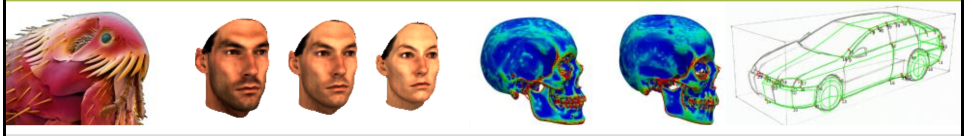


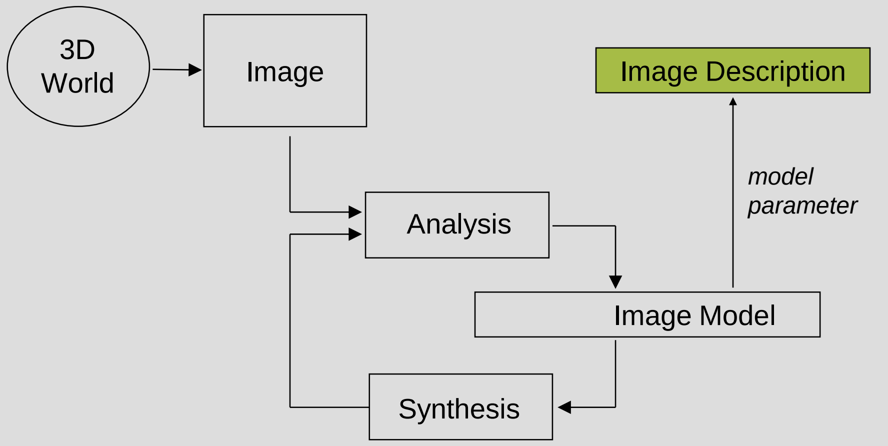
Probabilistic Morphable Models

Thomas Vetter

UNIVERSITÄT BASEL
> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE
Cape Town | 2018

Photo by Pete Souza/The White House via Getty Images.

Analysis by Synthesis

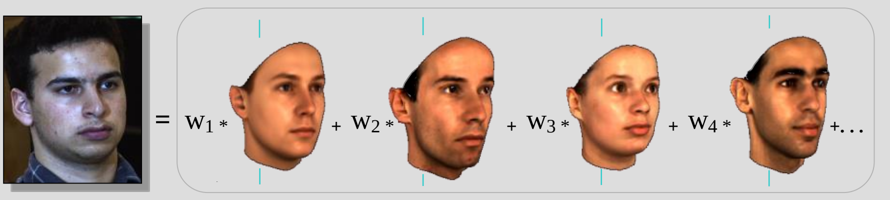


UNIVERSITÄT BASEL
> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE Cape Town | 2018

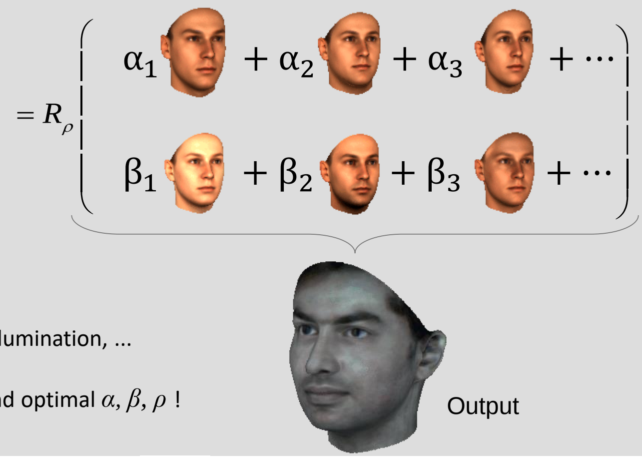
Example based image modeling of faces

2D Image

3D Face Scans



Morphable Models for Image Registration

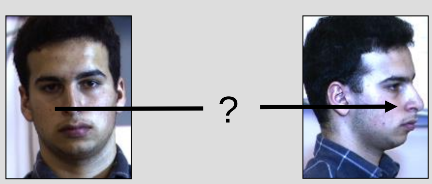


$\boldsymbol{R}$ = Rendering Function
ρ = Parameters for Pose, Illumination, ...

Optimization Problem: Find optimal α, β, ρ !

Probabilistic Morphable Models

1. Model-based image registration using Gaussian Processes for shape deformations



2. *“Probabilistic registration”:* Find the distribution of possible transformations h(θ) that transforms I_R to I_T .

$$P(\theta | I_T, I_R)$$

Gaussian Process Morphable Models:

- A Gaussian process $h \sim GP(\mu, k)$ on X is completely defined by its mean function

$$\mu : X \to \mathbb{R}^3$$

and covariance function

$$k : X \times X \to \mathbb{R}^{3\times 3}$$

- A low rank approximation can by computed using the Nyström approximation.

$$h(\theta) \approx \mu + \sum_i^d \theta_i \sqrt{\lambda_i} \Phi_i$$

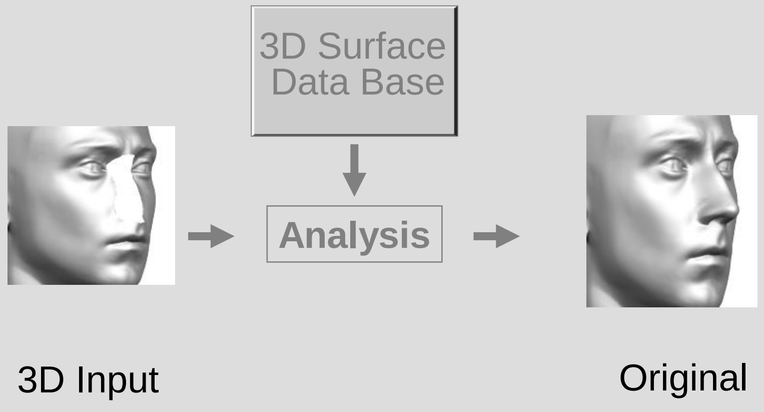
with $\theta \sim N(0, I_d)$

Advantage of Gaussian Process Morphable Models

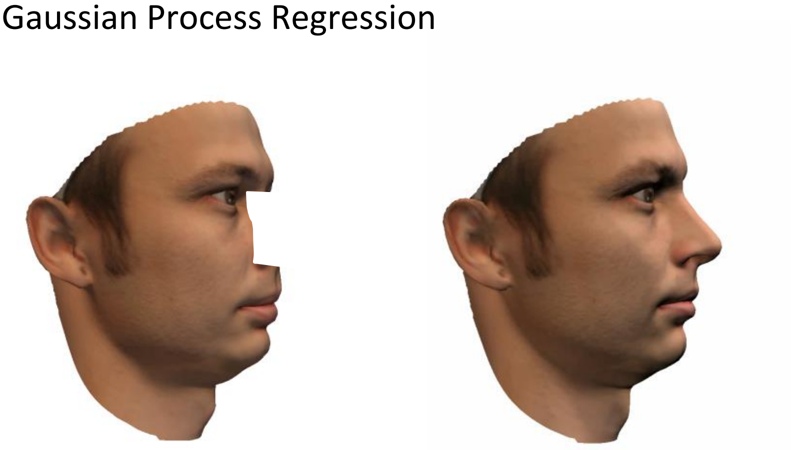
- Probabilistic formalism !
- Extremely flexible concept. By varying the covariance function k a variety of ‘different’ algorithms of deformation modelling are included.
  - Thin Plate Splines
  - Free Form deformations
  - …
  - Standard PCA-Model

“Scalismo” an open source library by Marcel Lüthi
see also our MOOC on FutureLearn “Statistical Shape Modlling”

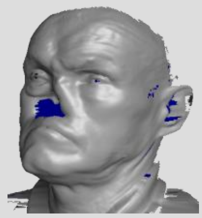
Surface Data Prediction
as Gaussian Process Regression



Surface Data Prediction
as Gaussian Process Regression

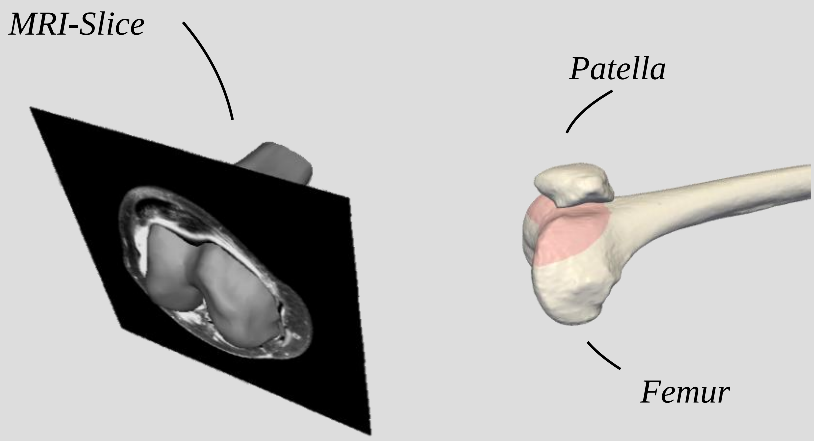


Application

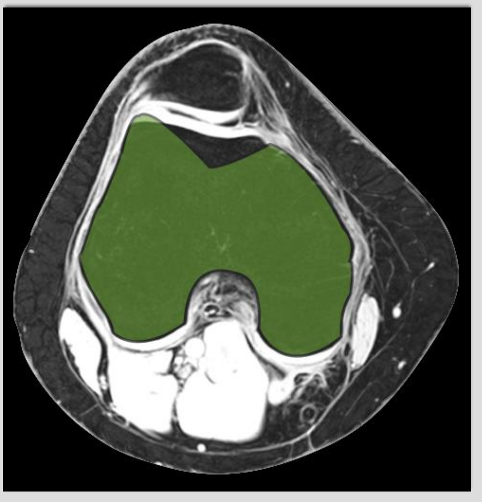
UNIVERSITÄT BASEL
> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE
Cape Town | 2018

Example use-case: Trochlea dysplasia



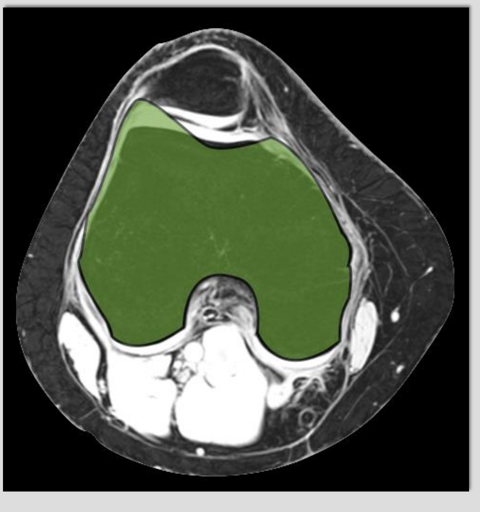
UNIVERSITÄT BASEL
> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE
Cape Town | 2018

Trochlea-Dysplasia



Surgical intervention: Increase goove

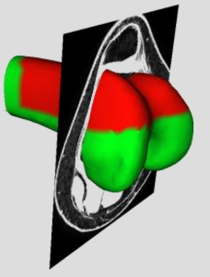
UNIVERSITÄT BASEL
> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE
Cape Town | 2018

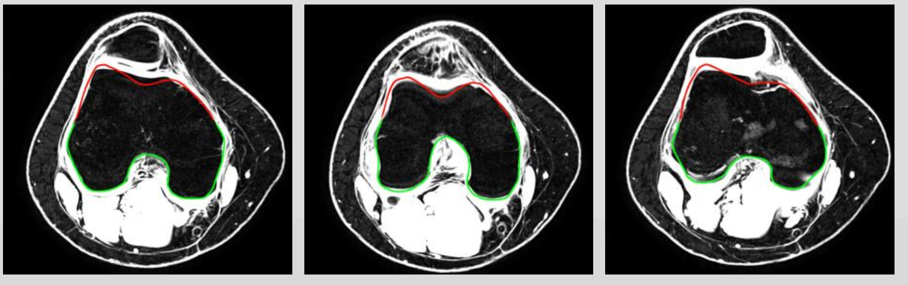


Surgical intervention: Augment bony structure

Automatic inference of pathology

Posterior Shape Models
T. Albrecht, M. Lüthi, T. Gerig, T. Vetter,
Medical Image Analysis, 2013





Probabilistic Inference for Image Registration

- Generative image explanation: How to find θ explaining I ?

$$p(\theta|I) = \frac{\ell(\theta; I)\, p(\theta)}{N(I)} \qquad N(I) = \int \ell(\theta; I) p(\theta) \mathrm{d}\theta$$

-----> Normalization intractable in our setting

- What can be done:
  1. Accept MAP as the only option
  2. Approximate posterior distribution (e.g. use sampling methods)

The Metropolis-Hastings Algorithm

- Need a distribution which can generate samples: $Q(\theta'|\theta)$
- Algorithm transforms samples from Q into samples from P:
  1. Draw a sample θ' from $Q(\theta'|\theta)$
  2. Accept θ' as new state θ with probability $p_{accept} = \min\left\{\frac{P(\theta')}{P(\theta)}\frac{Q(\theta|\theta')}{Q(\theta'|\theta)}, 1\right\}$
  3. State θ is current sample, repeat for next sample

---> Generates unbiased but correlated samples from P

- Markov Chain Monte Carlo Sampling: Result: $\{\theta_1, \theta_2, \theta_3, \dots \dots\}$

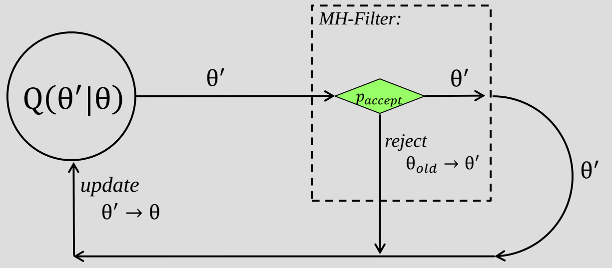
MH Inference of the 3DMM

- Target distribution is our “posterior”:
- P: $\tilde{P}(\theta|I_T) = \ell(\theta|I_T, I_R)p(\theta)$
  - Unnormalized
  - Point-wise evaluation only

- Parameters
  - Shape: 50 – 200, low-rank parameterized GP shape model
  - Color: 50 – 200, low-rank parameterized GP color model
  - Pose/Camera: 9 parameters, pin-hole camera model
  - Illumination: 9*3 Spherical Harmonics for illumination/reflectance

  - ≈ 300 dimensions (!!)

Metropolis Filtering

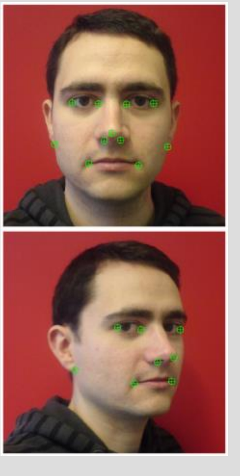


- Markov Chain Monte Carlo Sampling: Result: $\{\theta_1, \theta_2, \theta_3, \dots \dots\}$

Results: 2D Landmarks

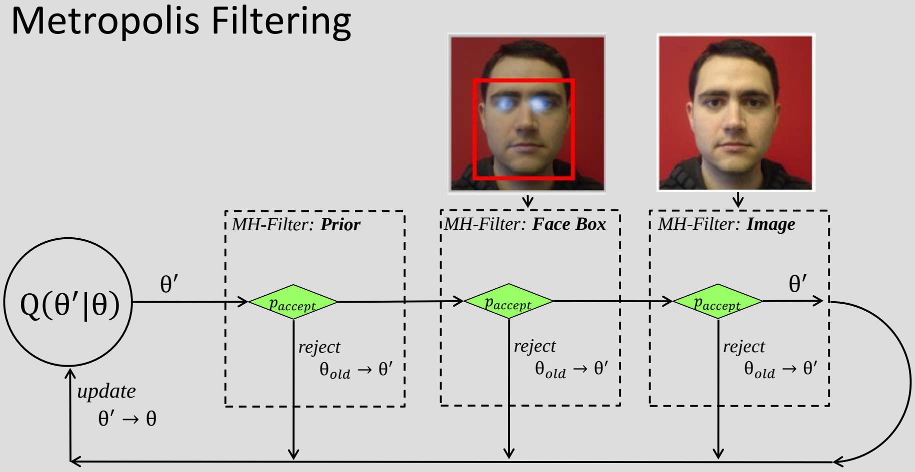
- Landmarks posterior:
  Manual labelling: $\sigma_{\mathrm{LM}} = 4\mathrm{pix}$
  Image: 512x512
- Certainty of pose fit?
  - Influence of ear points?
  - Frontal better than side-view?

$\mathrm{Yaw}, \sigma_{\mathbf{LM}} = 4\mathrm{pix}$	with ears	w/o ears
Frontal	$1.4° \pm \mathbf{0.9}°$	$-0.8° \pm \mathbf{2.7}°$
Side view	$24.8° \pm \mathbf{2.5}°$	$25.2° \pm \mathbf{4.0}°$



Integration of Bottom-Up

Metropolis Filtering



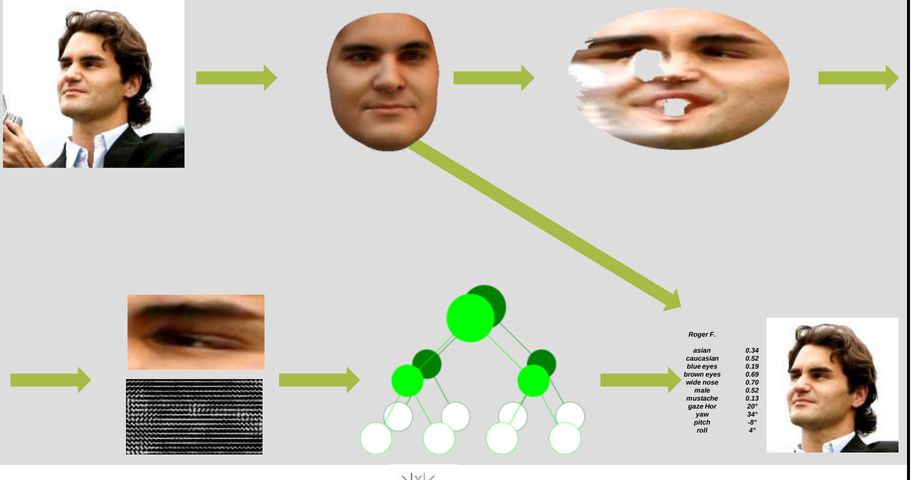
$$P_0(\theta) \xrightarrow{l(\theta,FB)} P(\theta|FB) \xrightarrow{l(\theta,I)} P(\theta|FB,I)$$

pose sampling from the detection posterior

UNIVERSITÄT BASEL

> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE Cape Town | 2018

Face analysis

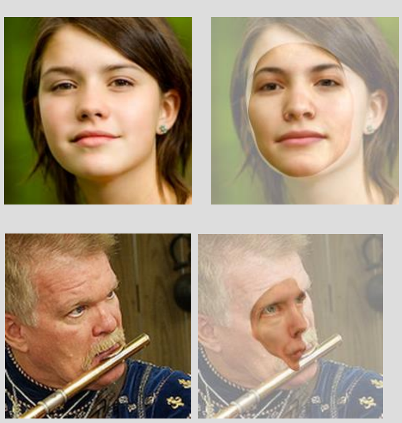


Occlusion-aware 3D Morphable Face Models

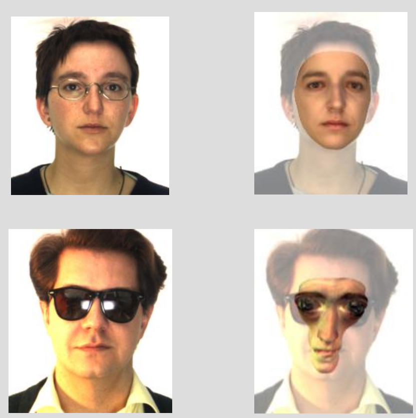
Bernhard Egger, Sandro Schönborn, Andreas Schneider, Adam Kortylewski, Andreas Morel-Forster, Clemens Blumer and Thomas Vetter

International Journal of Computer Vision, 2018

Face Image Analysis under Occlusion

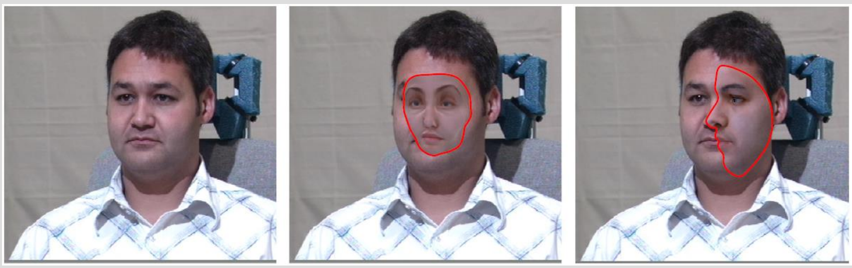


Source: AFLW Database



Source: AR Face Database

There is nothing like: no background model



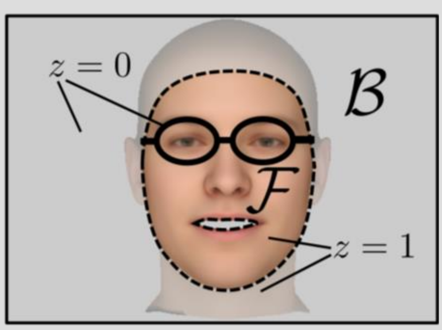
Maximum Likelihood Formulation:

$$\ell(\theta; I) = \prod_{x \in I} \ell(\theta; I(x)) \quad = \prod_{x \in Fg} \ell(\theta; I(x)) \times \prod_{x \in Bg} \ell(\theta; I(x))$$

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

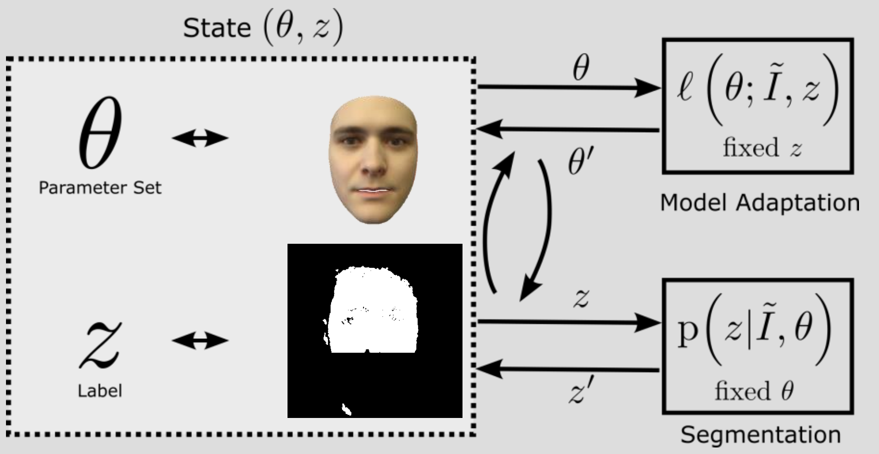
UNIVERSITÄT BASEL
> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE Cape Town | 2018

Occlusion-aware Model



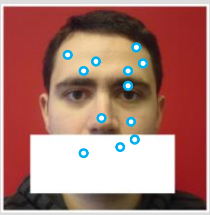
$$l(\theta; \tilde{I}, z) = \prod_i l_{face}(\theta; \tilde{I}_i)^z \cdot l_{non-face}(\theta; \tilde{I}_i)^{1-z}$$

Inference



Initialisation: Robust Illumination Estimation

Init z



Init θ_{camera}

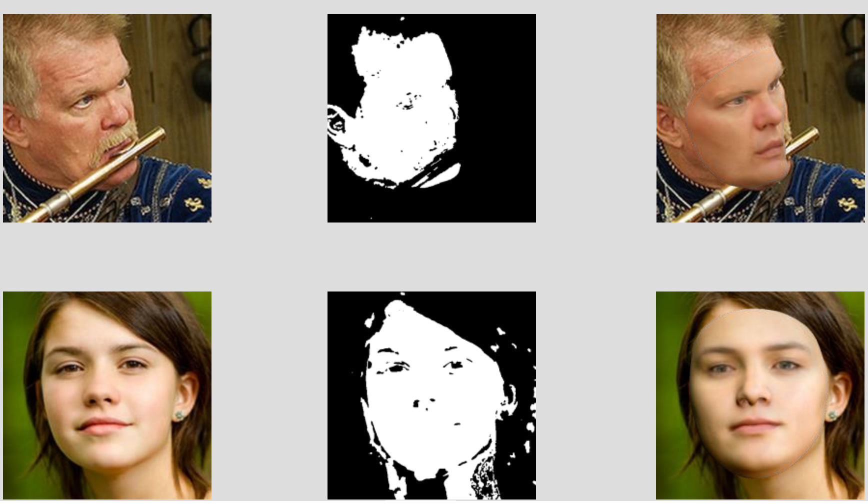
Init θ_{light}

Results: Qualitative

Source: AR Face Database

Results: Qualitative

Source: AFLW Database

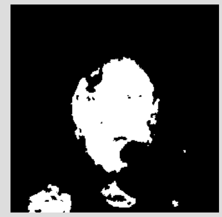


UNIVERSITÄT BASEL

> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE — Cape Town | 2018

Results: Applications

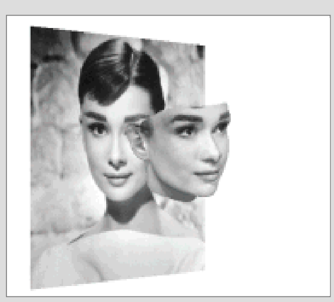
Source: LFW Database

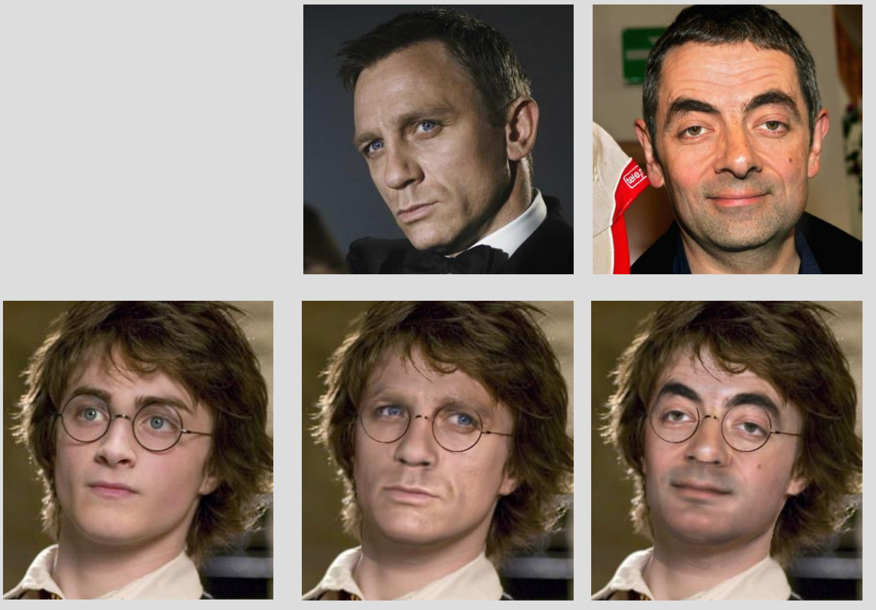


UNIVERSITÄT BASEL

> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE — Cape Town | 2018

Modeling of 2D Images





UNIVERSITÄT BASEL
> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE
Cape Town | 2018

Portraits made to Measure

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

Aggressive

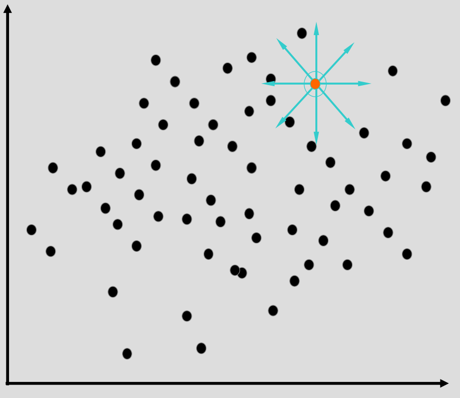
Trustworthy

UNIVERSITÄT BASEL

> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE Cape Town | 2018

Modeling the Appearance of Faces

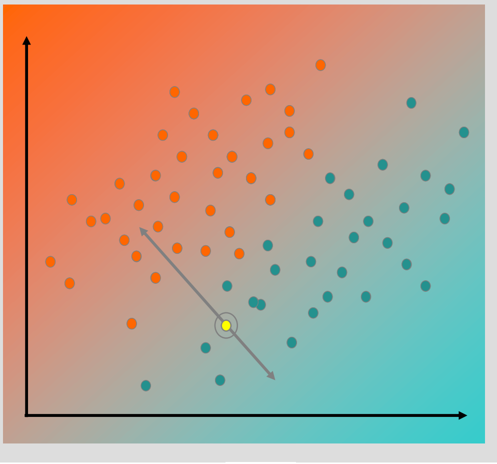
- Which directions code for specific attributes ?



UNIVERSITÄT BASEL

> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE Cape Town | 2018

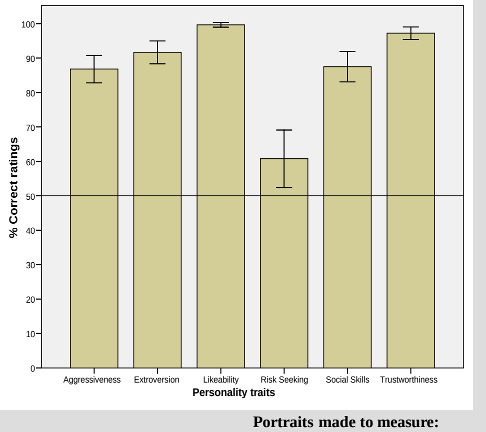
Learning from Examples



UNIVERSITÄT BASEL

> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE   Cape Town | 2018

Portraits made to Measure



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

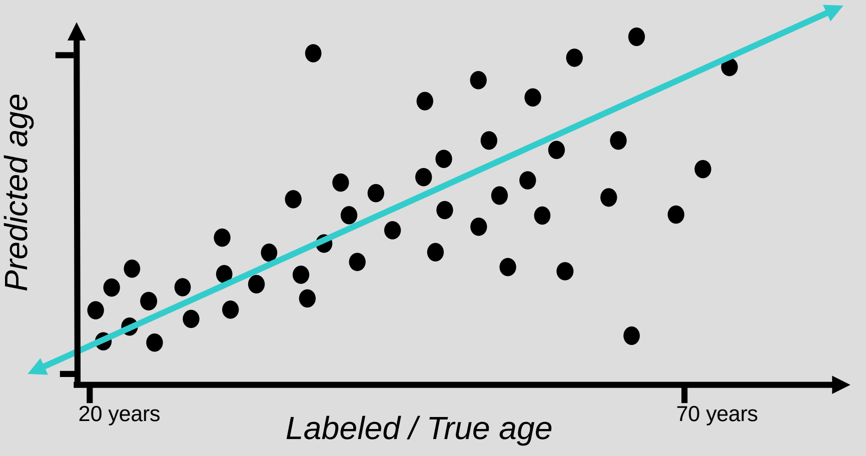
UNIVERSITÄT BASEL

> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE   Cape Town | 2018

Simulation of Aging of Human Faces in Images

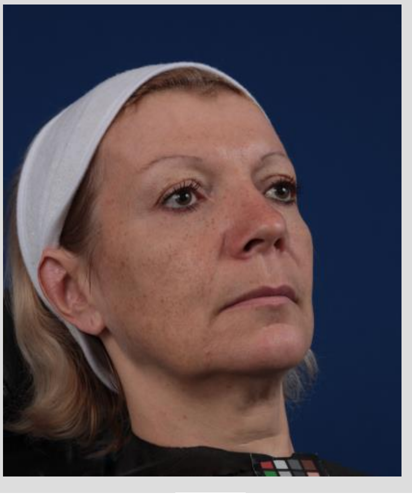
Aging model:

model predicts perceived age

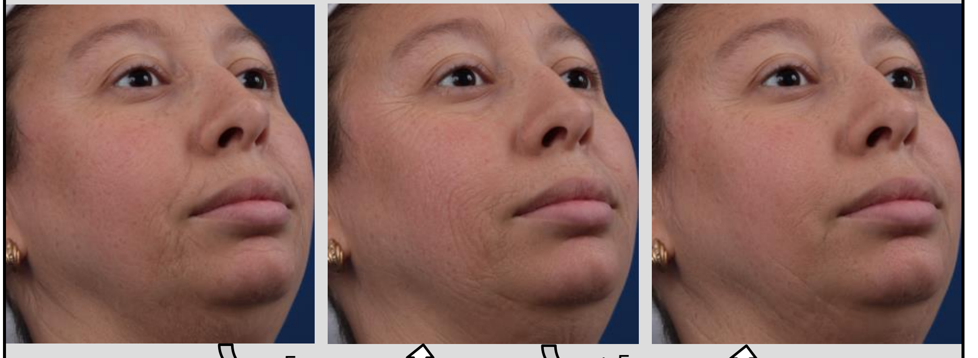


UNIVERSITÄT BASEL
> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE Cape Town | 2018

Ageing: linear shape model only



Example-based: The Problem



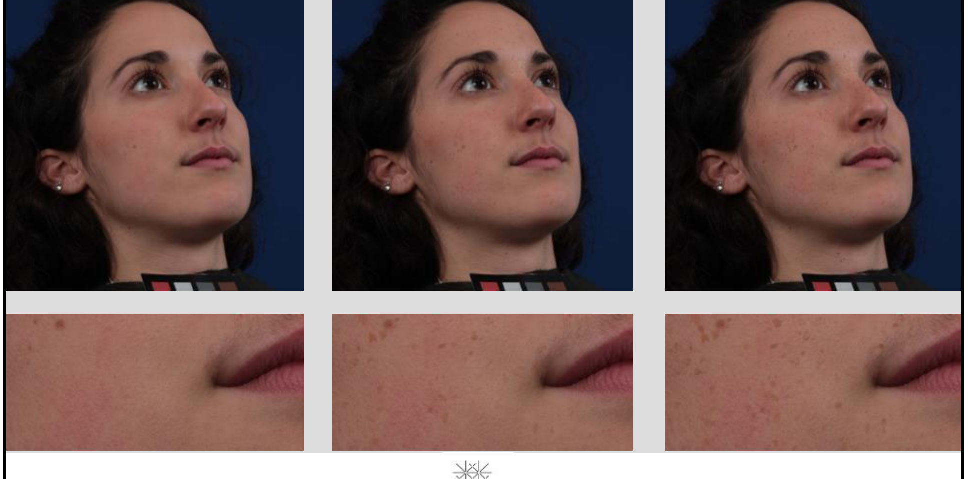
+ 5 years
+ 5 years

Target Image
AGE: 40

Shape and Skin of donor
AGE: 45

Shape and Skin of donor
AGE: 50

Parametric Pigmentation Model



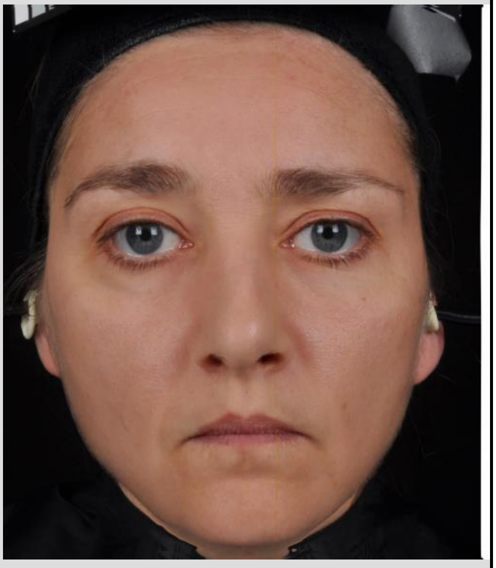
UNIVERSITÄT BASEL

> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE

Cape Town | 2018

Aging Model

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



UNIVERSITÄT BASEL

> DEPARTMENT OF MATHEMATICS AND COMPUTER SCIENCE

Cape Town | 2018

Acknowledgement

Sandro Schönborn

Bernhard Egger

Andreas Schneider

Andreas Forster

Marcel Lüthi

Jean Pierrard

Mirella Walker

https://gravis.unibas.ch