega_I) &= \frac{\exp(-\frac{1}{2}(\mathbf{x}-\bar{\mathbf{x}})^T\Sigma^{-1}(\mathbf{x}-\bar{\mathbf{x}}))}{(2\pi)^{N/2}|\Sigma|^{1/2}} \\
&= \frac{\exp(-\frac{1}{2}\sum_{i=1}^{N}\frac{y_i^2}{\lambda_i})}{(2\pi)^{N/2}\prod_{i=1}^{N}\lambda_i^{1/2}} \\
&\simeq \left[\frac{\exp(-\frac{1}{2}\sum_{i=1}^{k}\frac{y_i^2}{\lambda_i})}{(2\pi)^{k/2}\prod_{i=1}^{k}\lambda_i^{1/2}}\right] . \left[\frac{\exp\left(-\frac{\epsilon^2(\mathbf{x})}{2\rho}\right)}{(2\pi\rho)^{(N-M)/2}}\right] \\
&= P_F(\mathbf{x}|\Omega_I) \, . \, \hat{P}_{\bar{F}}(\mathbf{x}|\Omega_I)
\end{aligned}
$$

Principal subspace and
Its orthogonal complement
for Gaussian density

Marginal density
in F space

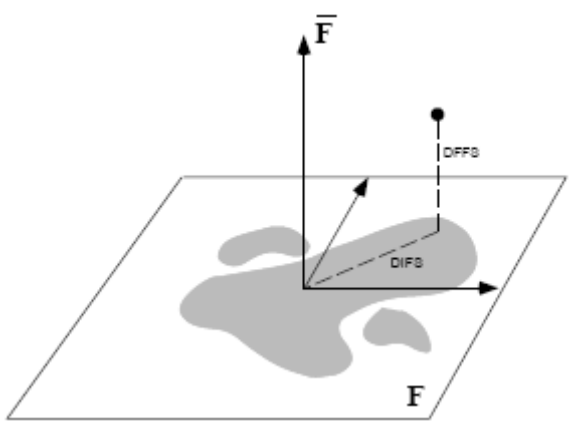
Marginal density in
complementary
space

Age Difference Classifier (contd)

Subspace Density Estimation : Extra personal class

Assume feature space F to be estimated by a parametric mixture model (mixture of Gaussian – use EM approach to estimate the parameters)

Assume components of complementary space to be Gaussian



(Courtesy : Moghaddam 1997)

$$\hat{P}(\mathbf{z}|\Omega_E) = P(\mathbf{y}|\Theta^*) \,.\, \hat{P}_{\bar{F}}(\mathbf{z}|\Omega_E)$$

$$P(\mathbf{y}|\Theta) = \sum_{i=1}^{N_c} w_i N(\mathbf{y}; \mu_i, \Sigma_i)$$

$$\Theta^* = argmax \left[\prod_{i=1}^{M} P(\mathbf{y}_i|\Theta) \right]$$

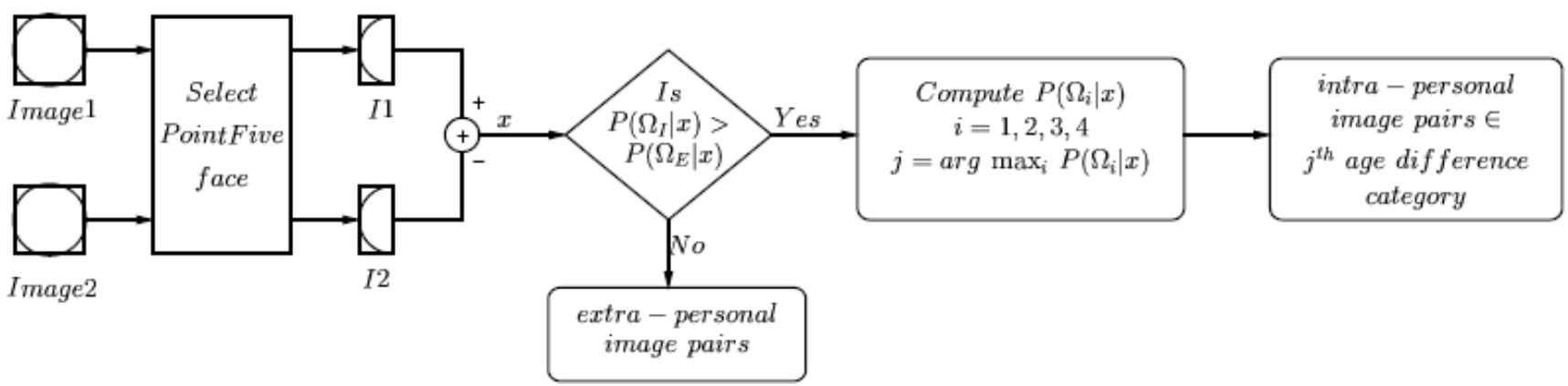
Age Difference Classifier (contd)

$$P(\Omega_I|\mathbf{x}) = \frac{P(\mathbf{x}|\Omega_I)P(\Omega_I)}{P(\mathbf{x}|\Omega_I)P(\Omega_I) + P(\mathbf{x}|\Omega_E)P(\Omega_E)}$$

if intra-personal

$$P(\Omega_i|\mathbf{x}) = \frac{P(\mathbf{x}|\Omega_i)P(\Omega_i)}{\sum_{j=1}^{4} P(\mathbf{x}|\Omega_j)P(\Omega_j)}$$

Age-difference based intra-personal class



Age based classification : Results

- Using 200 pairs of PointFive faces we created an intra-personal space and an extra-personal space
- Intra-personal difference images (465 pairs) and extra-personal difference images were computed from the passport images.

<u>First Stage</u>

- 99 % of the intra-personal difference images and 83 % of the extra-personal difference images were classified correctly as intrapersonal and extrapersonal respectively
- The misclassified intrapersonal pairs differed significantly due to glasses or due to facial hair or a combination of both.

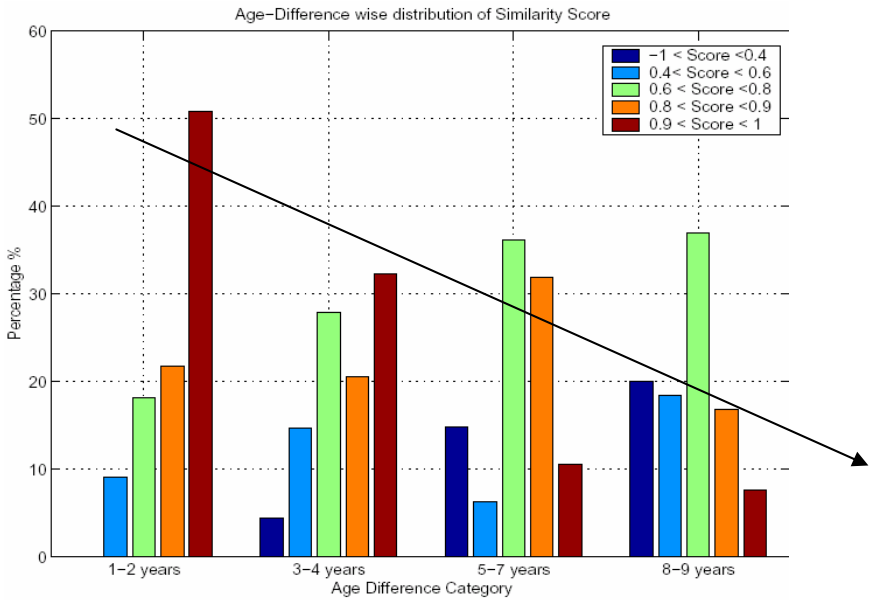
Age based classification : Results (contd)

Second Stage

	Age-Difference Classifier			
	Ω_1	Ω_2	Ω_3	Ω_4
Ω_1 (1-2 yrs)	**51 %**	2 %	9 %	38 %
Ω_2 (3-4 yrs)	17 %	**37 %**	11	35 %
Ω_3 (5-7yrs)	6 %	1 %	**61 %**	32 %
Ω_4 (8-9 yrs)	1 %	1 %	12 %	**86 %**

- Intra-personal image pairs with little variations due to facial expressions / glasses / facial hair were more often classified correctly to their age difference category.
- Image pairs with significant variations in the above factors were incorrectly classified under 8-9 yrs category.

Similarity Measure



Similarity measure was computed as the correlation of principal components corresponding to 95 % of the variance

Similarity scores between intra-personal images dropped as age-difference increased

Age Based Similarity Measure

Age Difference	First Set		Second Set					
			Expression		Glasses		Facial Hair	
	μ	σ^2	μ	σ^2	μ	σ^2	μ	σ^2
1-2 yrs	0.85	0.02	0.70	0.021	0.83	0.01	0.67	0.04
3-4 yrs	0.77	0.03	0.65	0.07	0.75	0.02	0.63	0.01
5-7 yrs	0.70	0.06	0.59	0.01	0.72	0.02	0.59	0.10
8-9 yrs	0.60	0.08	0.55	0.10	0.68	0.18	0.55	0.10

Conclusions & Future Work

- The Craniofacial growth model is effective in predicting one's appearances across age (for young adults)

- The Bayesian age-difference classifier can be used to verify adult face images across age progression. The lesser the variations due to facial hair, facial expressions and glasses on age separated face image, the better the success of the age-difference classifier.

- A study of facial similarity across time shows that similarity between age separated face images decreases with age.

- In future, we wish to develop a model for textural variations in adult faces across progression.

References :

•Narayanan Ramanathan and Rama Chellappa, "**Modeling Age Progression in Young Faces**" (accepted in CVPR 2006, New York)

•Narayanan Ramanathan and Rama Chellappa, "**Face Verification across Age Progression**" (accepted in IEEE Transactions on Image Processing)

•Narayanan Ramanathan and Rama Chellappa, "**Face Verification across Age Progression**", IEEE Computer Vision and Pattern Recognition (CVPR) vol. 2, pp: 462-469, June 2005, San Diego.

Narayanan Ramanathan, Amit K. Roy Chowdhury and Rama Chellappa, "**Facial Similarity across Age, Disguise, Illumination and Pose**", IEEE International Conference in Image Processing, vol. 3, pp: 1999-2002, October 2004, Singapore.