Characterization and Classification of Faces across Age Progression

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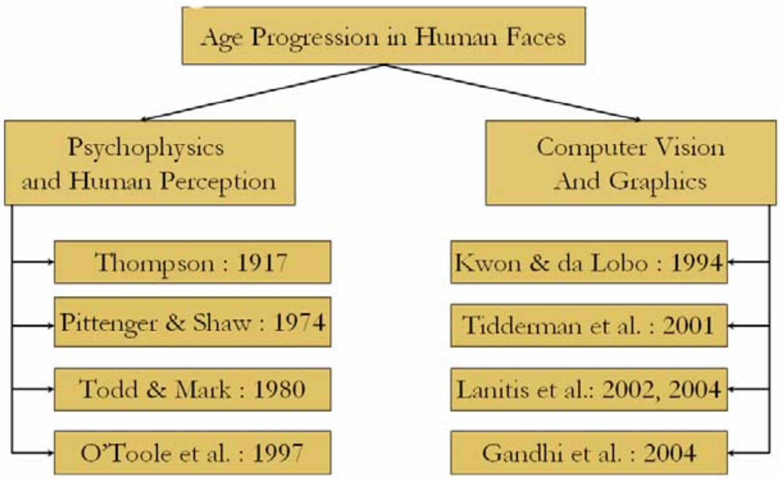
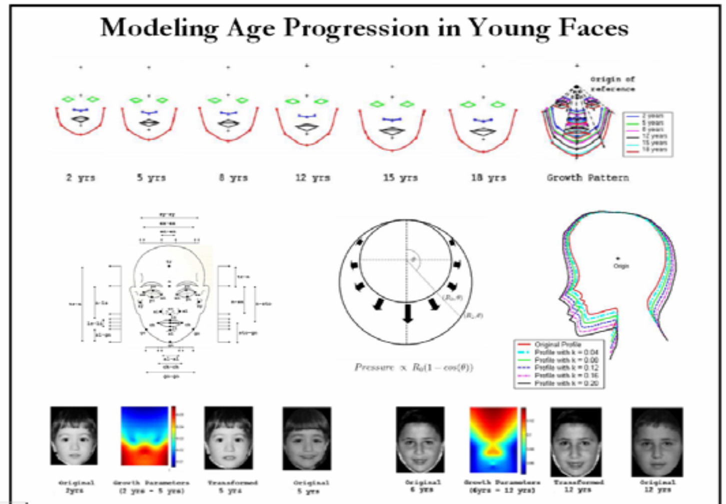
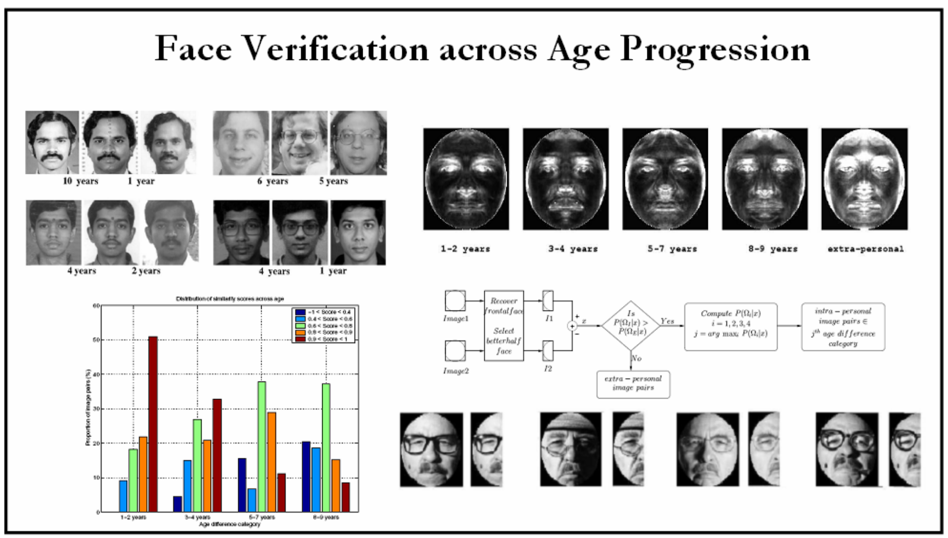
Overview



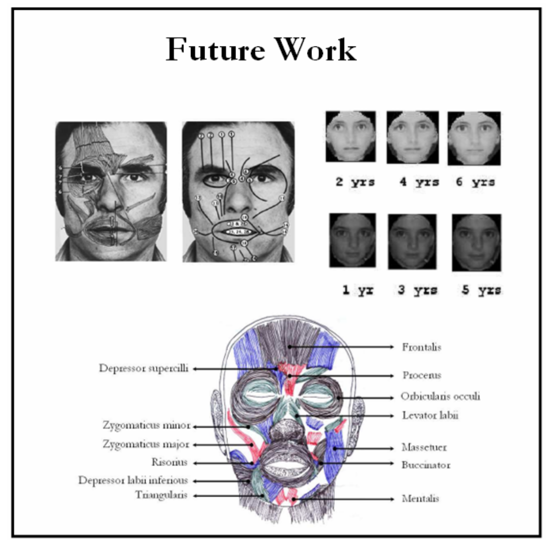
Age Progression in Human Faces
Psychophysics and Human Perception
Computer Vision And Graphics
Thompson : 1917
Pittenger & Shaw : 1974
Todd & Mark : 1980
O'Toole et al. : 1997
Kwon & da Lobo : 1994
Tidderman et al. : 2001
Lanitis et al.: 2002, 2004
Gandhi et al. : 2004



Modeling Age Progression in Young Faces
2 yrs
5 yrs
8 yrs
12 yrs
15 yrs
18 yrs
Growth Pattern



Face Verification across Age Progression
10 years
1 year
6 years
5 years
4 years
2 years
4 years
1 year
1-2 years
3-4 years
5-7 years
8-9 years
extra-personal



Future Work
2 yrs
4 yrs
6 yrs
1 yr
3 yrs
5 yrs
Depressor supercilii
Zygomaticus minor
Zygomaticus major
Risorius
Depressor labii inferious
Triangularis
Frontalis
Procerus
Orbicularis occuli
Levator labii
Masseter
Buccinator
Mentalis

Motivation

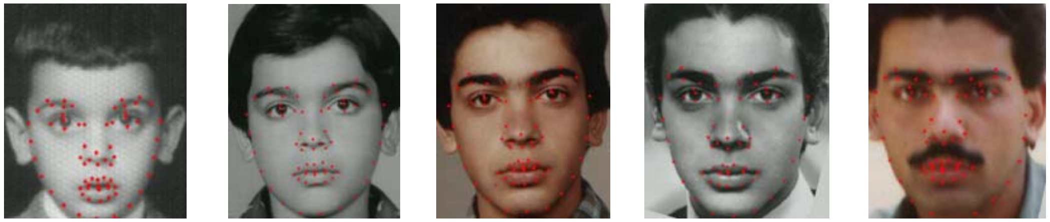
- Facial aging effects are manifested in different forms in different ages :
  - Shape variations (during formative years)
  - Textural variations (during adulthood).
- Developing models that characterize age progression in faces has many significant applications
  - Face recognition/verification across age progression
  - Automatic age identification and age-based classification of faces
  - Prediction of one's appearance across years
  - Developing age-based HCI systems

Previous Work

Age Progression in Human Faces

- Psychophysics and Human Perception
  - Thompson : 1917
  - Pittenger & Shaw : 1974
  - Todd & Mark : 1980
  - O'Toole et al. : 1997
- Computer Vision And Graphics
  - Kwon & da Lobo : 1994
  - Tidderman et al. : 2001
  - Lanitis et al.: 2002, 2004
  - Gandhi et al. : 2004

Modeling Age Progression in Young Faces



7 yrs   13 yrs   14 yrs   17 yrs   20 yrs

- Craniofacial growth is one of the most prominent manifestations of aging effects in children.
- Skin textural variations are minimal during formative years (but for facial hair during teenage years).
- Modeling age progression in young faces essentially implies modeling the flow of facial features across different ages.

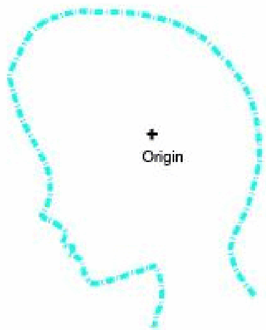
Modeling Age Progression in Young Faces (contd.)

- Challenges
  - Different facial features grow at different rates
  - Facial growth rates depend upon factors such as gender, ethnicity, age group etc.

- Mark et al (1981) identified the following geometric invariants in facial growth
  - Preservation of angular coordinates of feature points
  - Preservation of bilateral symmetry
  - Preservation of object continuity

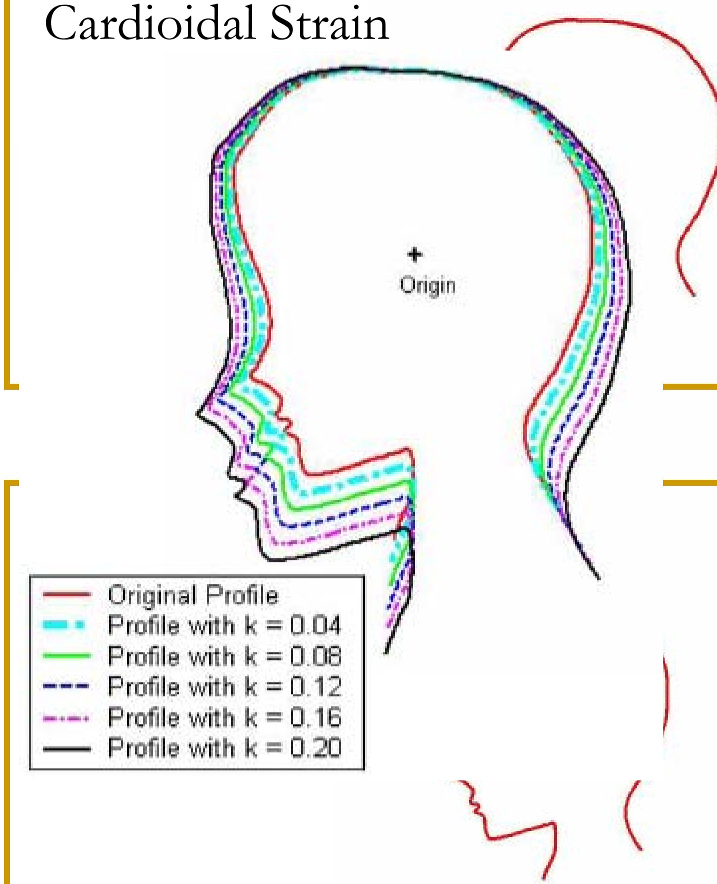
Craniofacial Growth models :

Affine Shear

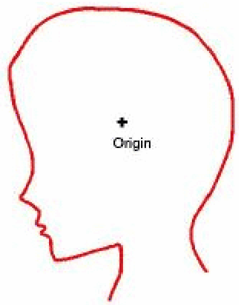


$$y_1 = y_0$$
$$x_1 = x_0 + ky_0$$

Cardioidal Strain



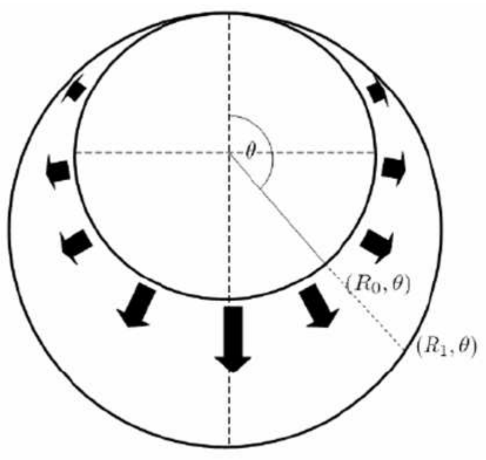
Revised Cardioidal Strain



$$R_1 = R_0 + k(R_0 - R_0 \cos(\theta_0))$$
$$\theta_1 = \theta_0$$

Craniofacial Growth Model

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



$Pressure \propto R_0(1 - cos(\theta))$

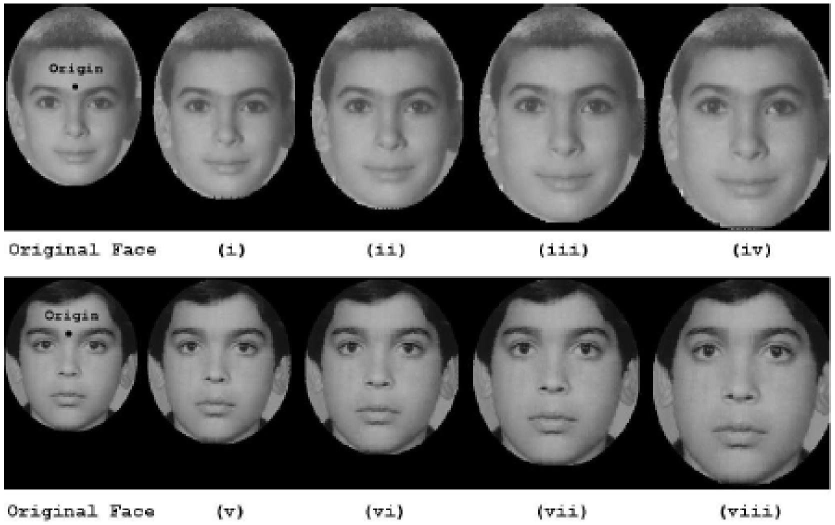
$$
\begin{aligned}
P &\propto R_0(1 - cos(\theta_0)) \\
R_1 &= R_0 + k(R_0 - R_0\cos(\theta_0)) \\
\theta_1 &= \theta_0
\end{aligned}
$$

k : analogous to the growth parameter

The pressure distribution is such that the geometric invariants identified with facial growth are preserved

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

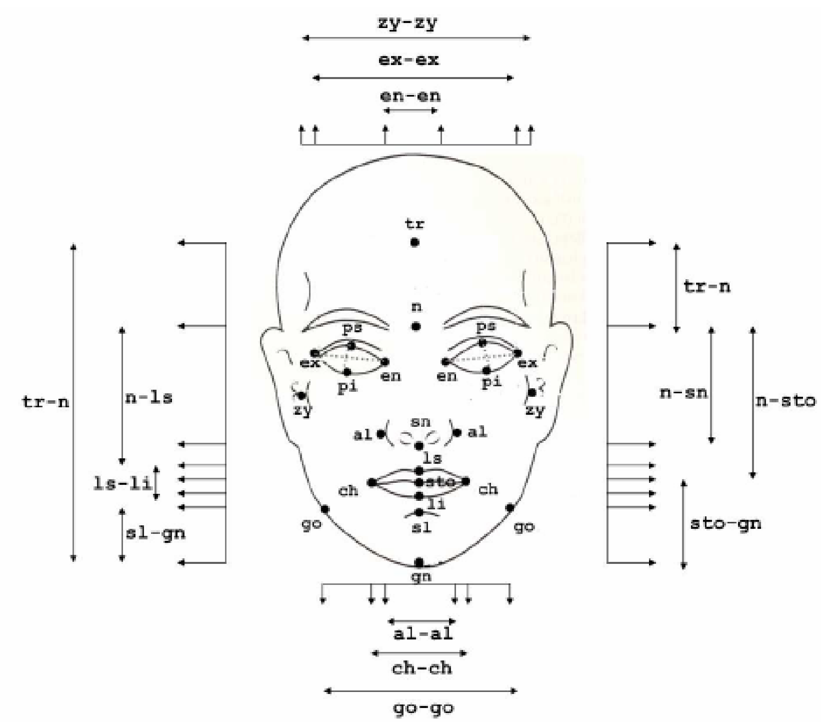


$$
\begin{aligned}
P &\propto R_0(1 - cos(\theta_0)) \\
R_1 &= R_0 + k(R_0 - R_0 \cos(\theta_0)) \\
\theta_1 &= \theta_0
\end{aligned}
$$

Growth parameters in different facial regions change with age

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

Face Anthropometry



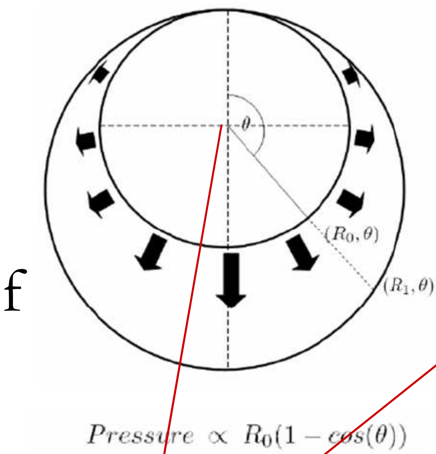
Leslie Farkas (1994) provides anthropometric face measurements (projective / tangential / angular) extracted from 57 facial landmarks.

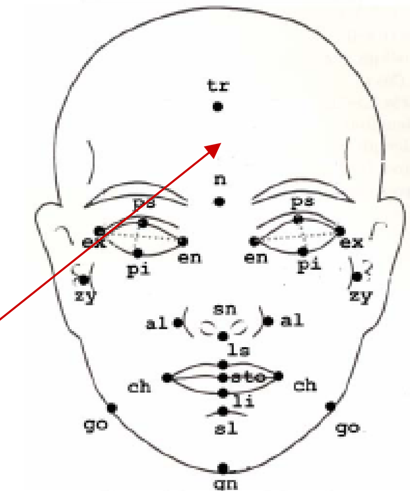
- We use 24 facial landmarks that can be reliably extracted from frontal face images and 52 projective measurements extracted from these landmarks.

We use proportion indices (ratios of anthropometric distances) to study facial growth. Example : facial index (n_gn / zy_zy) , intercanthal index (en_en / ex_ex) etc.

Model Computation

- Facial feature localization : Localization of the 24 facial landmarks
- Selection of the ‘optimal’ origin of reference for the craniofacial growth model
- From anthropometric measurements taken across years it is observed that the RTI of *tr_n* was 11 % for men and 2 % for women, implying lesser growth across years.





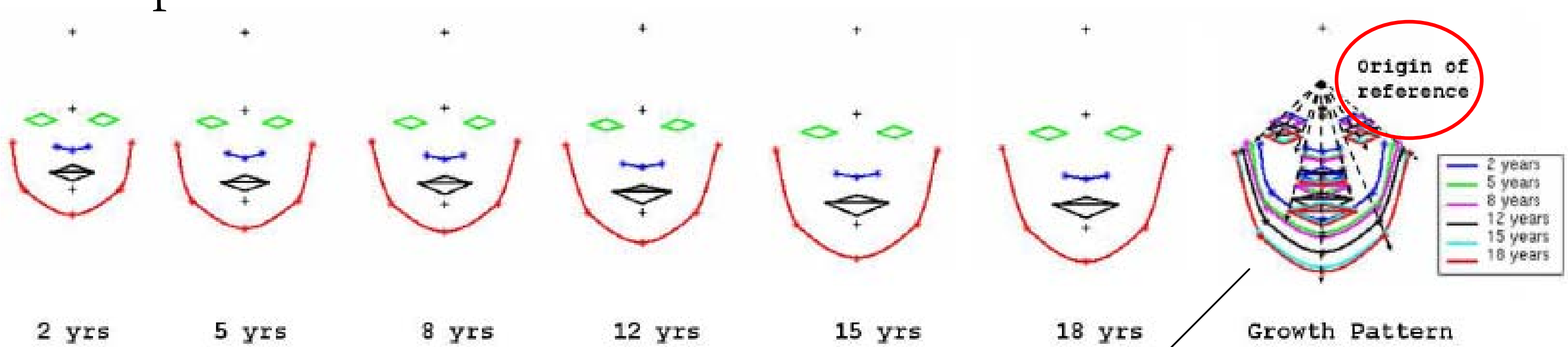
Origin of reference

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

Model Computation (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

Model Computation (contd.)

Age based proportion indices translate into linear and non-linear equations in **k** : [k_1 , k_2 ……, k_{15}]

$$\left[\frac{(n\_gn)_{t_1}}{(zy\_zy)_{t_1}} = c_{t_1}\right] \Rightarrow \left[\frac{(R_{gn})_{t_1} - (R_n)_{t_1}}{2 \times (R_{zy})_{t_1} \times \cos(\theta_{zy})} = c_{t_1}\right]$$

$$\left[\frac{(R_{gn})_{t_0}(1 + k_{gn}(1 - \cos(\theta_{gn}))) - (R_n)_{t_0}(1 + k_n(1 - \cos(\theta_n)))}{(R_{zy})_{t_0}(1 + k_{zy}(1 - \cos(\theta_{zy})))} = c_{t_1}\right] \Rightarrow \boxed{\left[\alpha_1 k_{gn} + \alpha_2 k_n + \alpha_3 k_{zy} = \alpha_4\right]}$$

$$\left[\frac{(sto\_gn)_{t_1}}{(gn\_zy)_{t_1}} = d_{t_1}\right] \Rightarrow \left[\frac{(R_{sto})_{t_1} - (R_{gn})_{t_1}}{\sqrt{((R_{gn})_{t_1} - (R_{zy})_{t_1}\sin(\theta_{zy}))^2 + ((R_{zy})_{t_1}\cos(\theta_{zy}))^2}} = d_{t_1}\right] \Rightarrow$$

$$\left[\frac{(R_{sto})_{t_0}(1 + k_{sto}(1 - \cos(\theta_{sto}))) - (R_{gn})_{t_0}(1 + k_{gn}(1 - \cos(\theta_{gn})))}{\sqrt{((R_{gn})_{t_0}(1 + k_{gn}(1 - \cos(\theta_{gn}))) - (R_{zy})_{t_0}(1 + k_{zy}(1 - \cos(\theta_{zy})))\sin(\theta_{zy}))^2 + ((R_{zy})_{t_0}(1 + k_{zy}(1 - \cos(\theta_{zy})))\cos(\theta_{zy}))^2}} = d_{t_1}\right]$$

$$\boxed{\Rightarrow \beta_1 k_{sto} + \beta_2 k_{gn} + \beta_3 k_{zy} + \beta_4 k_{sto}^2 + \beta_5 k_{gn}^2 + \beta_6 k_{zy}^2 + \beta_7 k_{sto} k_{gn} + \beta_8 k_{gn} k_{zy} = \beta_9}$$

Model Computation (contd.)

Linear and Non-linear constraints on growth parameters

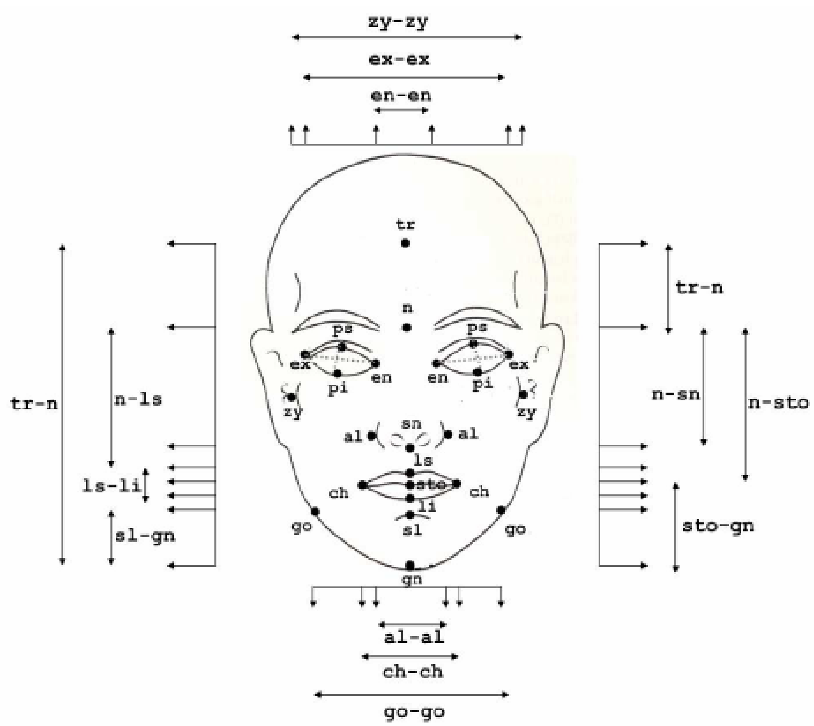
$$r_1 : \left[\frac{n-gn}{zy-zy} = c_1\right] \equiv \ \alpha_1^{(1)} k_1 + \alpha_2^{(1)} k_7 + \alpha_3^{(1)} k_{12} = \beta_1$$

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

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

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

$$+ \alpha_5^{(4)} k_7^2 + \alpha_6^{(4)} k_{12}^2 + \alpha_7^{(4)} k_4 \ k_7 + \alpha_8^{(4)} k_7 \ k_{12} = \beta_4$$



Glossary

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

c_i $\longrightarrow$ Ratios of age-based facial measurements

Computing Growth Parameters

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

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

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

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

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

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

$$\phi(\mathbf{x}) = |\mathbf{x}|^2\log(|\mathbf{x}|)$$

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

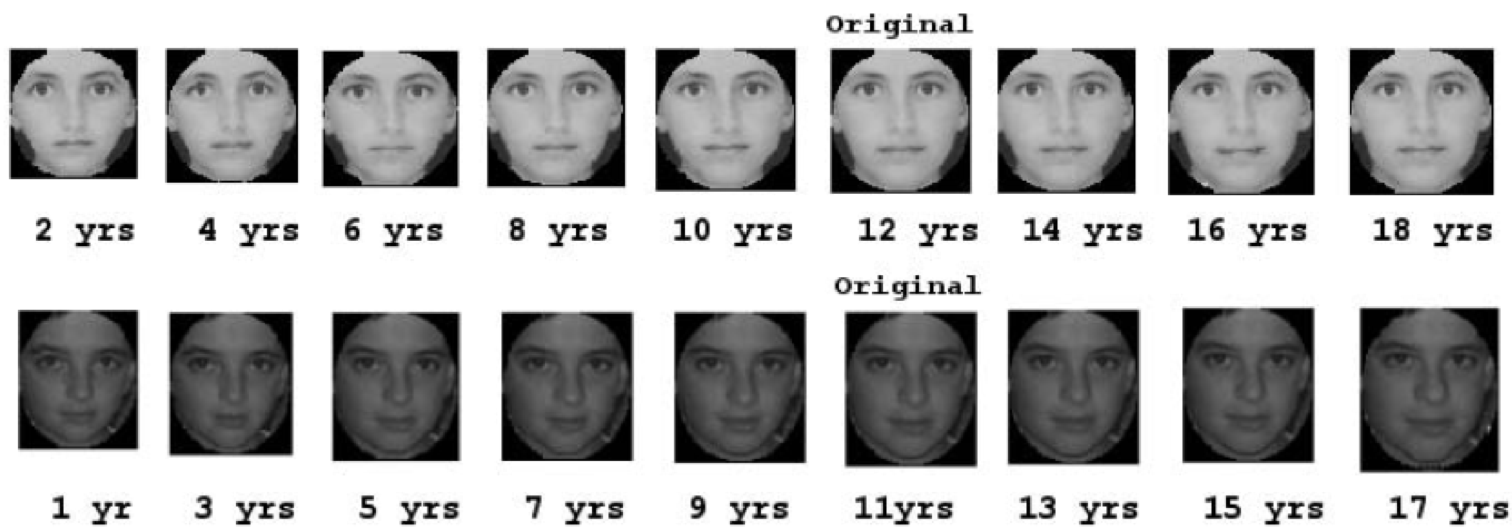
Age Transformation Results

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

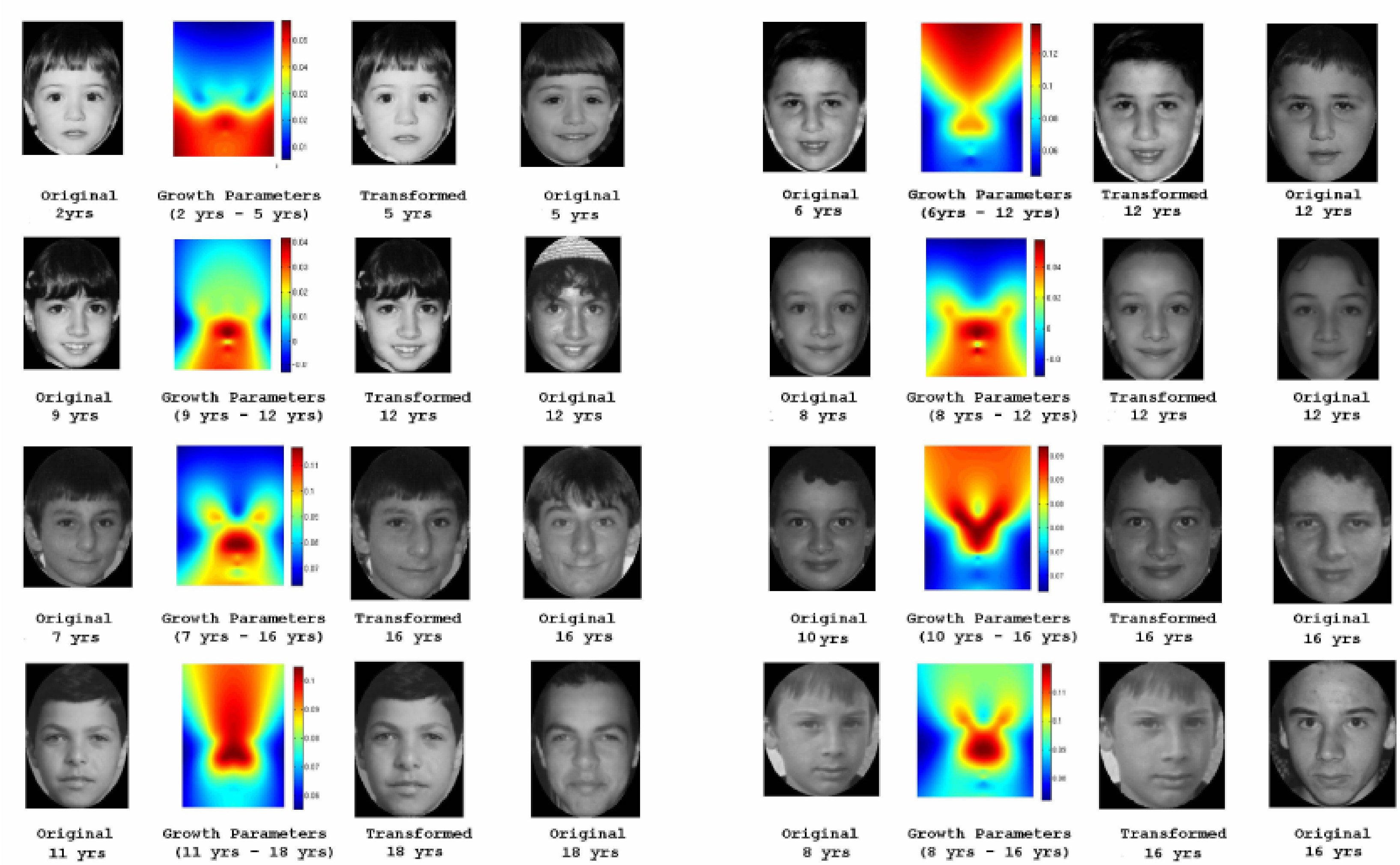
A transformation from ‘p’ years to ‘q’ years : $q > p$

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

A transformation from ‘p’ years to ‘q’ years : $q < p$



Age Progression Results :



Face recognition across Age Progression

- On a database of 233 images of 109 individuals (a few individuals with multiple age separated images), we perform a face recognition experiments (eigenfaces)

- For each probe image (age known apriori), the gallery images are transformed before performing face recognition.

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

Discussion and Conclusions

- The craniofacial growth model computes growth parameters that are unique to each individual. Further, it takes into account the individual's gender, ethnic origin etc.

- The craniofacial growth model can be used to perform face recognition and face verification across age transformations for children. It provides better feature alignment across age transformations.

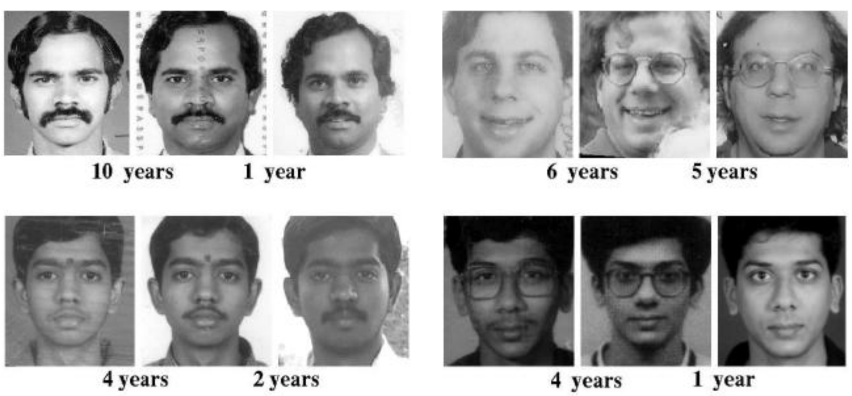
- The proposed model does not account for the loss of facial fat in infants. Further, it does not model variations in facial textures.

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

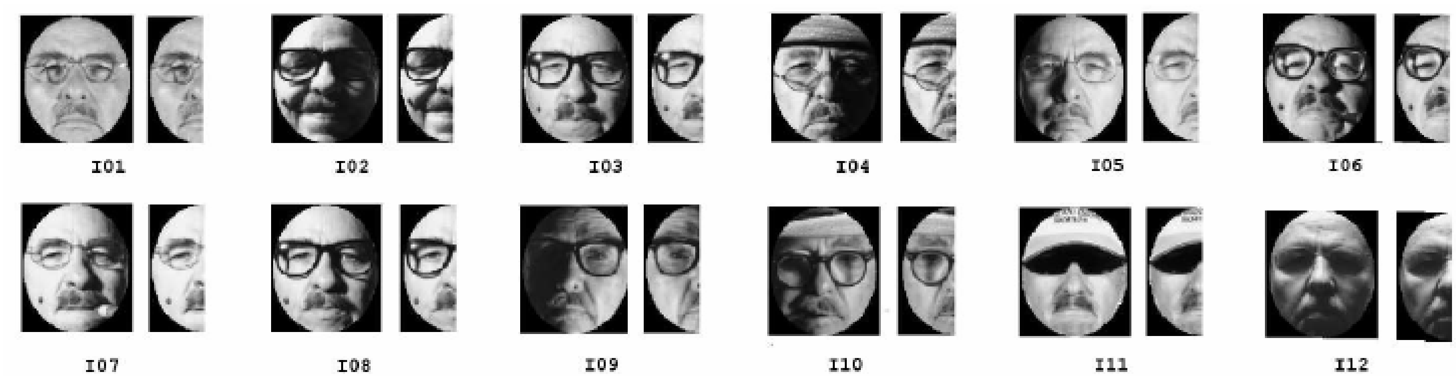
Illumination and Pose compensation :

- Often, the illumination conditions under which two face images (age separated) of an individual were taken, differ. Further, age separated face images differ in head pose orientations.

- In passport images, head pose variations are subtle. Though illumination conditions are controlled in general, there were instances of self shadows due to unbalanced illumination.

- We draw inspiration from Vetter's 3D morphable model approach and propose a method to correct for subtle pose variations in faces.

Illumination compensation : Half-Faces



$$\bar{X}^{(i)}_{MIC} = \frac{(X^i_c - \bar{X}^i_c)}{\| X^i_c - \bar{X}^i_c \|}$$

→ Mean Intensity Curve

$$MIC_d = \| \bar{X}^{(1)}_{MIC} - \bar{X}^{(2)}_{MIC} \|$$

$$\bar{X}_{OptimalMIC} \triangleq \frac{1}{2N} \sum_{i=1}^{N} (\bar{X}^{(1)}_{MIC_i} + \bar{X}^{(2)}_{MIC_i})$$

→ Optimal Mean Intensity Curve

$$j = \min_{i=1,2} \| \bar{X}_{OptimalMIC} - \bar{X}^{(i)}_{MIC} \|$$

Half-faces : Evaluation

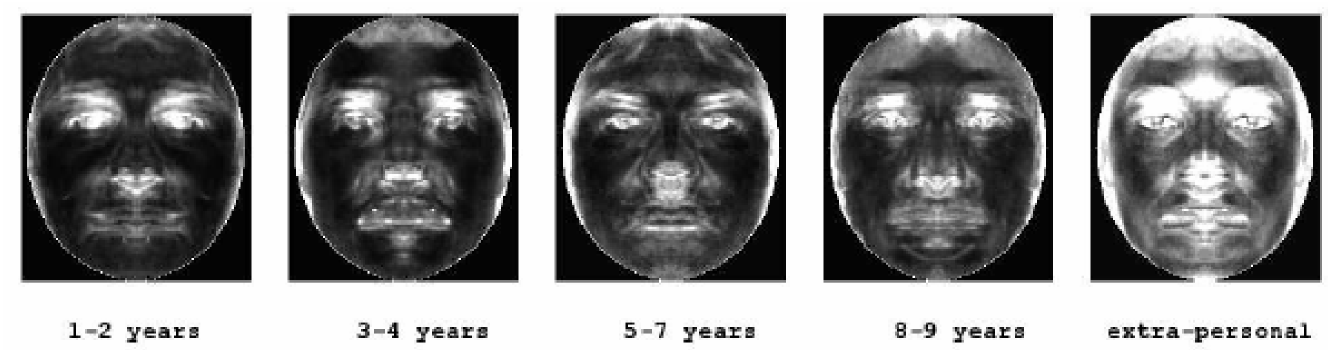
A face recognition experiment (round-robin fashion) on the PIE dataset gave a **27 % rise** in performance while using PointFive faces

f02 f03 f04 f05 f10 f13 f15 f16 f22

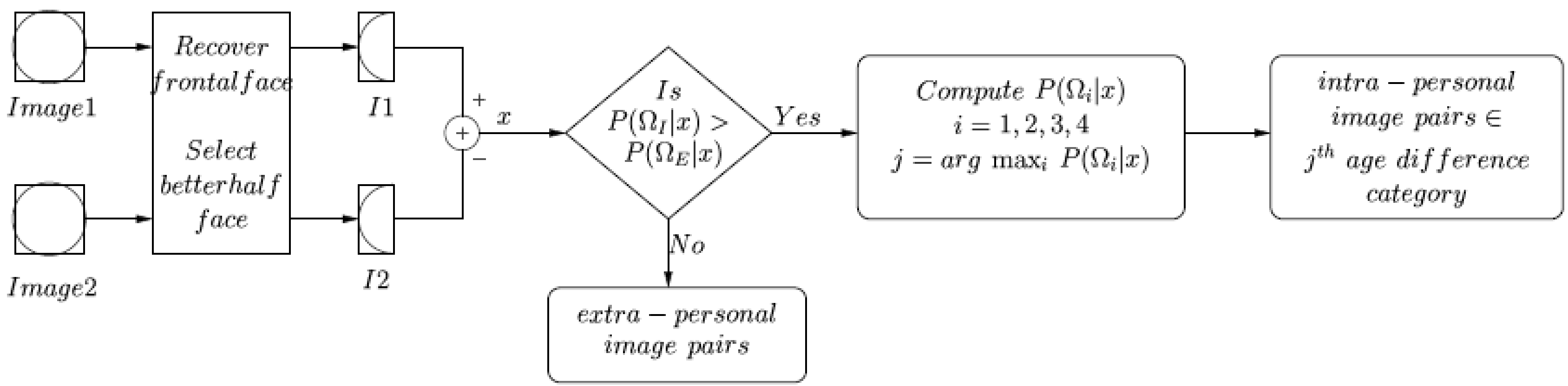
Half-faces vs Full faces [a]: Rank 1 recognition scores (%)										
Gallery		f_{02}	f_{03}	f_{04}	f_{05}	f_{10}	f_{13}	f_{15}	f_{16}	f_{22}
Probes	f_{02}	-	c{97}	93{60}	38{29}	41{26}	29{4}	38{3}	35{3}	32{4}
	f_{03}	99{c}	-	c{c}	60{38}	62{41}	43{4}	41{3}	38{3}	46{3}
	f_{04}	72{44}	c{91}	-	c{84}	97{79}	56{4}	51{1}	40{1}	57{3}
	f_{05}	29{12}	47{21}	99{41}	-	c{c}	50{6}	37{4}	26{1}	51{6}
	f_{10}	26{10}	54{16}	97{49}	c{c}	-	56{6}	37{4}	18{4}	51{6}
	f_{13}	21{3}	41{3}	51{7}	53{6}	65{7}	-	97{68}	57{32}	c{c}
	f_{15}	44{3}	51{4}	51{4}	28{4}	26{4}	99{90}	-	97{82}	c{c}
	f_{16}	46{3}	46{4}	32{4}	18{4}	22{4}	82{49}	99{96}	-	90{65}
	f_{22}	29{3}	46{3}	54{4}	49{6}	37{7}	99{c}	c{c}	66{47}	-
Mean		46{22}	61{30}	72{54}	56{34}	56{34}	64{33}	63{35}	47{22}	66{36}

Age Difference Classifier :

- In adults, facial aging effects are manifested in the form of wrinkles and other skin artifacts. Loss in elasticity of muscles, loss in facial fat etc. results in the sagging of facial features and hence wrinkles appear on faces.
- In our formulation, the age difference classifier is based on the difference image obtained from age separated face images.



Age Difference Classifier : Overview



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

if intra-personal

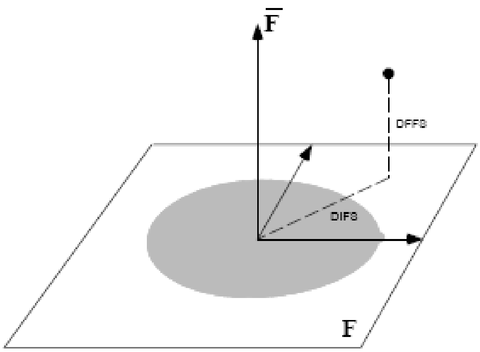
$$P(\Omega_i|\mathbf{x}) = \frac{P(\mathbf{x}|\Omega_i)P(\Omega_i)}{\sum_{j=1}^{4} P(\mathbf{x}|\Omega_j)P(\Omega_j)}$$

Age-difference based intra-personal class

Age Difference Classifier (contd)

Subspace Density Estimation : Intra Personal class

Assume Gaussian distribution of Intra – personal image differences



(Courtesy : Moghaddam 1997)

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

Principal subspace and its orthogonal complement for Gaussian density

Marginal density in F space

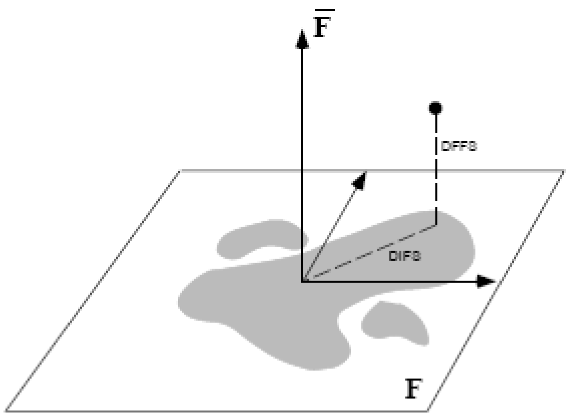
Marginal density in complementary space

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



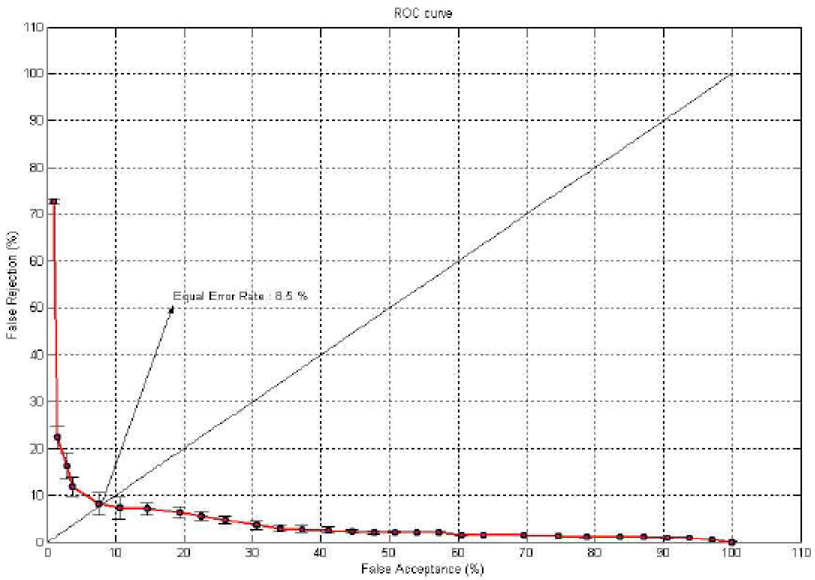
(Courtesy : Moghaddam 1997)

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

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

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

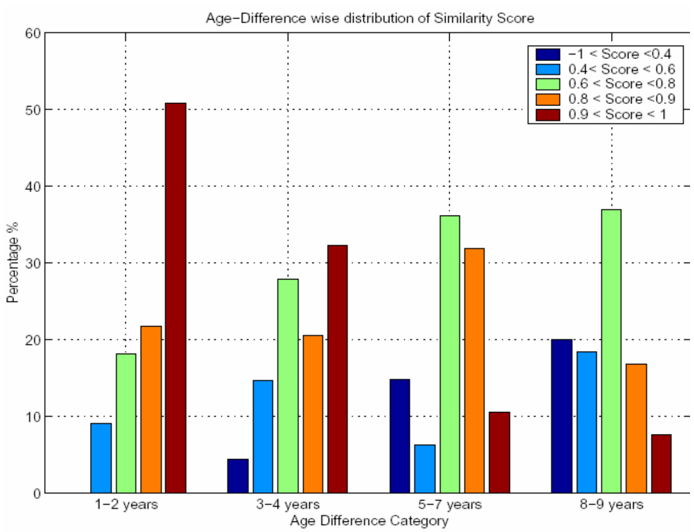
Experimental Results



Type	Class	1-2 yrs	3-4 yrs	5-7 yrs	8-9 yrs
Original set of images	Ω_1	**41.0 (1.1)**	12.0 (6.9)	9.0 (5.0)	38.0 (7.2)
	Ω_2	8.0 (5.0)	**46.0 (5.6)**	8.0 (4.9)	37.0 (9.2)
	Ω_3	10.0 (3.3)	8.0 (6.3)	**53.0 (4.4)**	28.0 (6.9)
	Ω_4	10.0 (2.3)	12.0 (7.3)	5.0 (5.4)	**73.0 (8.2)**

- 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

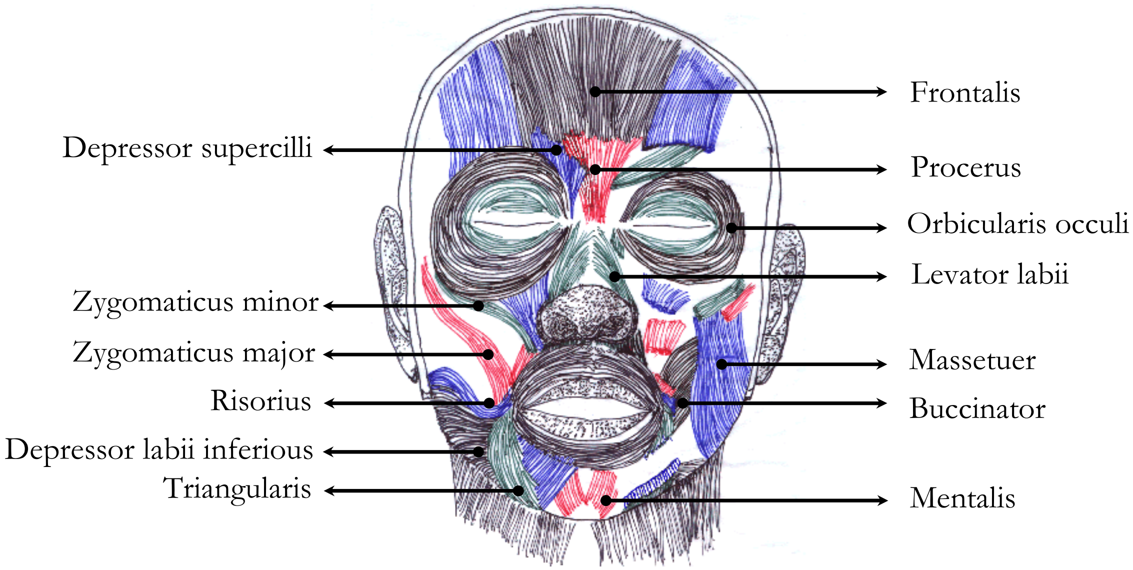
Future Work

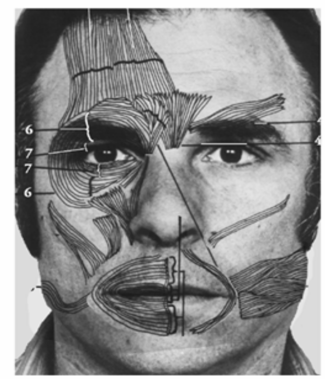
- <u>Modeling Age Progression in Adult Faces</u>

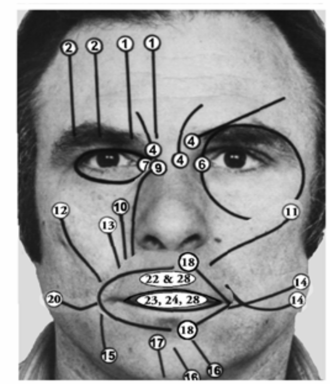
  Some of the reasons attributed to the appearance of wrinkles and other skin artifacts on faces are

  - Loss of elasticity of facial muscles & skin : This results in the sagging of facial features
  - There exists a layer of subcutaneous fat between the skin layer and the muscle layer. Loss of facial fat also causes furrows and wrinkles
  - Repetitive facial expressions
  - Overexposure to sun's rays, smoking etc.

Future Work (contd.)







- Facial muscle characterization has been used to analyzing facial expressions.
- FACS (Facial Action Coding Systems) provides a detailed analysis of the role of different muscles in causing different facial expression. Muscle orientation, degree of freedom are discussed.

Future Work (contd.)

- Keith Waters (1987) proposed models for different facial muscles : Linear muscle, Sheet muscle, Sphincter muscle – based on muscle orientations and degrees of freedom.

- Objectives :
  - Characterizing the elastic properties of facial muscles as a function of age.
  - Developing a realistic skin model where wrinkles and other artifacts can be simulated by varying functions of facial muscles.

Future Work

- Modeling age progression in Infants : Developing a craniofacial growth model that would take into account the loss of facial fat that is commonly observed in infants

- Automatic age estimation : Developing an anthropometry based age classification approach for the age category : 0 – 18 years

Thank You