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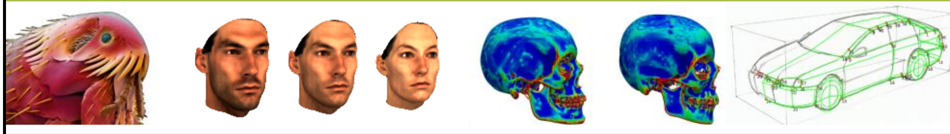

Probabilistic Morphable Models

Thomas Vetter

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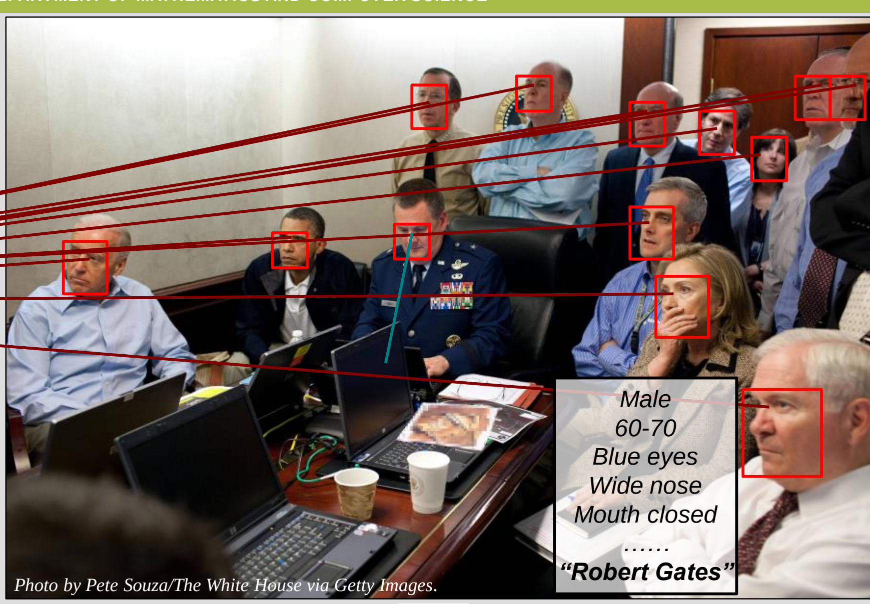

Photo by Pete Souza/The White House via Getty Images.

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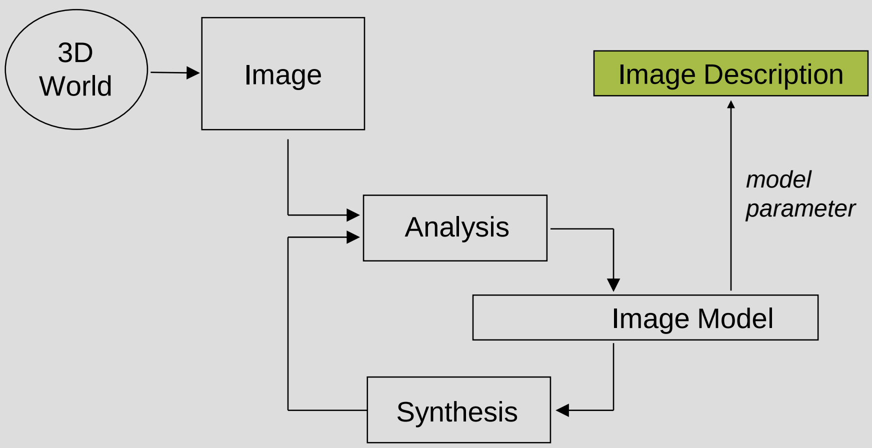
Analysis by Synthesis



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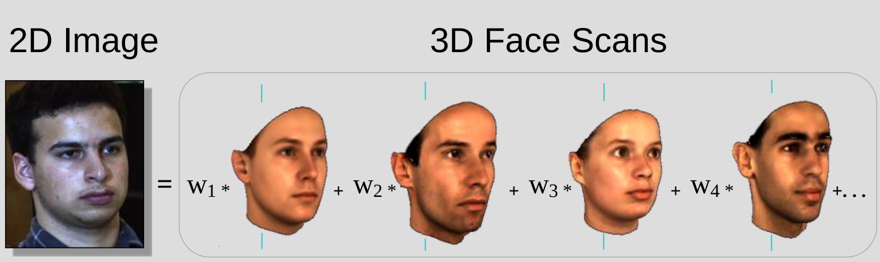
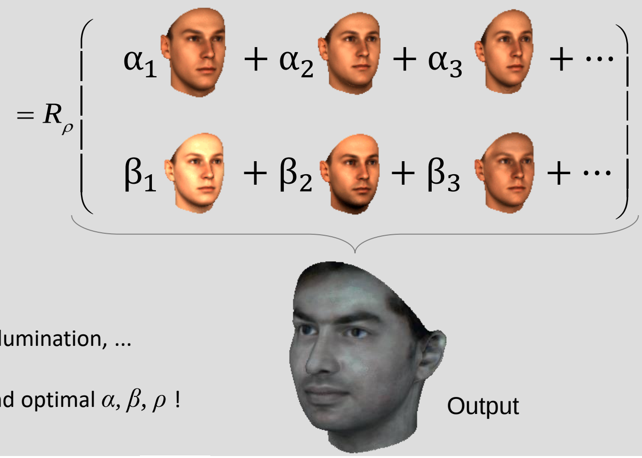
Example based image modeling of faces



Morphable Models for Image Registration



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

Optimization Problem: Find optimal α, β, ρ !

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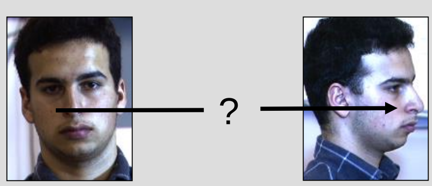
Probabilistic Morphable Models

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.

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

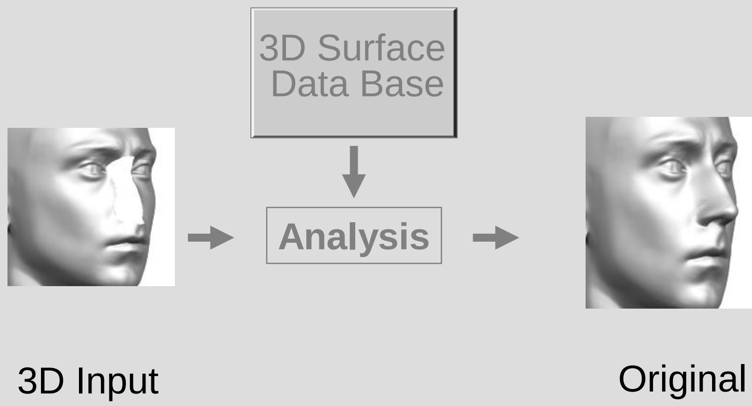
with $\theta \sim N(0, I_d)$

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



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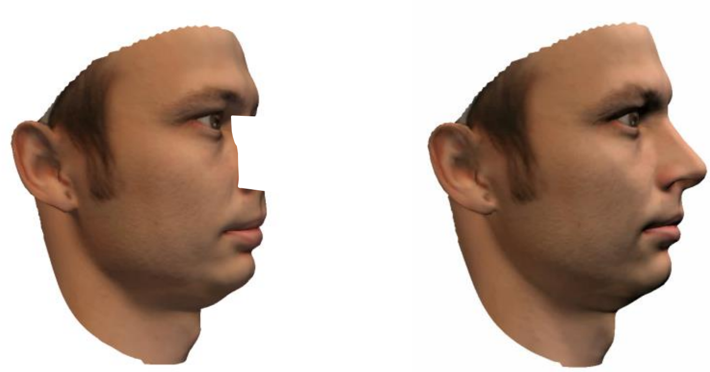
Surface Data Prediction
as Gaussian Process Regression



Application

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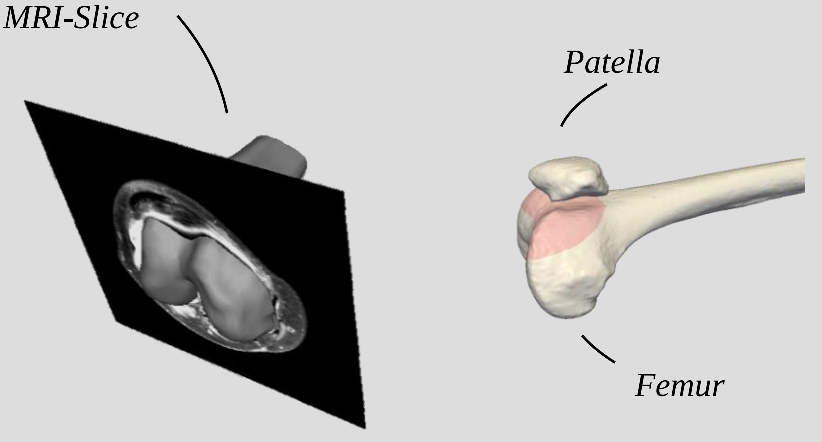
Example use-case: Trochlea dysplasia



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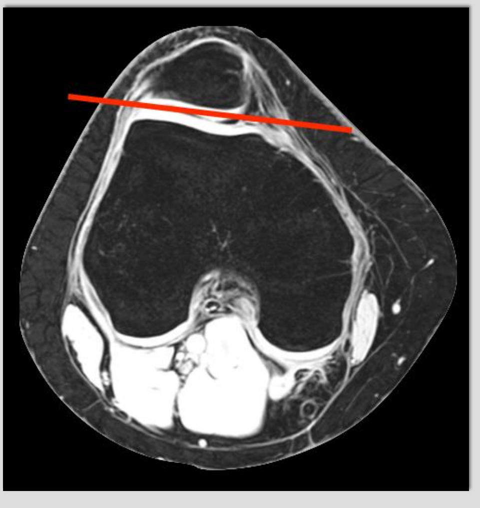
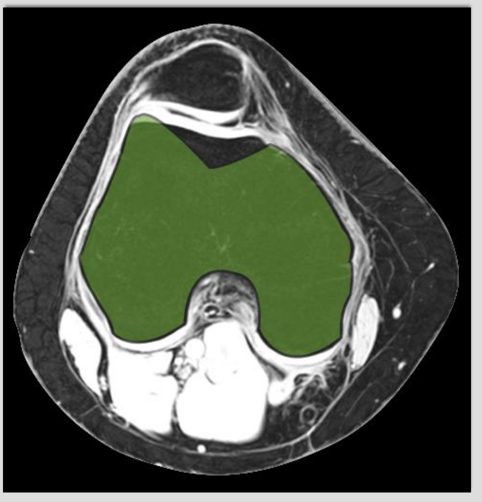
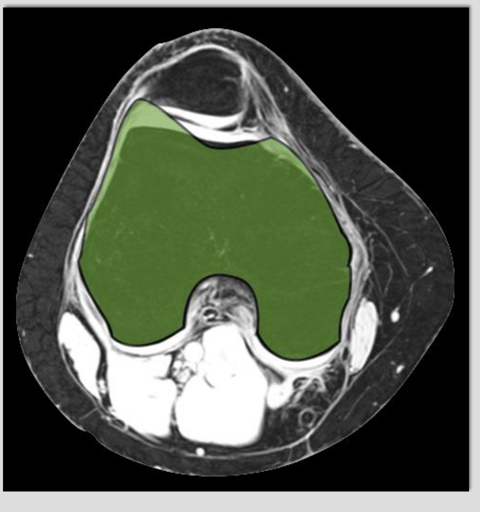


Trochlea-Dysplasia



Surgical intervention: Increase goove



Surgical intervention: Augment bony structure

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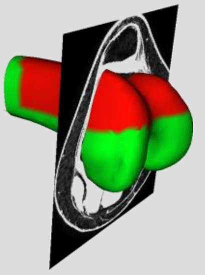
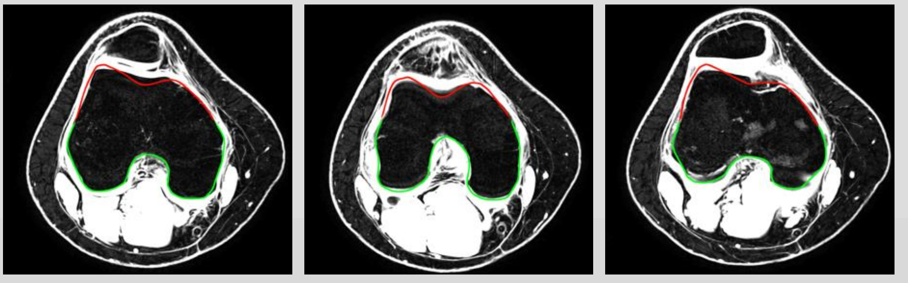
Automatic inference of pathology

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





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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: $\{\theta_1, \theta_2, \theta_3, \dots\dots\}$

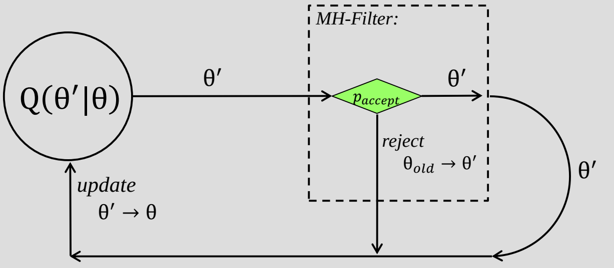
MH Inference of the 3DMM

- 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: $\{\theta_1, \theta_2, \theta_3, \dots \dots\}$

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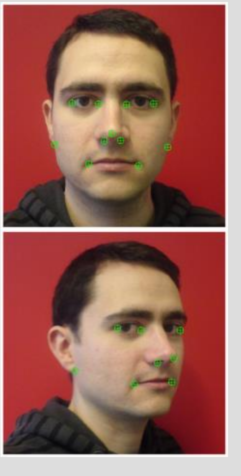
Results: 2D Landmarks

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

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



Integration of Bottom-Up

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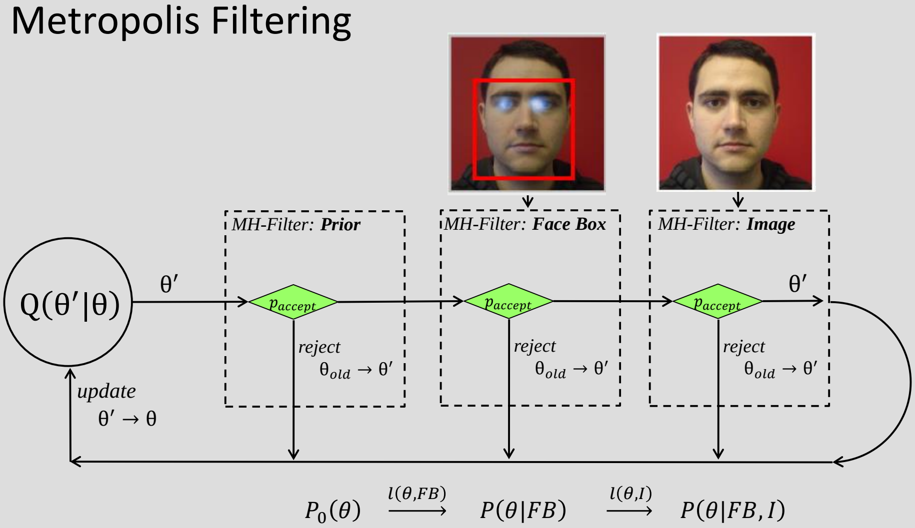
Metropolis Filtering



pose sampling from the detection posterior

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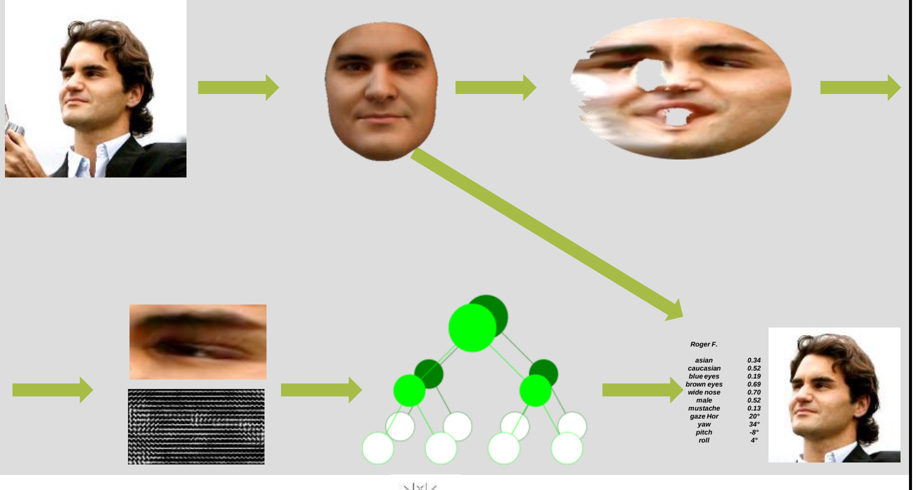
Face analysis



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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

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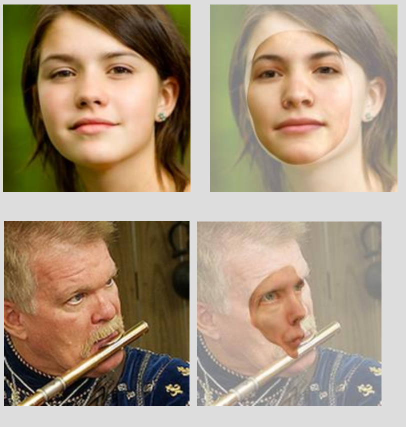
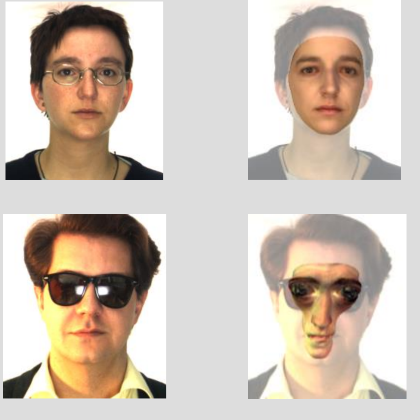
Face Image Analysis under Occlusion

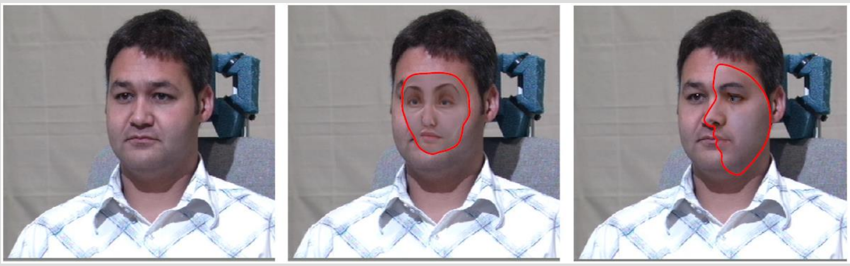


Source: AFLW Database



Source: AR Face Database

There is nothing like: no background model



Maximum Likelihood Formulation:

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

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

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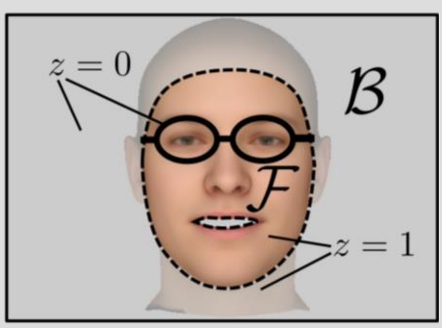
Occlusion-aware Model



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

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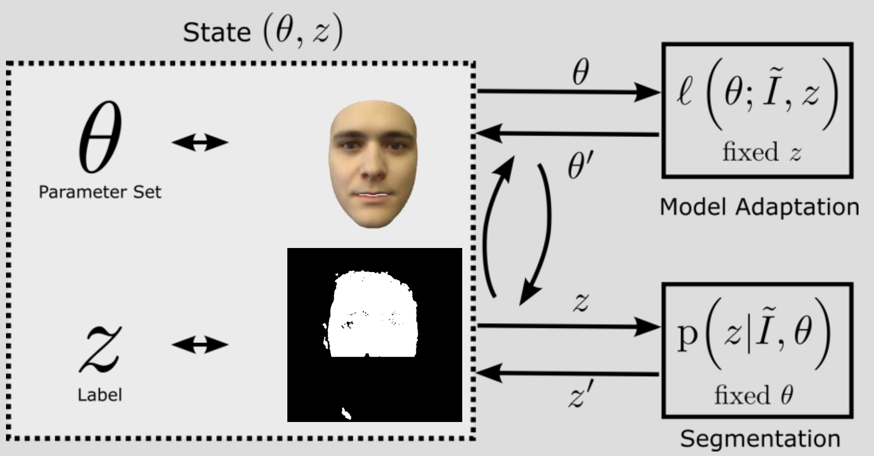
Inference



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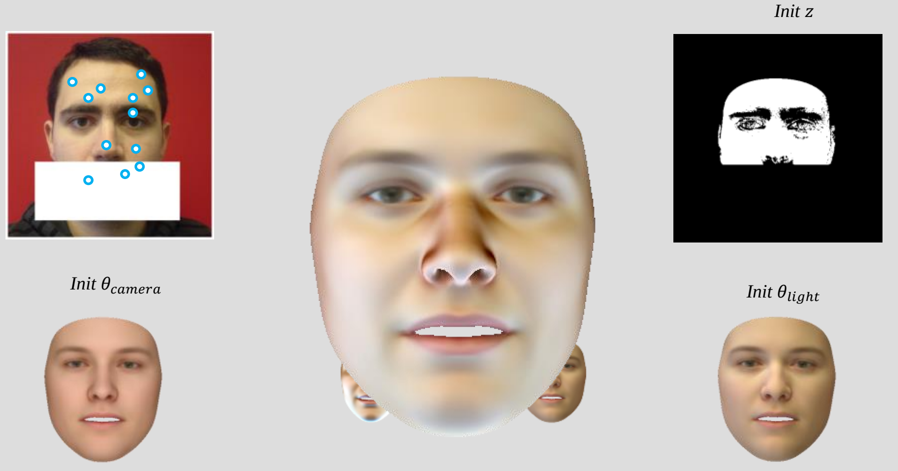
Initialisation: Robust Illumination Estimation



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Results: Qualitative

Source: AR Face Database

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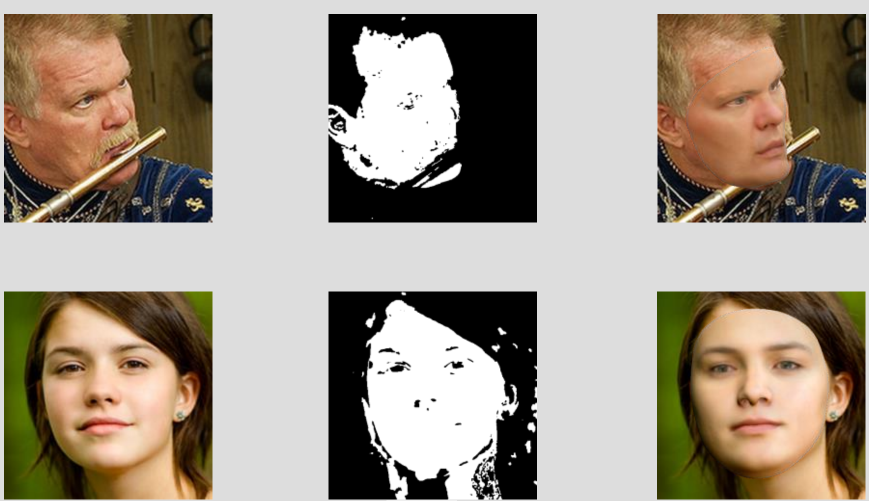
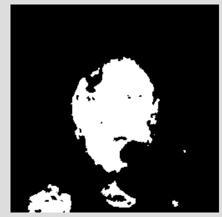
Results: Qualitative

Source: AFLW Database



Results: Applications

Source: LFW Database



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