

Face Image Analysis Applications

Probabilistic Morphable Models

Summer School, June 2017

Thomas Vetter

University Basel

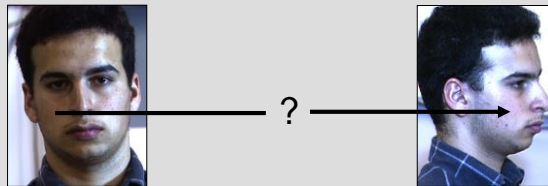


UNIVERSITÄT BASEL

> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE

Face Identification by Image Comparison

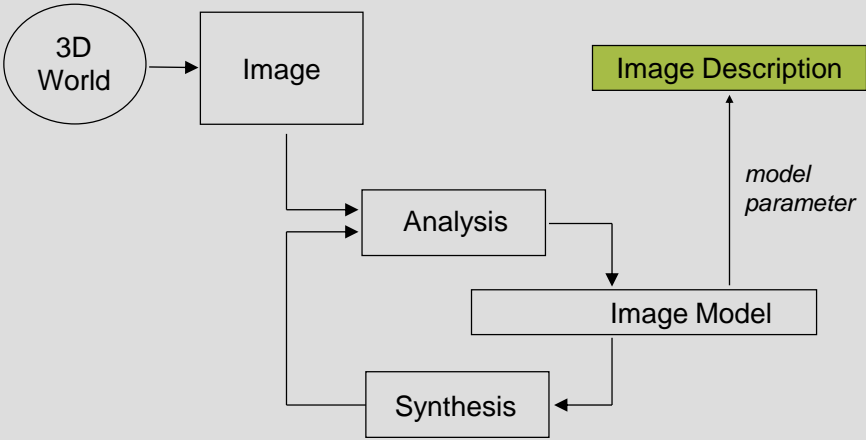
... done by pixel analysis



But which pixel to compare with which ?

Shape information tells us which pixel to compare

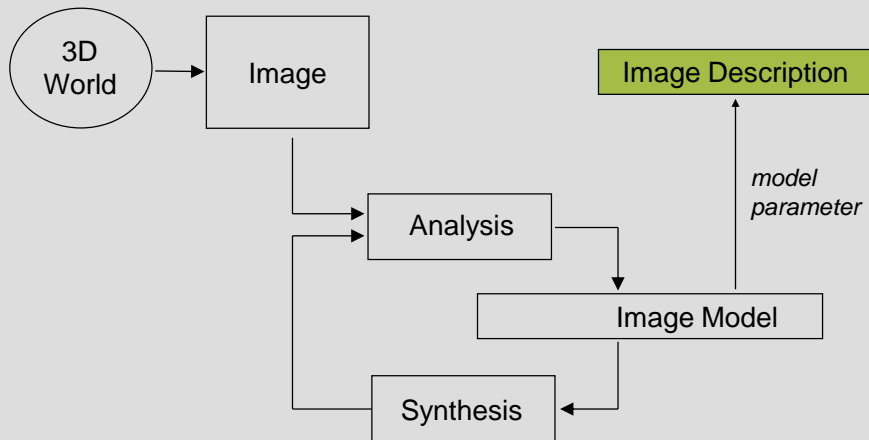
Analysis by Synthesis



Change Your Image ...



Analysis by Synthesis



THE BIG QUESTION:

How is this Image Model structured?

Is it:

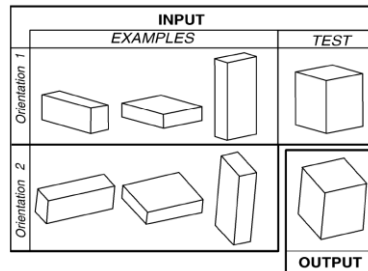
2D, an image based rendering model?

Or

3D, a full 3D computer graphics model?

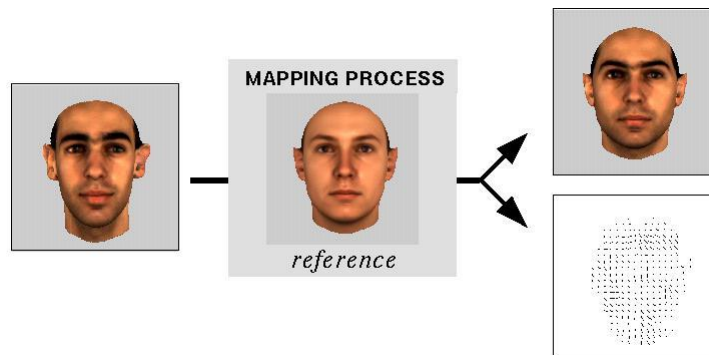
Possibly, there is no final answer!

Linear Object Class Idea

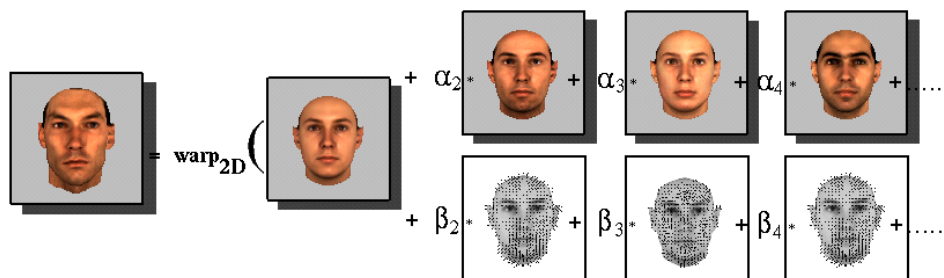


Linear Object Classes and Image Synthesis from a Single Example Image.
Thomas Vetter and Tomaso Poggio *IEEE PAMI* 1997, 19(7), 733-742.

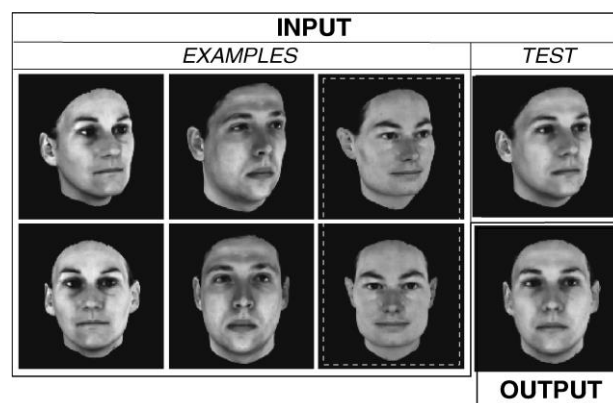
Separating shape and texture in 2D images



2D Morphable Face Image Model



Linear Object Class Idea



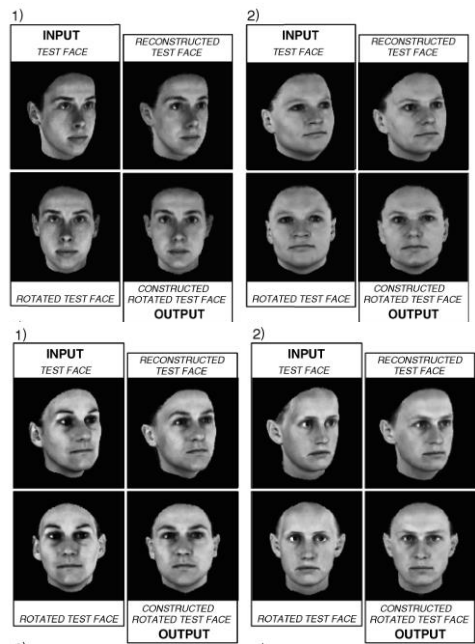
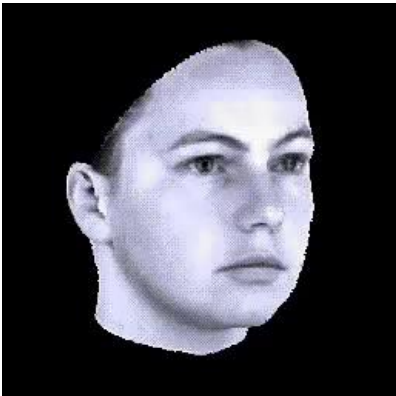
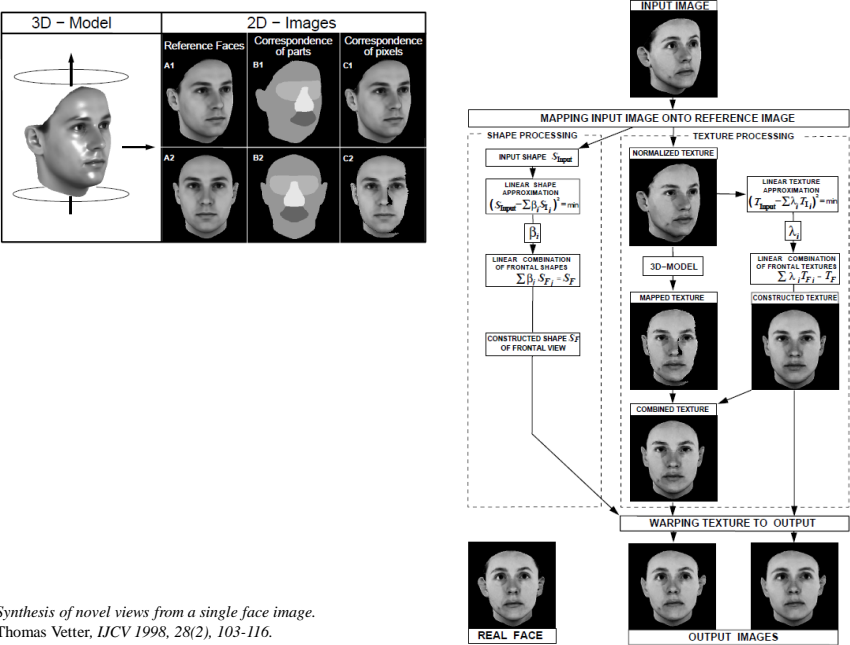


Image based rendering



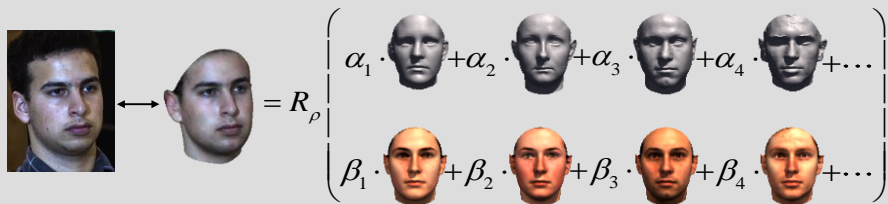


Synthesis of novel views from a single face image.
 Thomas Vetter, IJCV 1998, 28(2), 103-116.

Morphable 2D Face Model

$$\begin{aligned}
 &= a_1 R + a_2 R + a_3 R + a_4 R + \dots \\
 &\quad \beta_1 R + \beta_2 R + \beta_3 R + \beta_4 R + \dots
 \end{aligned}$$

Morphable 3D Face Model



$$= R_{\rho} \left(\begin{array}{l} \alpha_1 \cdot \text{face}_1 + \alpha_2 \cdot \text{face}_2 + \alpha_3 \cdot \text{face}_3 + \alpha_4 \cdot \text{face}_4 + \dots \\ \beta_1 \cdot \text{face}_1 + \beta_2 \cdot \text{face}_2 + \beta_3 \cdot \text{face}_3 + \beta_4 \cdot \text{face}_4 + \dots \end{array} \right)$$

Morphable Models for Image Registration



$$= R_{\rho} \left(\begin{array}{l} \alpha_1 \cdot \text{face}_1 + \alpha_2 \cdot \text{face}_2 + \alpha_3 \cdot \text{face}_3 + \dots \\ \beta_1 \cdot \text{face}_1 + \beta_2 \cdot \text{face}_2 + \beta_3 \cdot \text{face}_3 + \dots \end{array} \right)$$

R = Rendering Function

ρ = Parameters for Pose, Illumination, ...

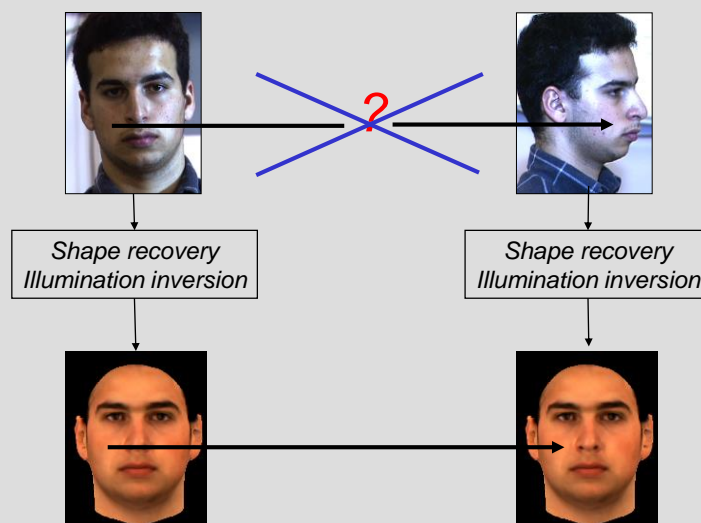
Optimization Problem: Find optimal α, β, ρ !



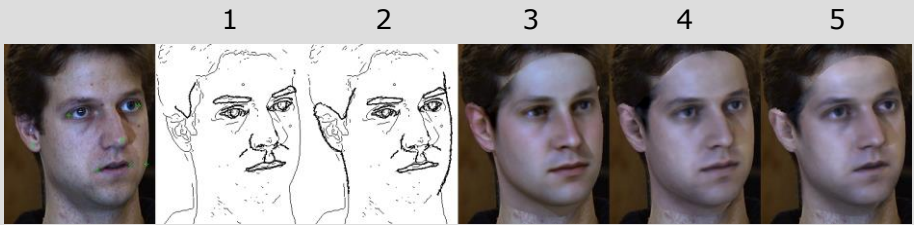
Output

Face Recognition

Normalizing for pose, illumination and ...

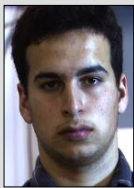


Multi-Features Fitting Algorithm

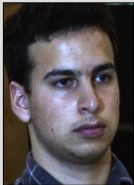
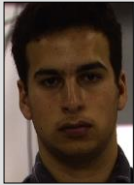


anchor	x				
edge	x	x		x	x
pixel int.			x	x	x
spec. highl.					x
tex. const.				x	x
prior		x	x	x	x

Face recognition

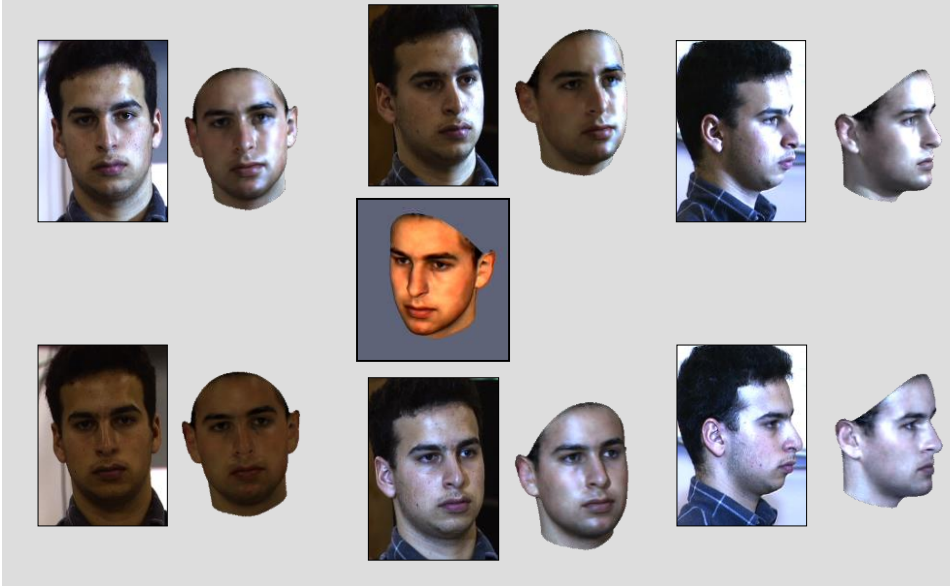


Complex Changes in Appearance

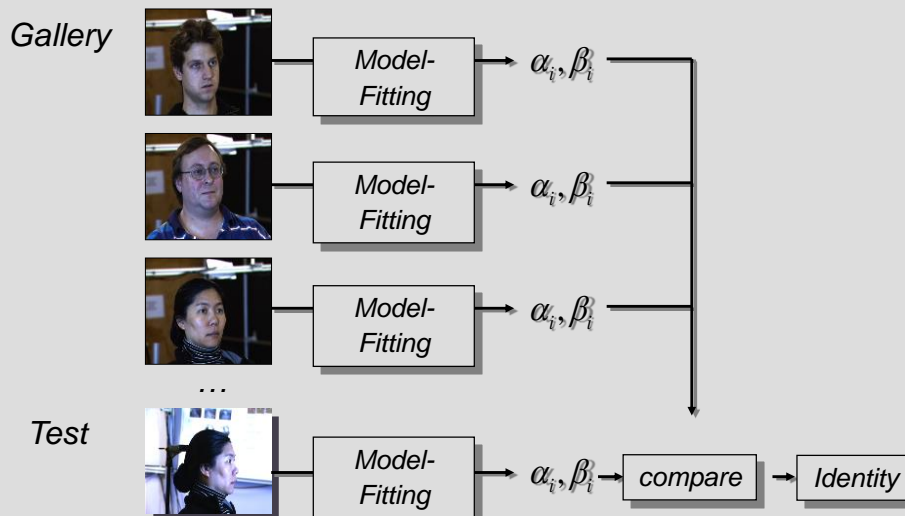


Images: CMU-PIE database. (2002)

3D Morphable Model



Identification by shape and texture coefficients only

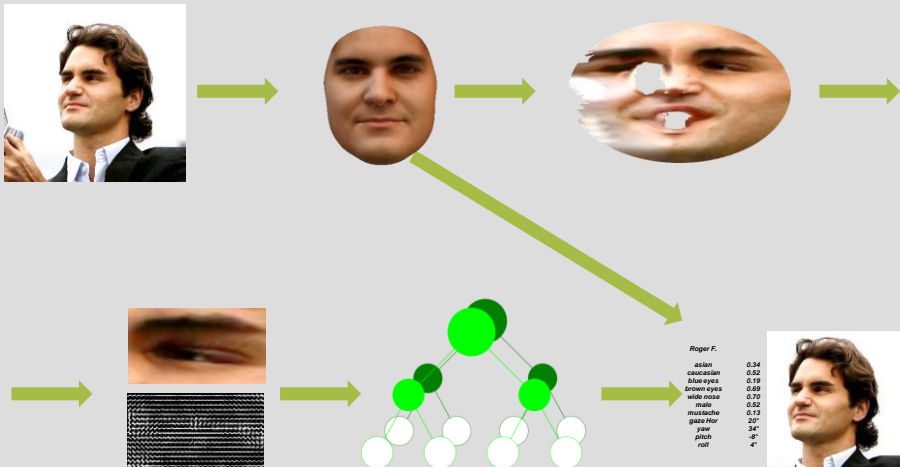


Correct Identification “1 out of 68” (%)

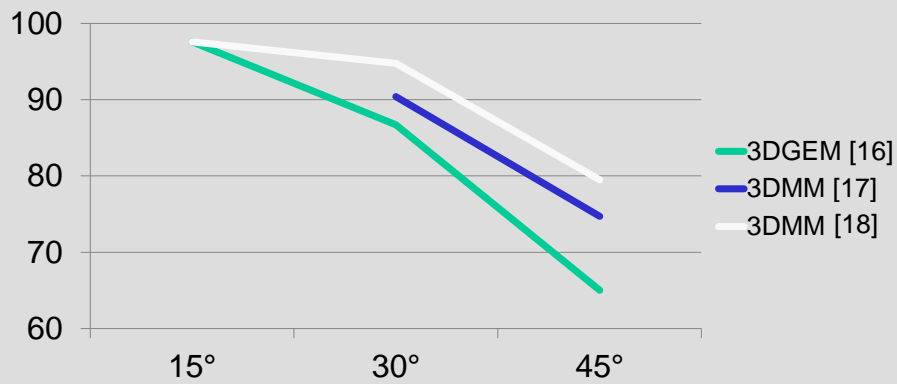
		▶ gallery		
		▶ front	▶ side	▶ profile
▶ probe	▶ front	▶ 99.8	▶ 99.5	▶ 83.0
	▶ side	▶ 97.8	▶ 99.9	▶ 86.2
	▶ profile	▶ 79.5	▶ 85.7	▶ 98.3
	▶ total	▶ 92.3	▶ 95.0	▶ 89.0

CMU-PIE database: 4488 images of 68 individuals
3 poses x 22 illuminations = 66 images per individual

Face analysis



Multi-PIE: Face recognition



[16] Prabhu et al., "Unconstrained Pose-Invariant Face Recognition using 3D Generic Elastic Models", PAMI 2011

[17] Schönborn et al., "A Monte Carlo Strategy to Integrate Detection and Model-Based Face Analysis", GCPR 2013

[18] Egger et al., "Pose Normalization for Eye Gaze Estimation and Facial Attribute Description", GCPR 2014

Try a new hairstyle!



3D Geometry
and Texture



3D Pose, Position
Illumination,
Foreground,
Background



Try a new hairstyle!



3D Geometry
and Texture



3D Pose, Position
Illumination,
Foreground,
Background

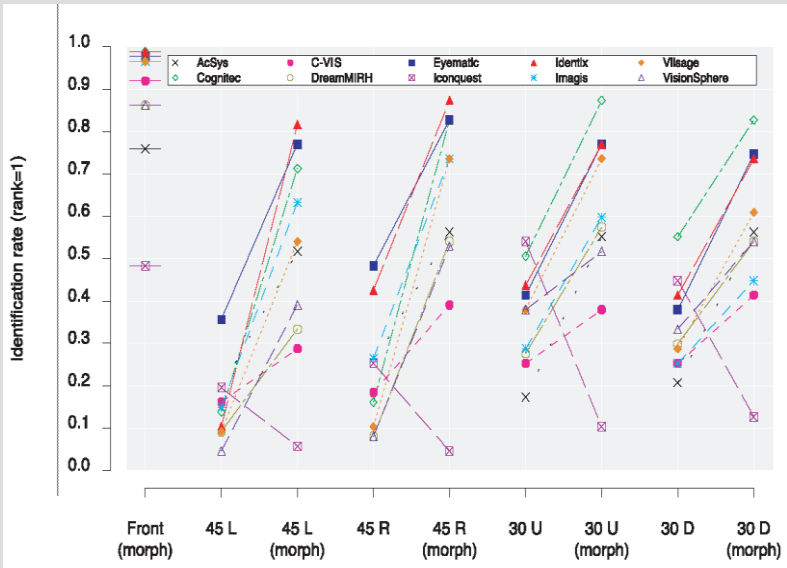


Image Preprocessing for FRVT 2002





Image Preprocessing for FRVT 2002





Skin Detail Analysis for Face Recognition



Skin Detail Analysis for Face Recognition

Jean Sebastian Pierrard , Thomas Vetter CVPR 2007

Overview

Characterizing moles

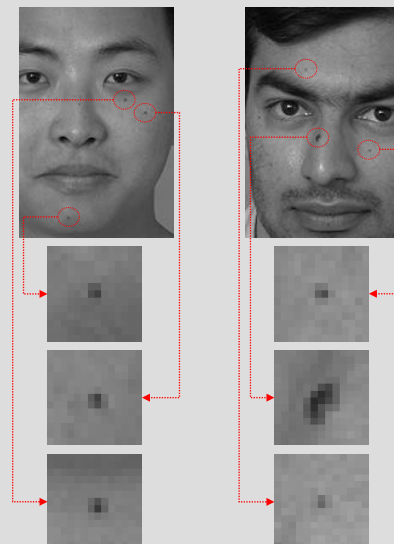
- ▶ Appearance → Blob detection
- ▶ Location → Skin segmentation
- ▶ Importance → Saliency measure

Recognition

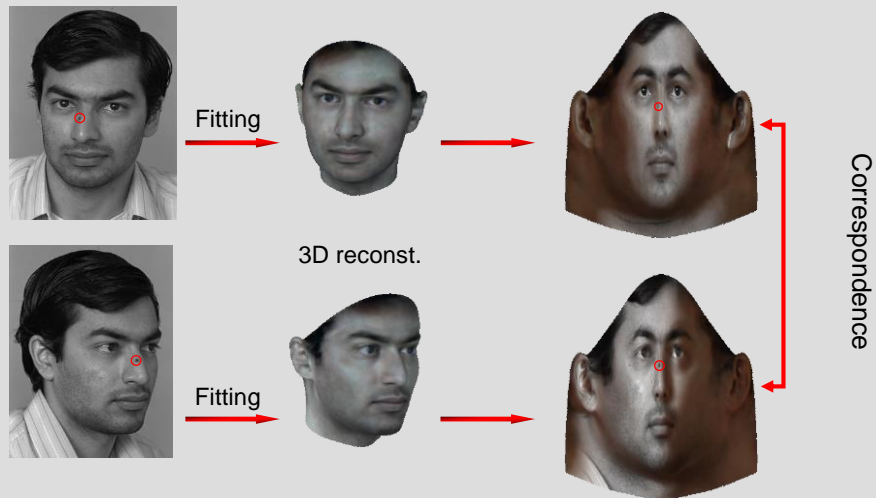
- ▶ Reference System → Morphable Model

Data used

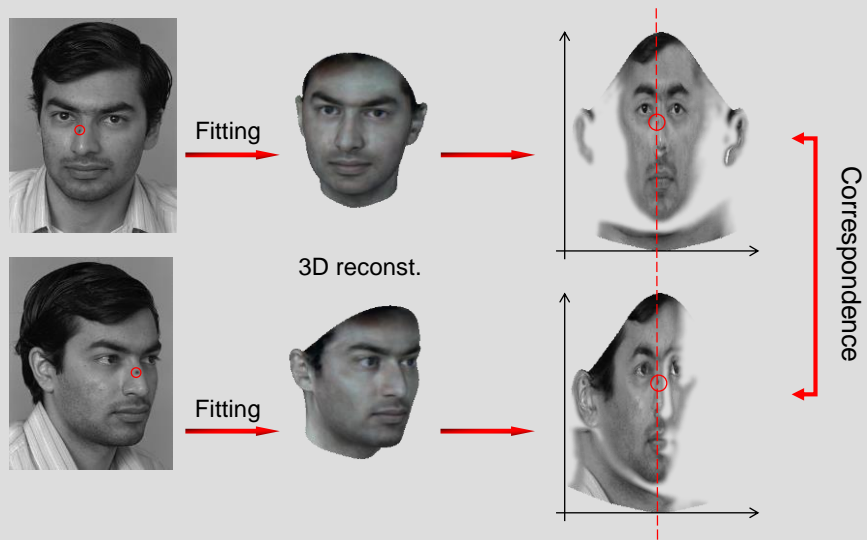
- ▶ Results based on subset of FERET-data base
 - ▶ Gray scale
 - ▶ Medium resolution (10-20k pixels face area)
 - ▶ Mole sizes: 2-20 pixels



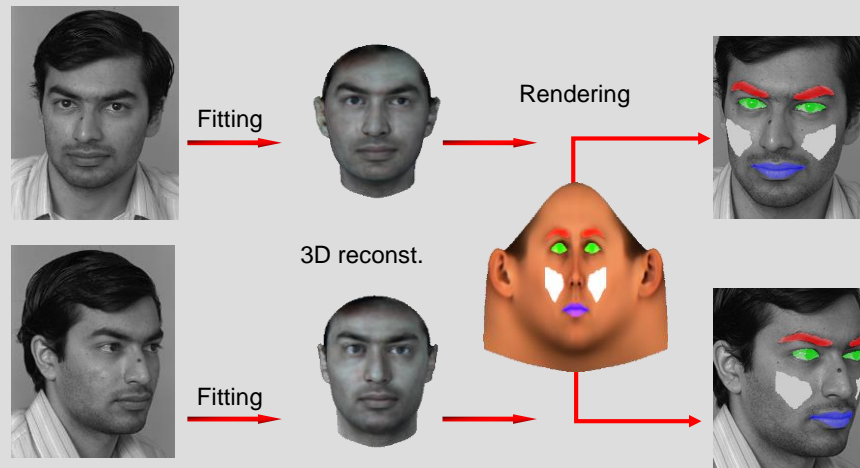
Morphable Model for Correspondence



3DMM maps visible region on a common reference

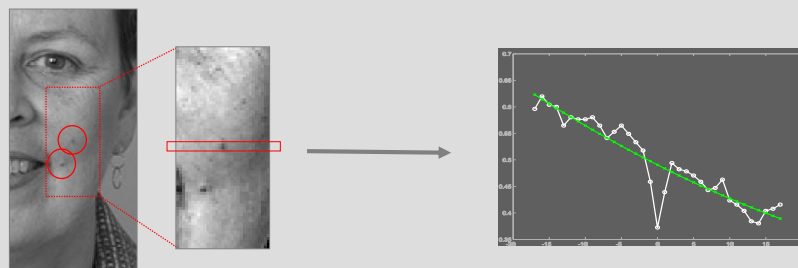


Morphable Model for Correspondence II

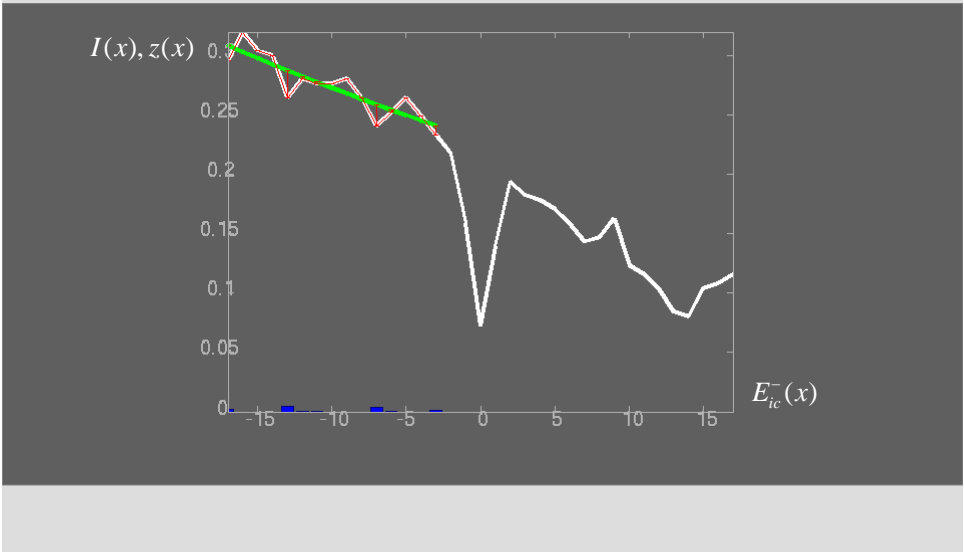


Mole Detection: Shading Problem

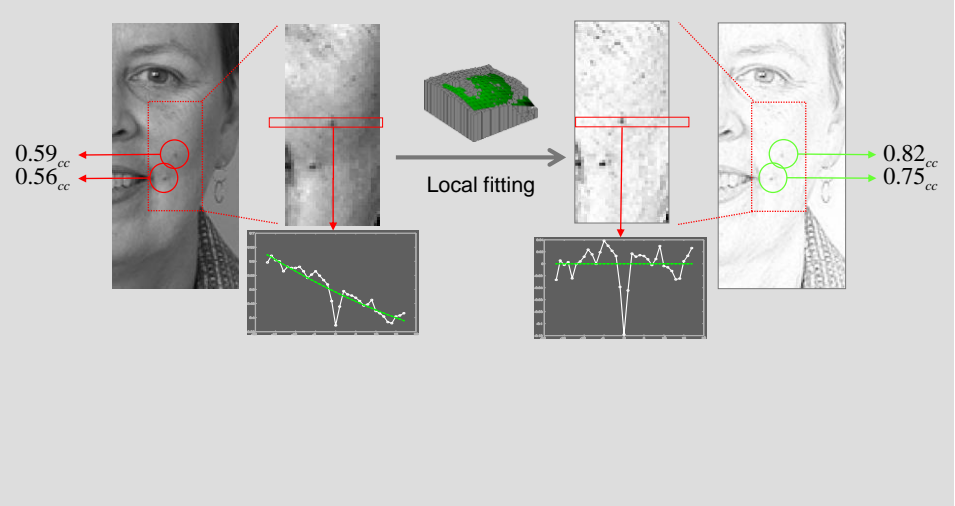
- Template matching is sensitive to intensity gradients !



Illumination Compensation

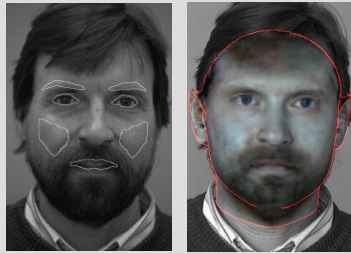


Mole Detection: Shading Problem



False Positives

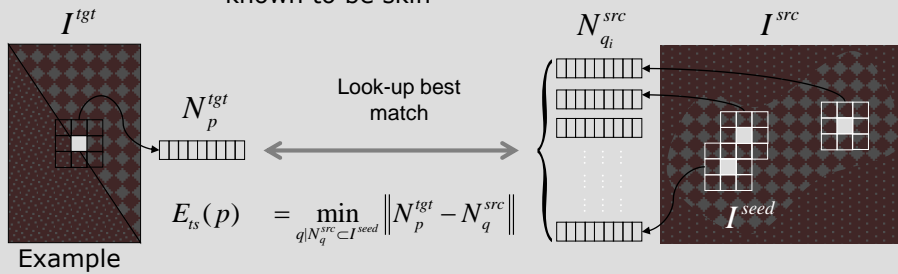
- ▶ Templates also match common facial features
- ▶ Sporadic hits due to hairstyle, beard, ...



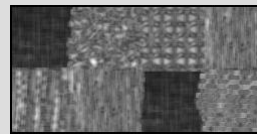
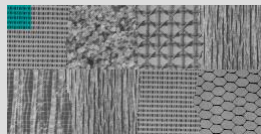
- ▶ We need to mask out non-skin regions / outliers
- ▶ 3DMM is **not** sufficient

(Skin) Texture Similarity

Basic idea: Compare image texture with samples that are known to be skin



Example

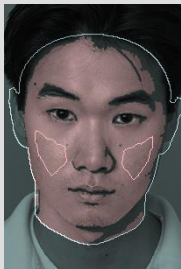


Skin Segmentation

- ▶ Texture similarity facilitates simple segmentation-by-thresholding method
- ▶ Get threshold from seed region:

$$\text{in } I^{skin}(p) = \begin{cases} 1 & \text{if } E_{ts}(p) \leq \max_{q \in I^{seed}} E_{ts}(q) \\ 0 & \text{otherwise} \end{cases}$$

- Result still affected by shading



I^{seed} = "cheeks"

Segmentation Results

Thresholding



GrabCut



Selection by Saliency



Recognition

- Find matching pairs of moles in reference frame



- Identification score:
weighted sum of saliencies from matched points

Face Recognition

- Based only on mole locations and saliency.

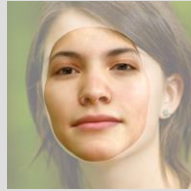
	Saliency threshold (<i>Gallery subset size</i>)					
	5 (156)		10 (107)		15 (83)	
Probe	Fail	Perf.	Fail	Perf.	Fail	Perf.
<i>bc</i>	69	55.77	39	63.55	26	68.67
<i>bd</i>	34	78.20	13	87.85	8	90.36
<i>be</i>	17	89.10	7	93.45	4	95.18
<i>bf</i>	20	87.18	5	95.32	5	93.97
<i>bg</i>	47	69.87	24	77.57	17	79.51
<i>bh</i>	68	56.41	30	71.96	21	74.70
<i>bk</i>	42	73.07	22	79.44	13	84.33

Occlusion-aware 3D Morphable Face Models

Bernhard Egger, Andreas Schneider, Clemens Blumer, Andreas Morel-Forster,
Sandro Schönborn, Thomas Vetter

27th British Machine Vision Conference, September 2016

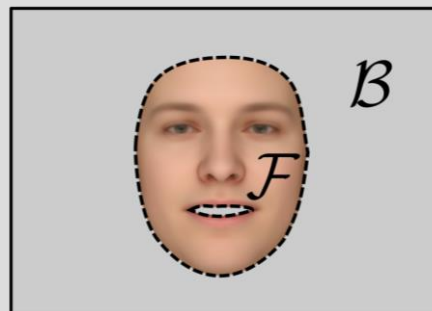
Face Image Analysis under Occlusion



Source: AFLW Database

Source: AR Face Database

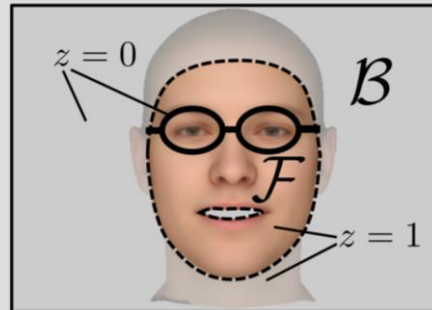
There is nothing like: no background model



$$\ell(\theta; I) = \prod_{x \in I} \ell(\theta; I(x)) = \prod_{i \in F} l_{face}(\theta; \tilde{I}_i) \prod_{i \in B} b(\tilde{I}_i)$$

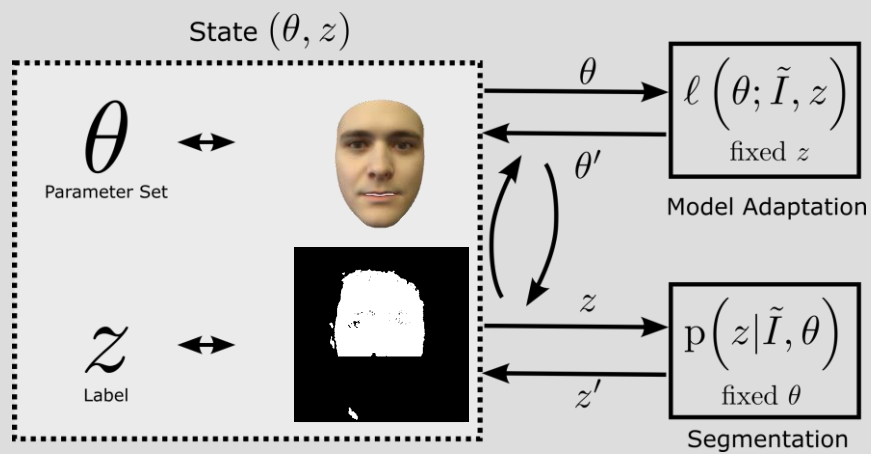
"Background Modeling for Generative Image Models"
Sandro Schönborn, Bernhard Egger, Andreas Forster, and Thomas
Vetter Computer Vision and Image Understanding, Vol 113, 2015.

Occlusion-aware Model

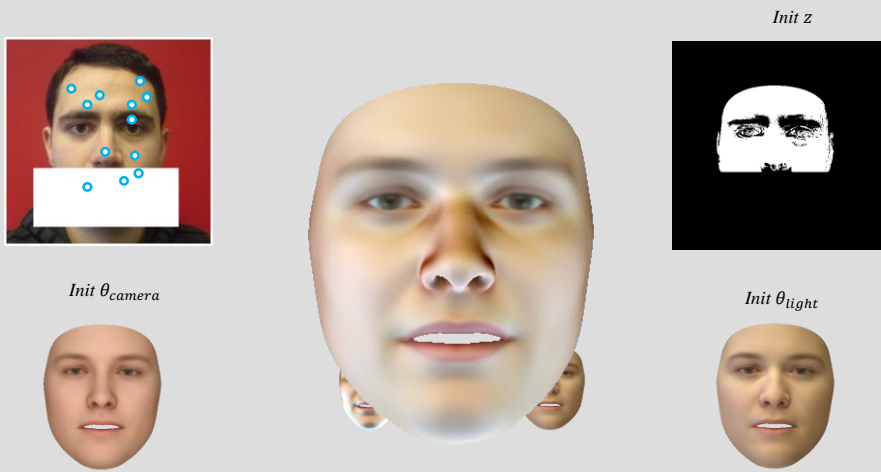


$$l(\theta; \tilde{I}, z) = \prod_i l_{face}(\theta; \tilde{I}_i)^z \cdot l_{non-face}(\theta; \tilde{I}_i)^{1-z}$$

Inference



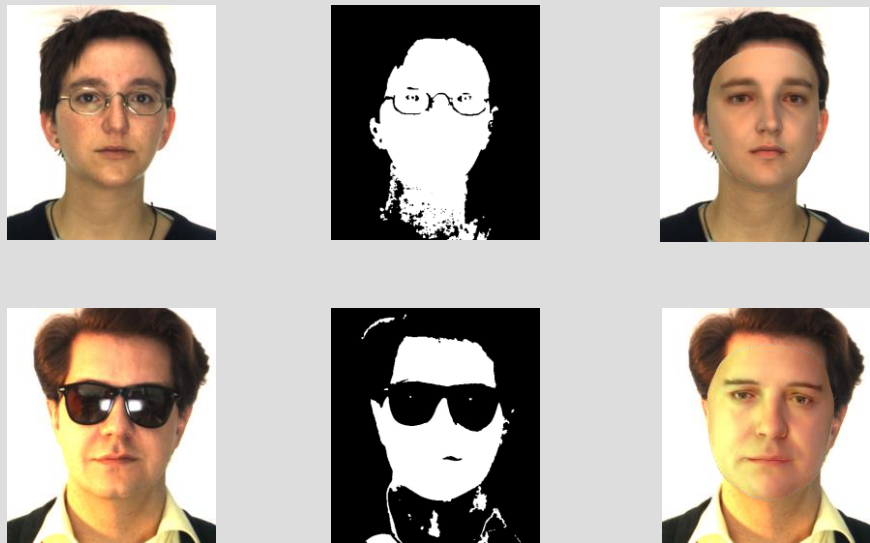
Initialisation: Robust Illumination Estimation



54

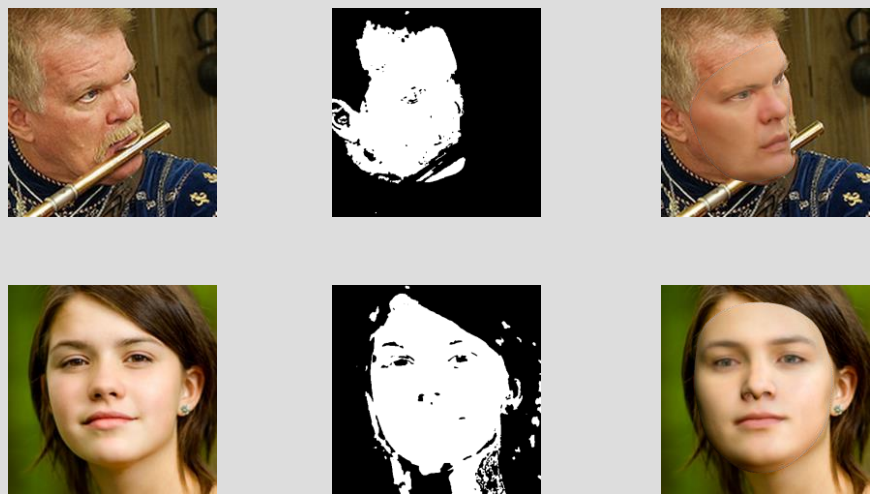
Results: Qualitative

Source: AR Face Database



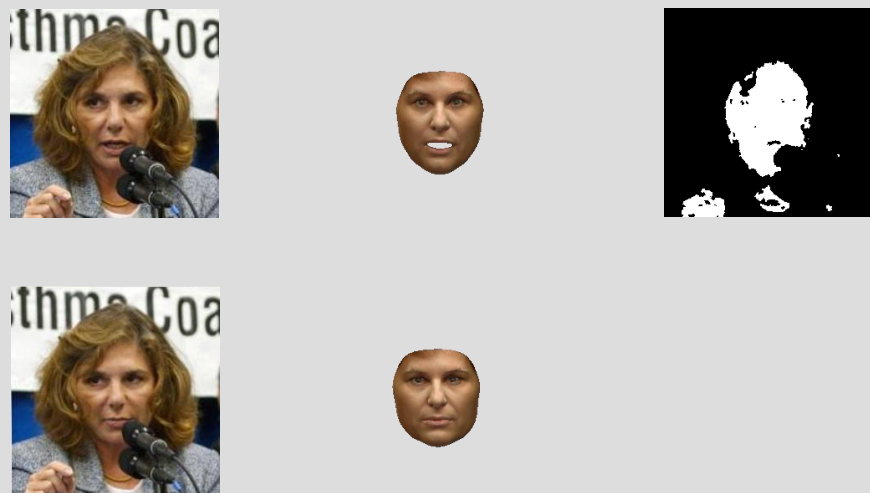
Results: Qualitative

Source: AFLW Database

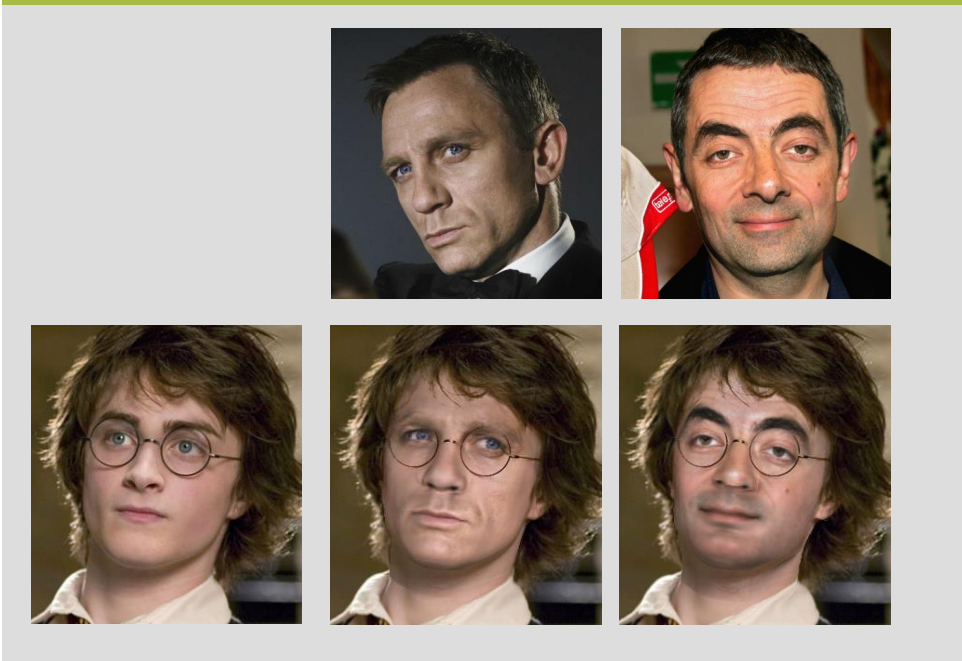
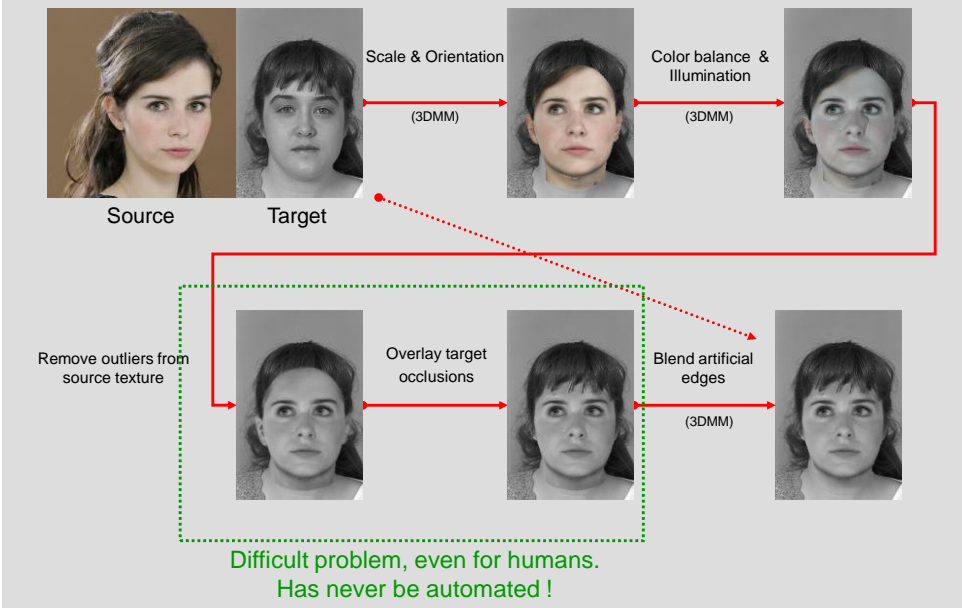


Results: Applications

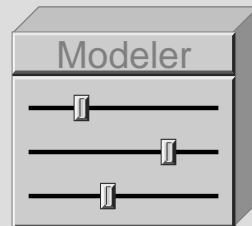
Source: LFW Database



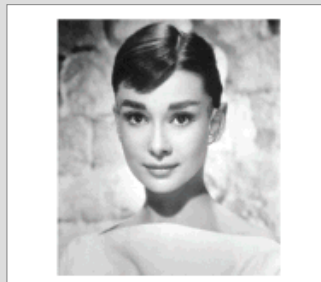
Face Exchange Tasks



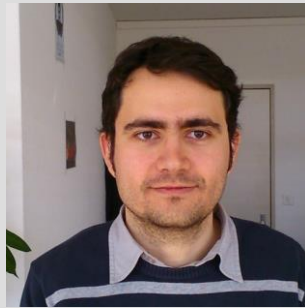
Manipulation of Faces



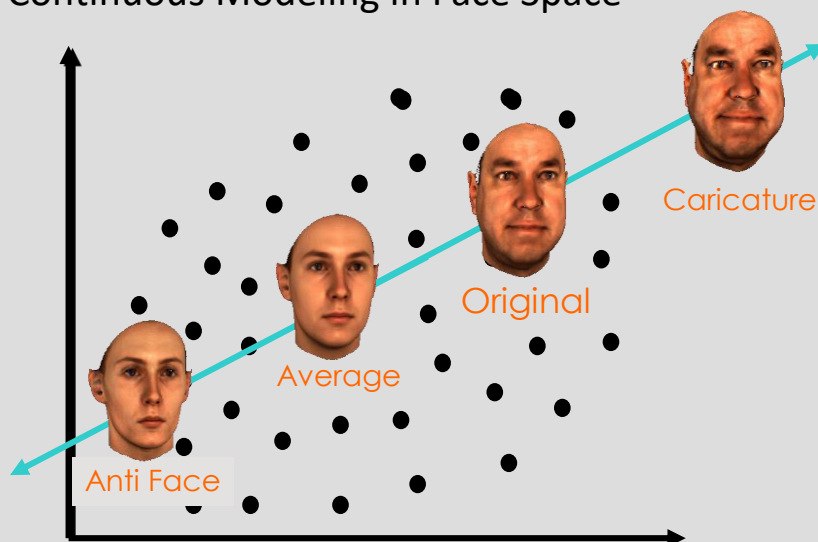
Modeling of 2D Images



Face Image Manipulation

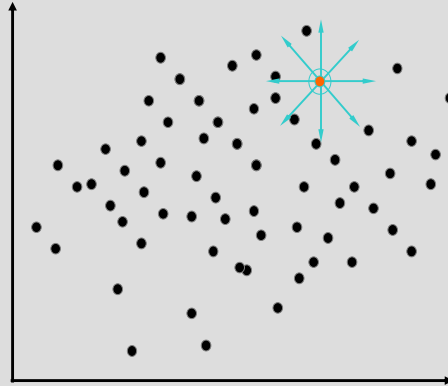


Continuous Modeling in Face Space

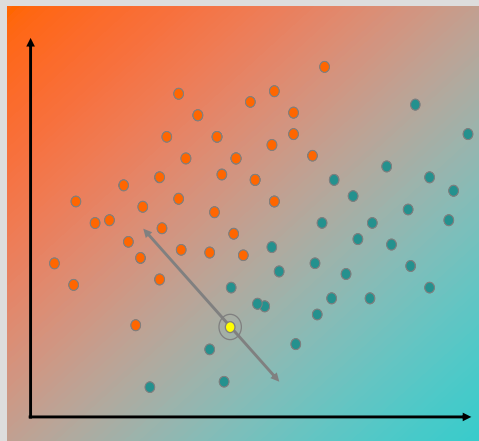


Modeling the Appearance of Faces

- Which directions code for specific attributes ?



Learning from Examples



Attributes of Faces

Gender



Weight



Original

Portraits made to Measure

- Computer can learn to model faces according to „human“ categories.

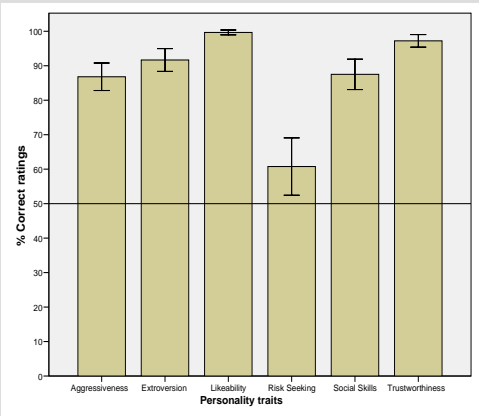


Aggressive



Trustworthy

Portraits made to Measure



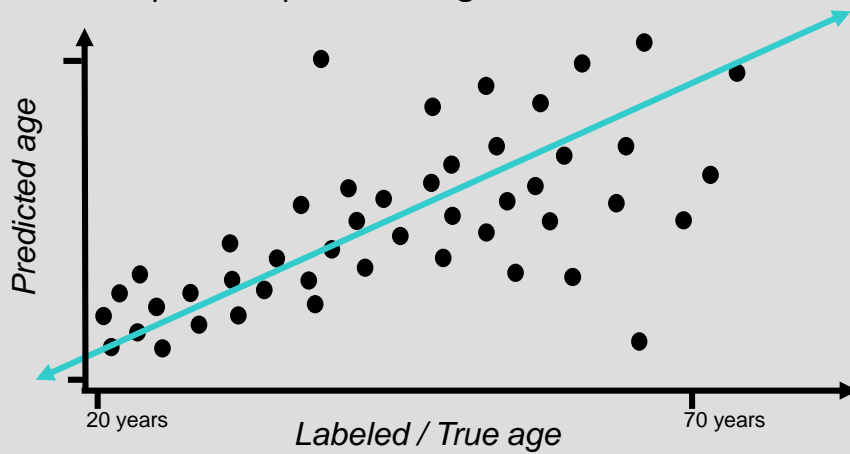
Portraits made to measure:
Mirella Walker and Thomas Vetter
Journal of Vision, 9(11):12, 1-13, 2009

Expressions



Simulation of Aging of Human Faces in Images

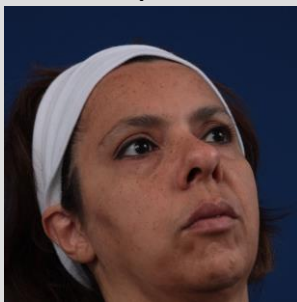
Aging model:
model predicts perceived age



Ageing: linear shape model only



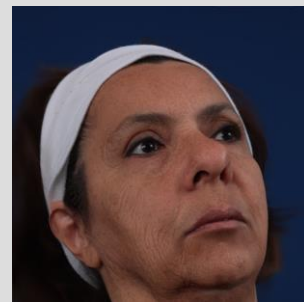
Example-based aging



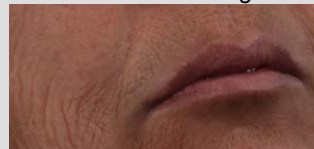
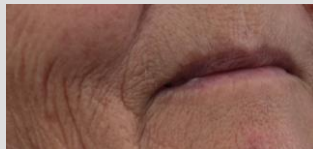
Target Image



Donor Image



*Shape and Skin of donor
transferred to target*



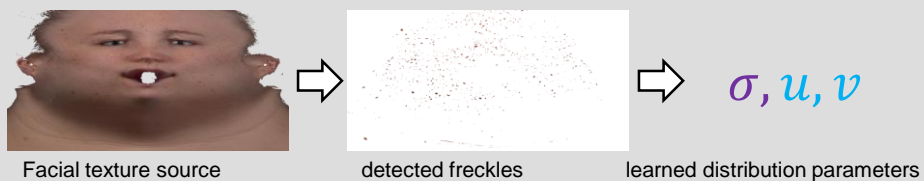
Example-based Texture: The Problem



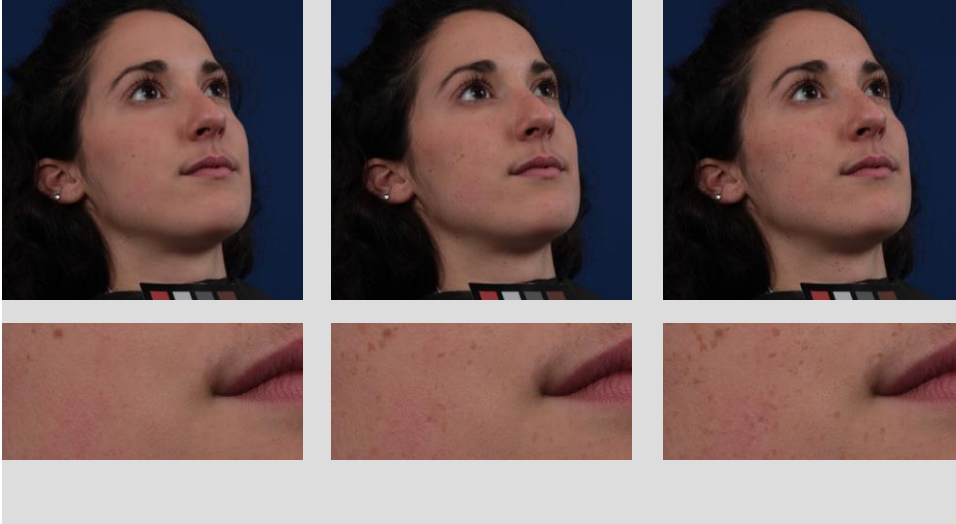
Parametric Pigmentation Model

$$\rho(\mathbf{x}, \mathbf{y}, \sigma) = \sum_{\mathbf{u}, \mathbf{v} \in \Omega} \mathcal{N}((\mathbf{x} - \mathbf{u}, \mathbf{y} - \mathbf{v})^T, \sigma)$$

- ▶ σ regulates the spread
- ▶ \mathbf{u}, \mathbf{v} learned freckle position from example data Ω
- ▶ The parameters $\sigma, \mathbf{u}, \mathbf{v}$ and different freckle shapes are learned by detecting freckles in given faces



Parametric Pigmentation Model



Aging Model

- ▶ Shape: continuous
- ▶ Pigmentation: stochastic
- ▶ Wrinkles: example based

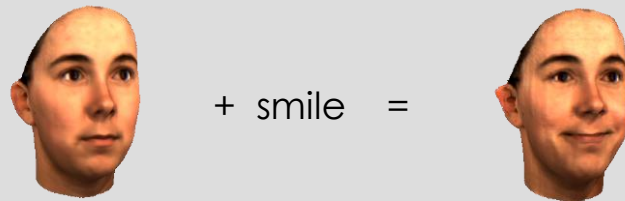


Transfer of Facial Expressions

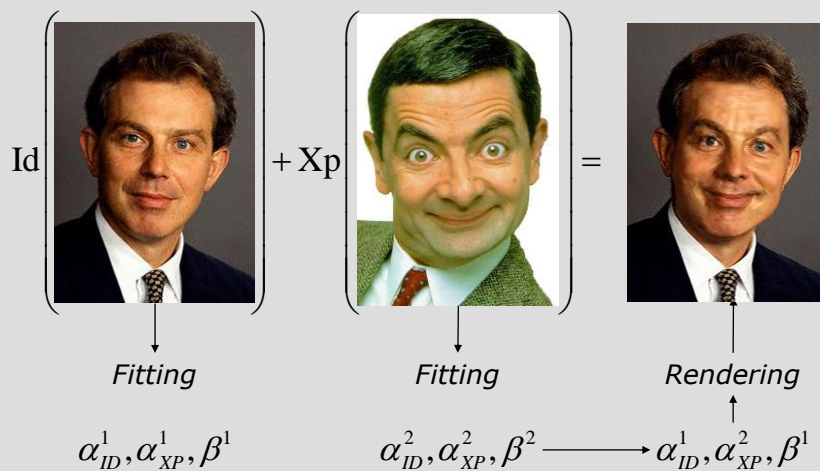
Original:



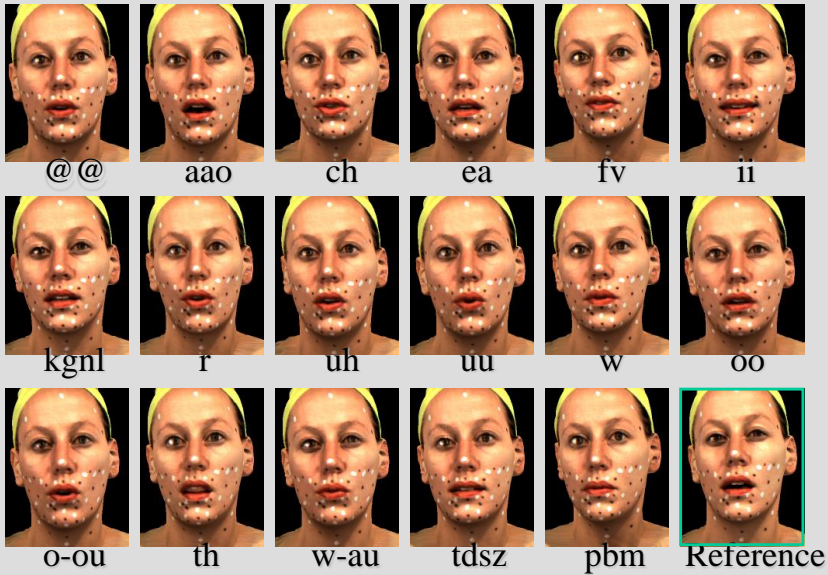
Novel Face:



Expression Transfer



3D Scans of Visemes



Mouth Mesh



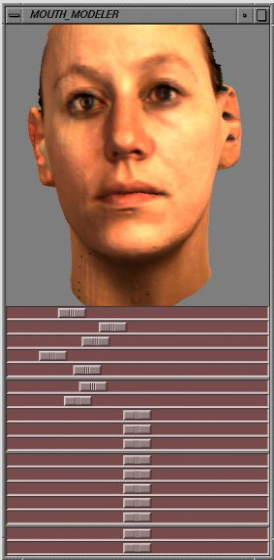
Mouth Modeler

Principal
Components



Mouth Modeler

Principal
Components



Mouth Modeler

Principal
Components



Speech Animation



Retargeting Face Motions

