3D Morphable Face Models

Bernhard Egger

IPAM Workshop I: Geometric Processing

University of Basel
FNSNF Fonds national suisse Schweizerischer Nationalfonds Fondo nazionale svizzero Swiss National Science Foundation
CSAIL
Massachusetts Institute of Technology

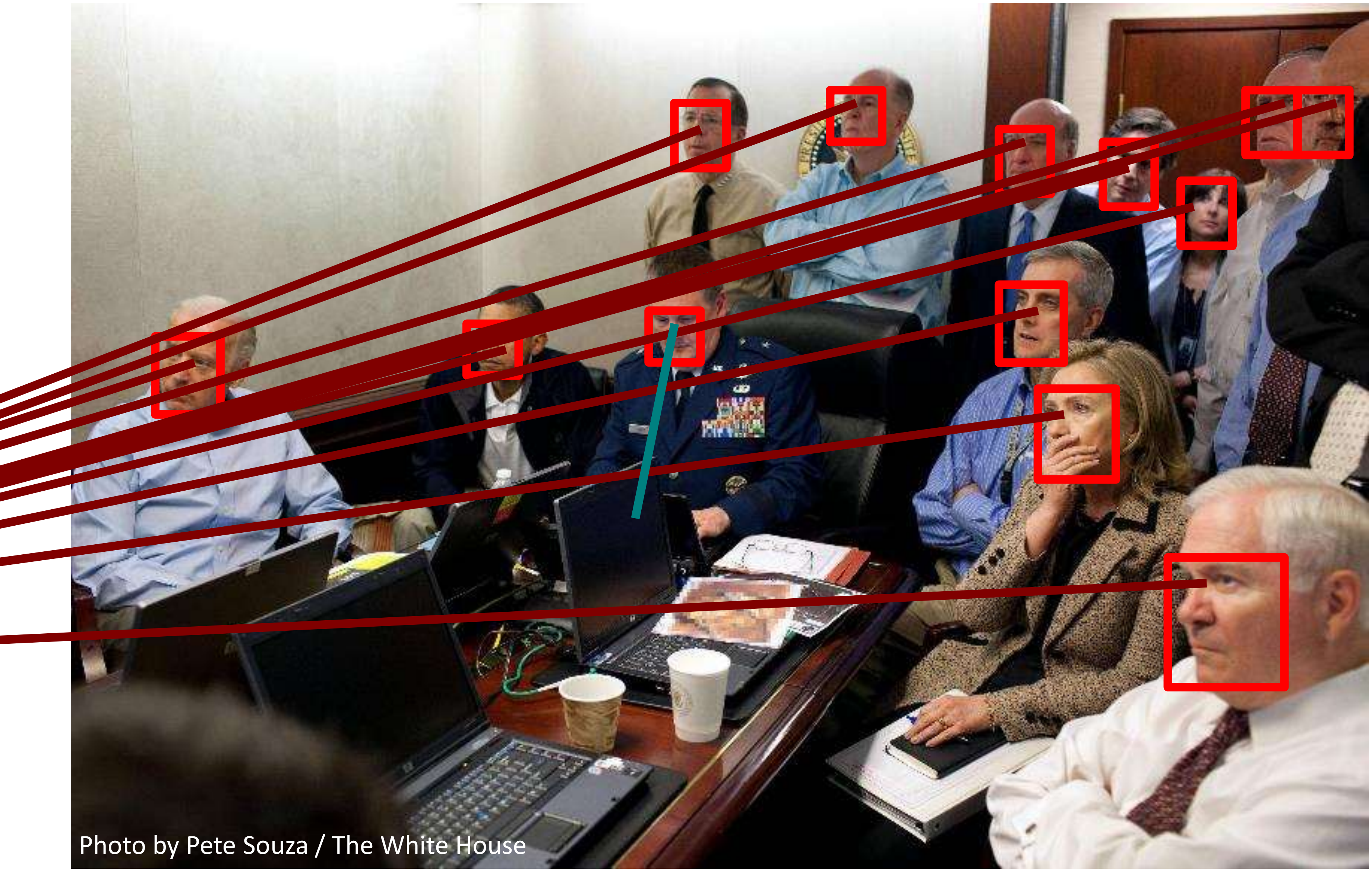


Photo by Pete Souza / The White House

SI99RAPH
Los Angeles

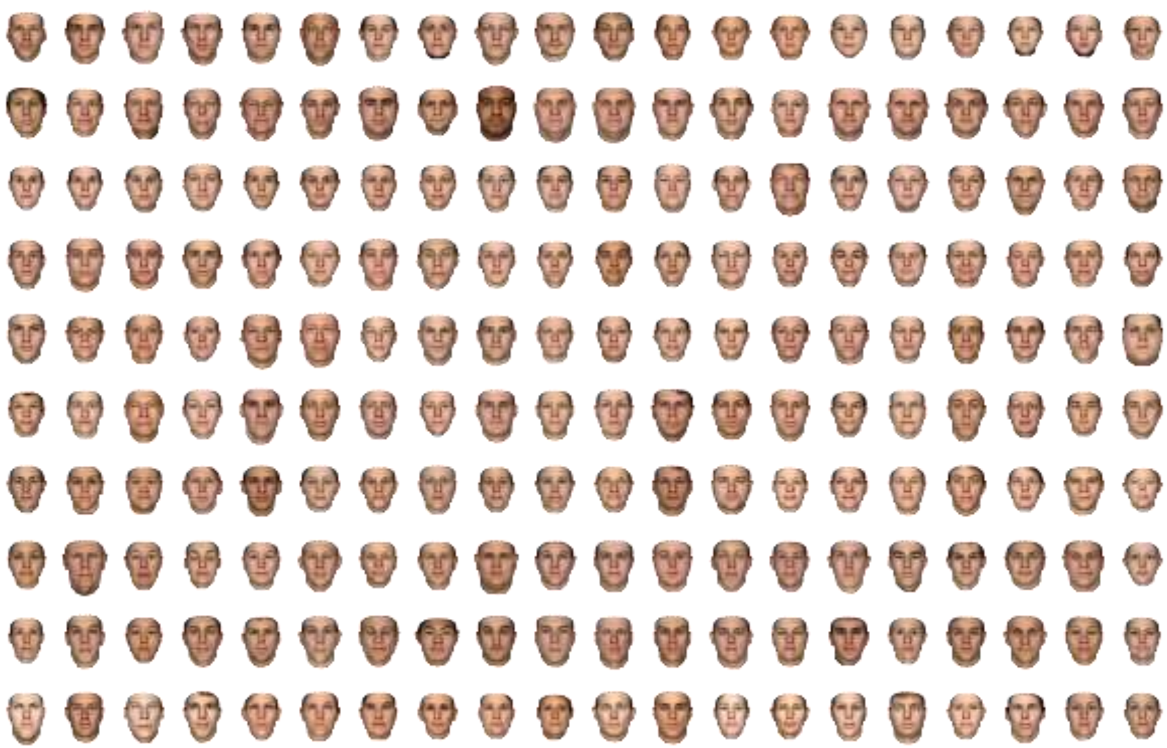
Graphics and Vision Research Group in Basel

gravis.unibas.ch

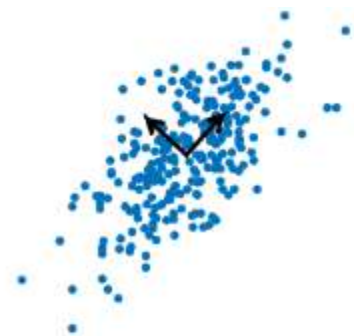
Thomas Vetter
Sandro Schönborn
Andreas Forster
Adam Kortylewsky
Clemens Blumer
Andreas Schneider
Ghazi Bouabene
Marcel Lüthi
Thomas Gerig

University of Basel

Probabilistic 3D Morphable Model



Probabilistic PCA



Gerig et al (2018). Morphable Face Models - An Open Framework, FG
Paysan et al (2009). A 3D Face Model for Pose and Illumination Invariant Face Recognition, AVSS
Blanz and Vetter (1999). A Morphable Model for the Synthesis of 3D Faces, SIGGRAPH

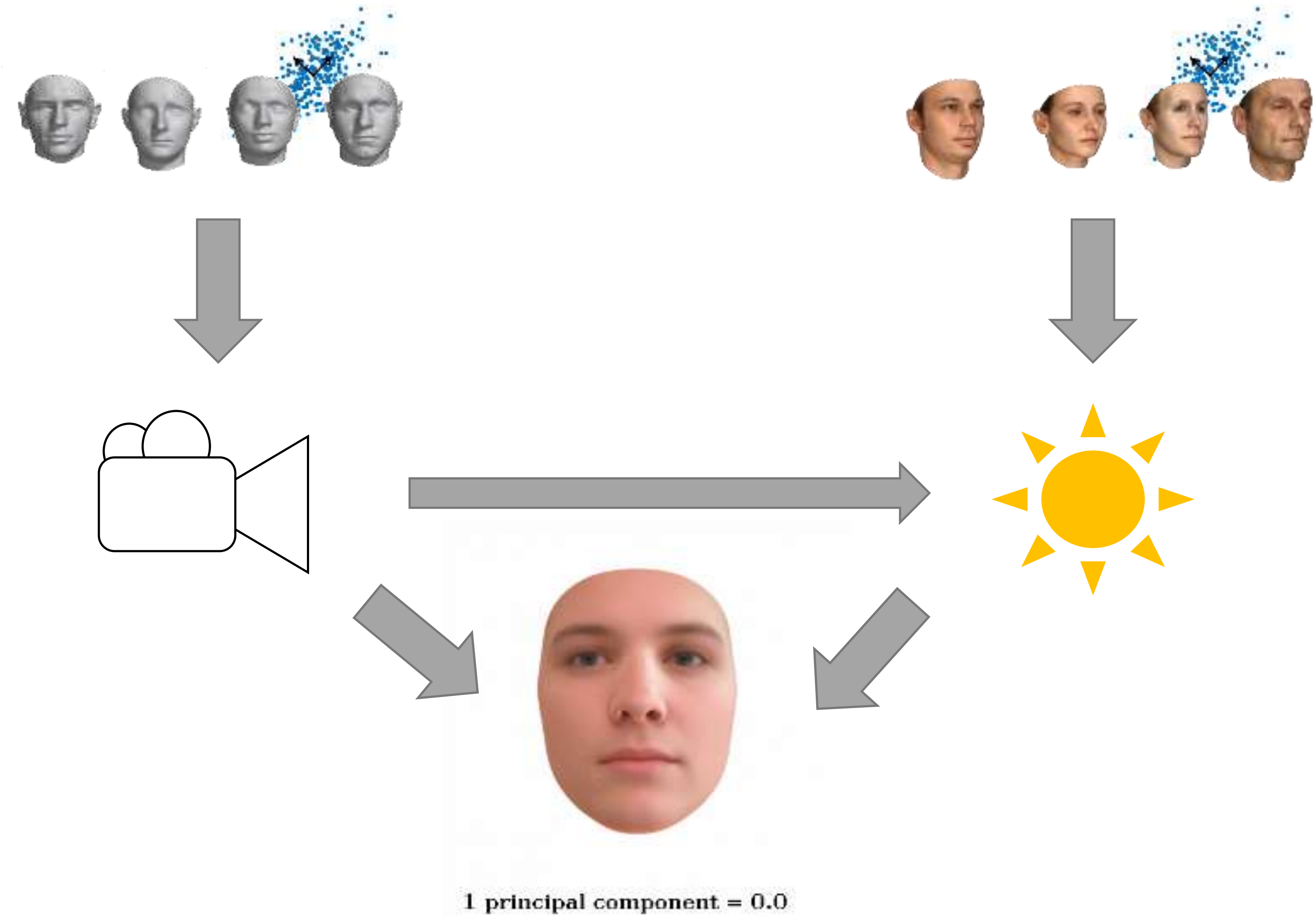
Gaussian Process Registration

(a) $s = 100, \sigma = 100$ mm

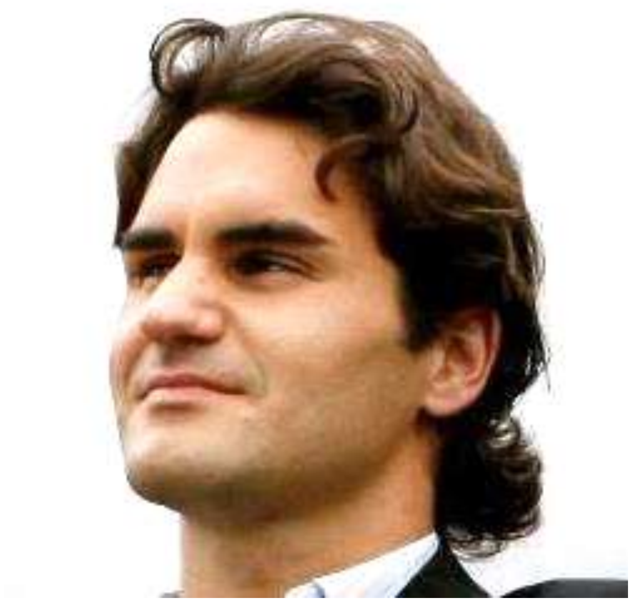
(b) $s = 10, \sigma = 30$ mm

Marcel Lüthi, Christoph Jud, Thomas Gerig, Thomas Vetter (2017) Gaussian Process Morphable Models
Gerig et al (2018). Morphable Face Models - An Open Framework, FG

Image Formation Process

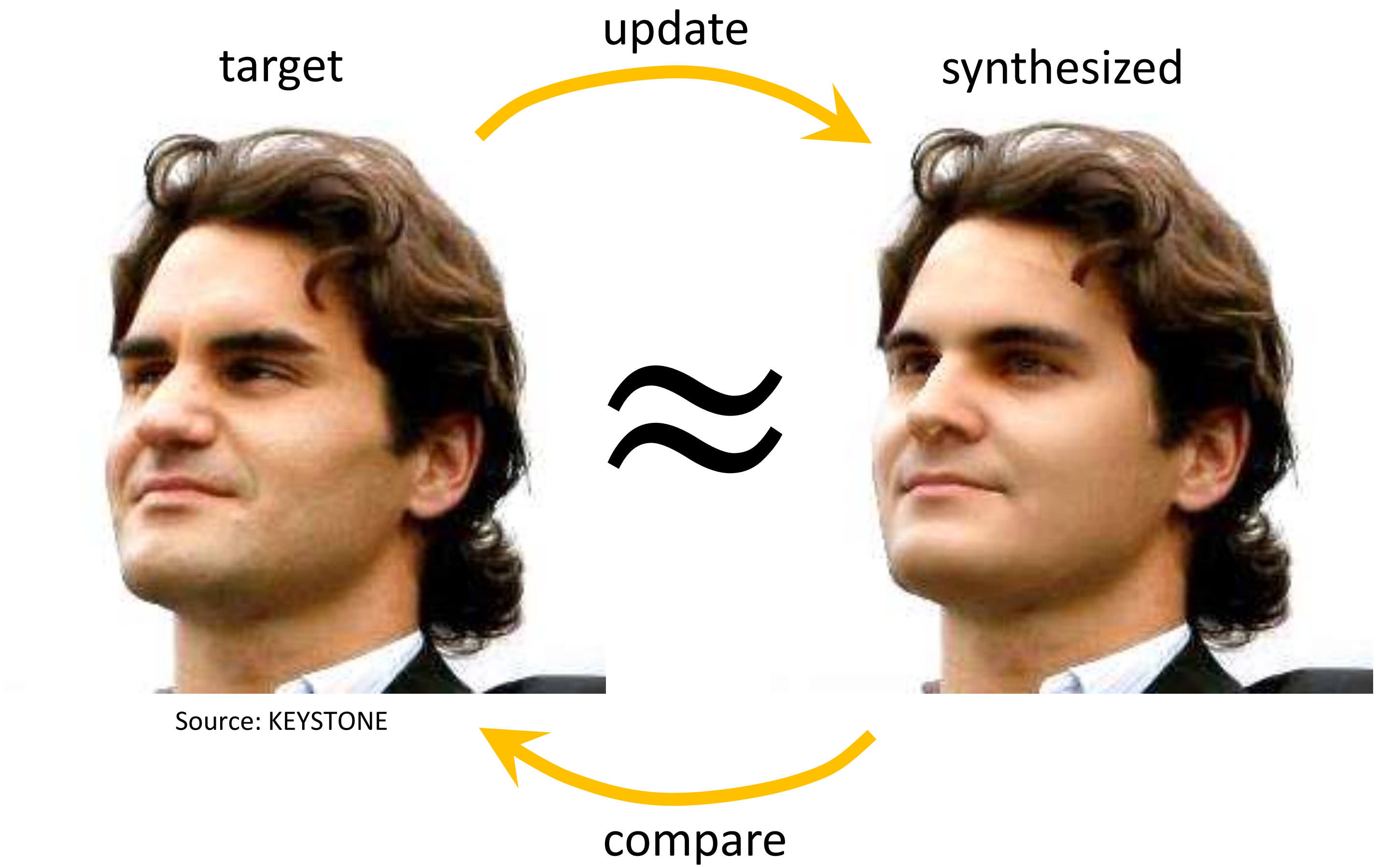


Goal: 3D Reconstruction from a Single Image



Source: KEYSTONE

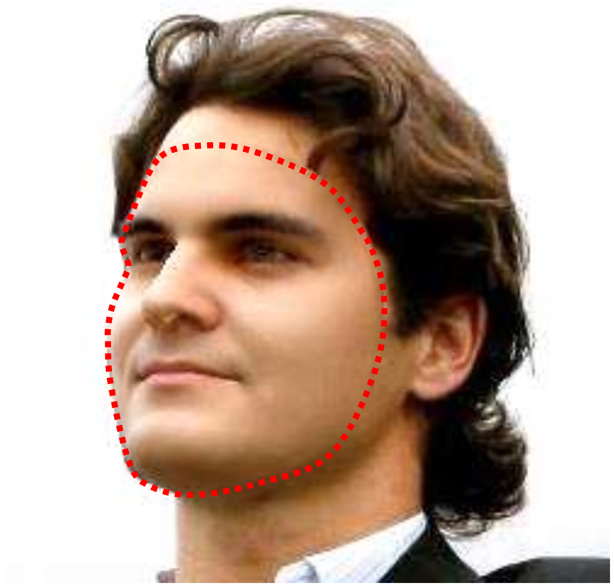
Approach: Analysis by Synthesis



Source: KEYSTONE

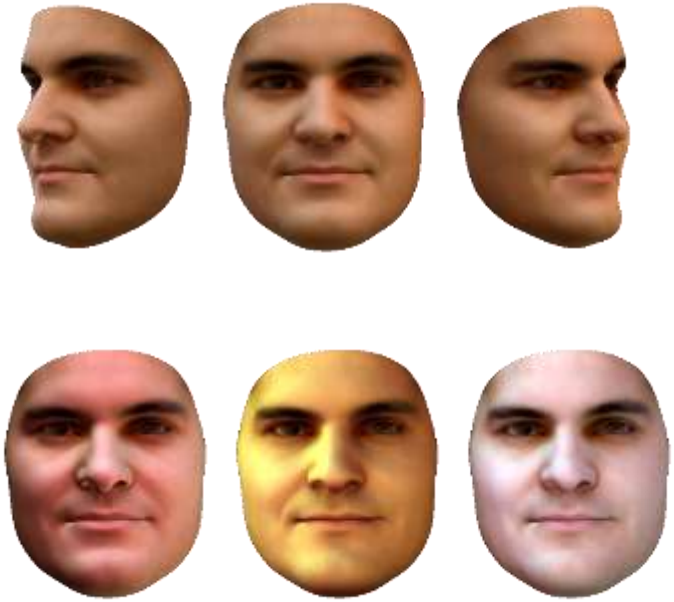
Analysis by Synthesis

parametrized representation



Source: KEYSTONE

changing camera and illumination



Classical Face Model Adaptation

Target $\tilde{I}$

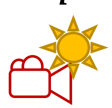
- Probabilistic Framework

$$P(\theta|\tilde{I}) \propto l(\theta;\tilde{I})\;P(\theta)$$

- Marko chain Monte Carlo-Sampling

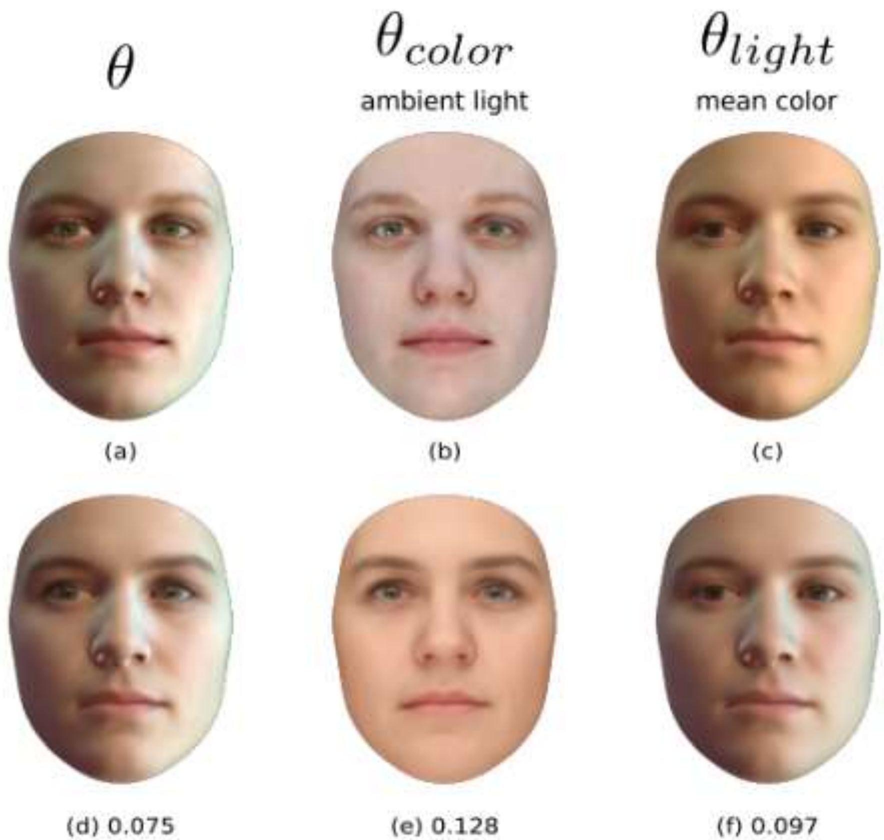
Fit $I(\theta)$

 $= R_p(\alpha_1 \cdot$  $+\alpha_2 \cdot$  $+ \cdots + \alpha_n \cdot$  $)$



Schönborn, **Egger**, Morel-Forster, Vetter (2017).
Markov Chain Monte Carlo for Automated Face Image Analysis IJCV

Color Illumination Ambiguity



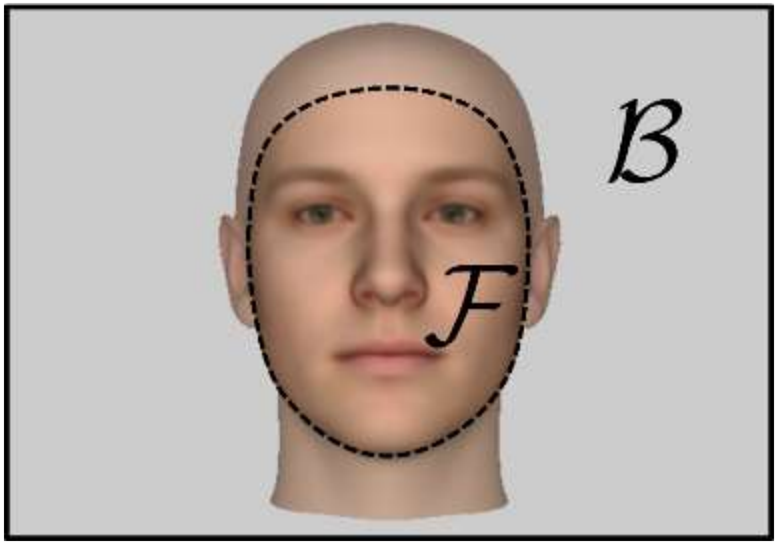
Results: Qualitative

Source: LFW Database

Schönborn, **Egger**, Morel-Forster, Vetter (2017). Markov Chain Monte Carlo for Automated Face Image Analysis, IJCV

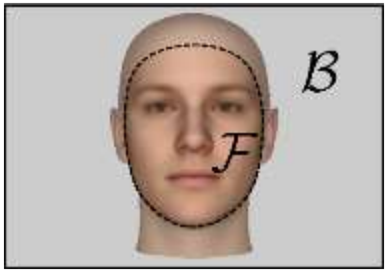
Classical Morphable Model

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



Schönborn, **Egger**, Morel-Forster, Vetter (2017).
Markov Chain Monte Carlo for Automated Face Image Analysis IJCV

Background model

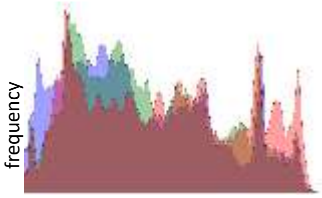


- All A-by-S methods assume a background model

(a) Target (b) Shrinking (c) Pose Misalignment

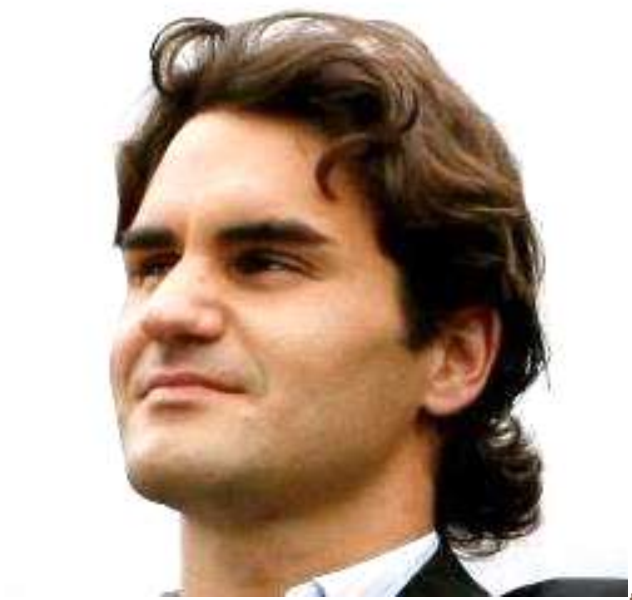
- Shrinking and the hacks

- Simple generic model is enough

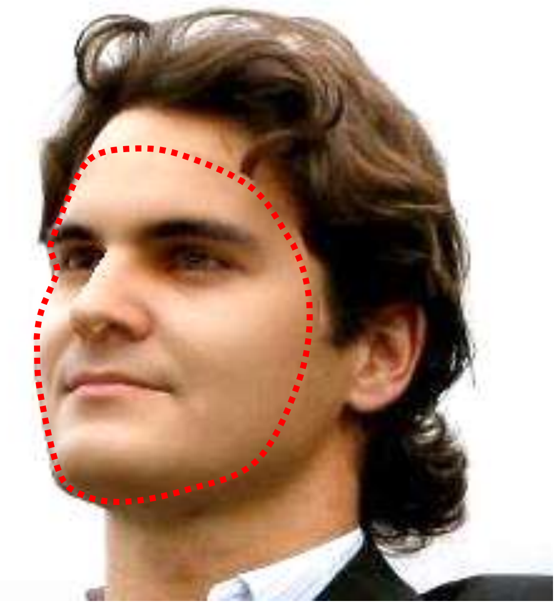


Background modeling for generative image models (2015) CVIU,
S Schönborn, B Egger, A Forster, T Vetter

The good



Source: KEYSTONE



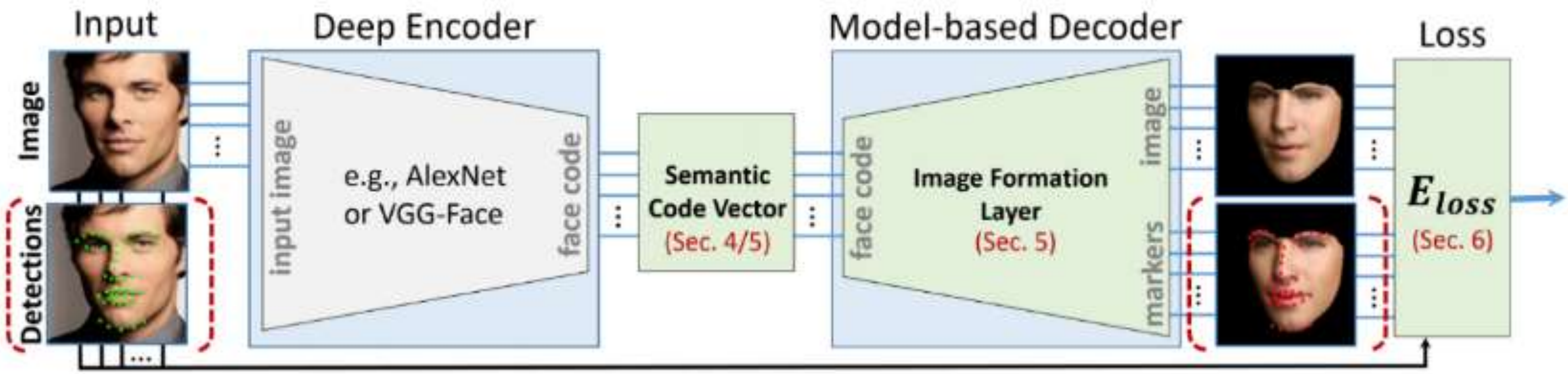
Schönborn, **Egger**, Morel-Forster, Vetter (2017).
Markov Chain Monte Carlo for Automated Face Image Analysis IJCV

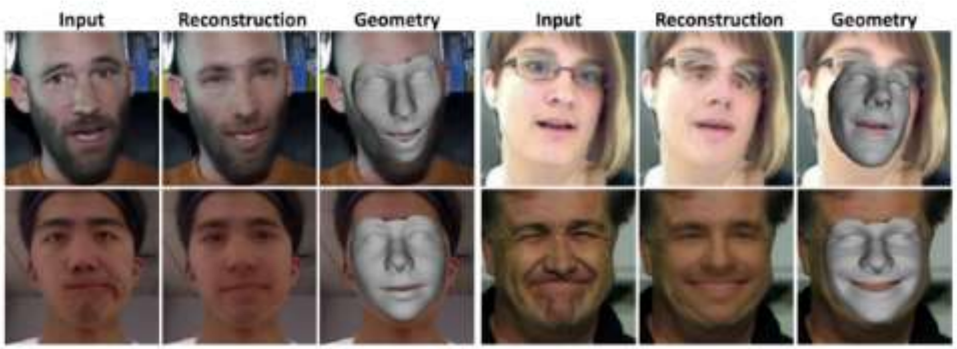
Face Image Analysis under Occlusion

Source: AFLW Database

Source: AR Face Database

End-to-end learned Fitter





Tewari, Zollhöfer, Kim, Garrido, Bernard, Pérez, Theobalt, 2016.
MoFA: Model-based Deep Convolutional Face Autoencoder for Unsupervised Monocular Reconstruction arXiv

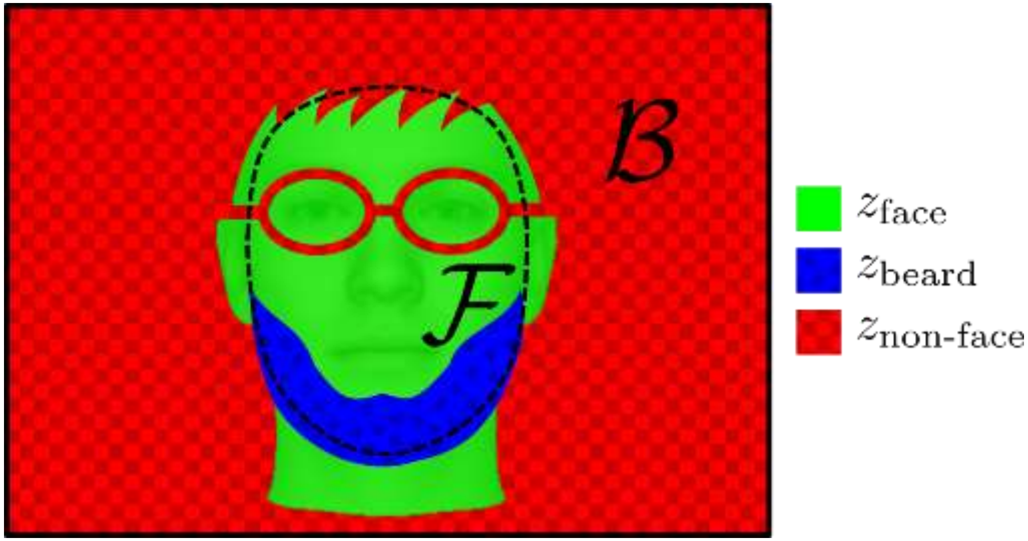
The bad

Semantic Morphable Model

Semantic Model Adaptation

$$l(\theta; \tilde{I}, z) = \prod_i \prod_k l_k(\theta; \widetilde{I_i})^{z_{ik}}$$

with $z_{ik} \in \{0,1\}$
and $\sum_k z_{ik} = 1 \; \forall i$

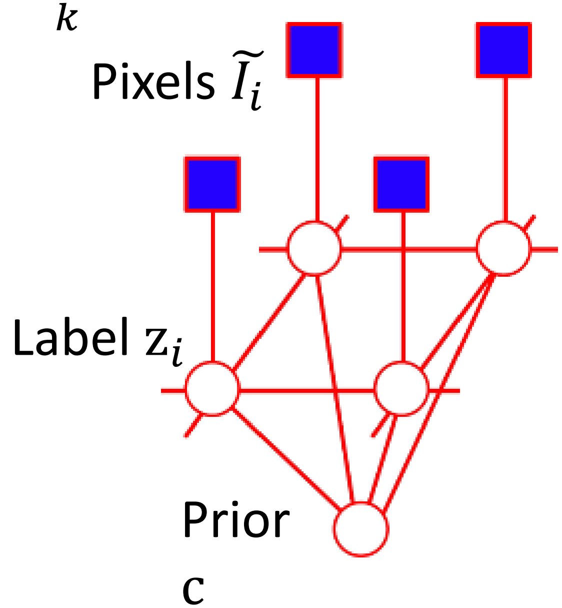


Egger, Schönborn, Schneider, Kortylewski, Morel-Forster, Blumer, Vetter (2018).
Occlusion-aware Morphable Models and an Illumination Prior for Face Image Analysis, IJCV

Semantic Model: Segmentation

likelihoods prior smoothness

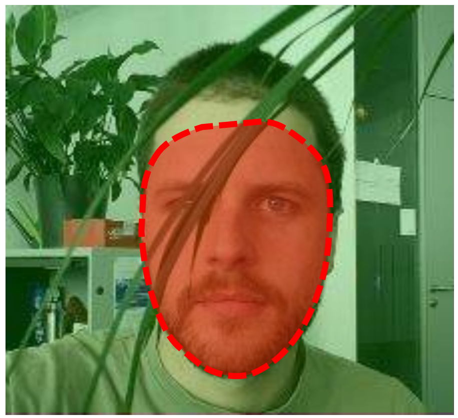
$$P\left(z|\tilde{I},\theta\right) \propto \prod_i \prod_k l_k\left(\theta;\widetilde{I_i}\right)^{z_{ik}} P(z_{ik}|\theta)P(c) \prod_{j\in n(i)} P\left(z_{ik},z_{jk}\right)$$



Egger, Schönborn, Schneider, Kortylewski, Morel-Forster, Blumer, Vetter (2018).
Occlusion-aware Morphable Models and an Illumination Prior for Face Image Analysis, IJCV

Generative Face Model

$\tilde{I}$



$I(\theta)$

$$l_{face}(\theta;\widetilde{I_i}) = \left\{ \right.$$

Egger, Schönborn, Schneider, Kortylewski, Morel-Forster, Blumer, Vetter (2018).
Occlusion-aware Morphable Models and an Illumination Prior for Face Image Analysis, IJCV

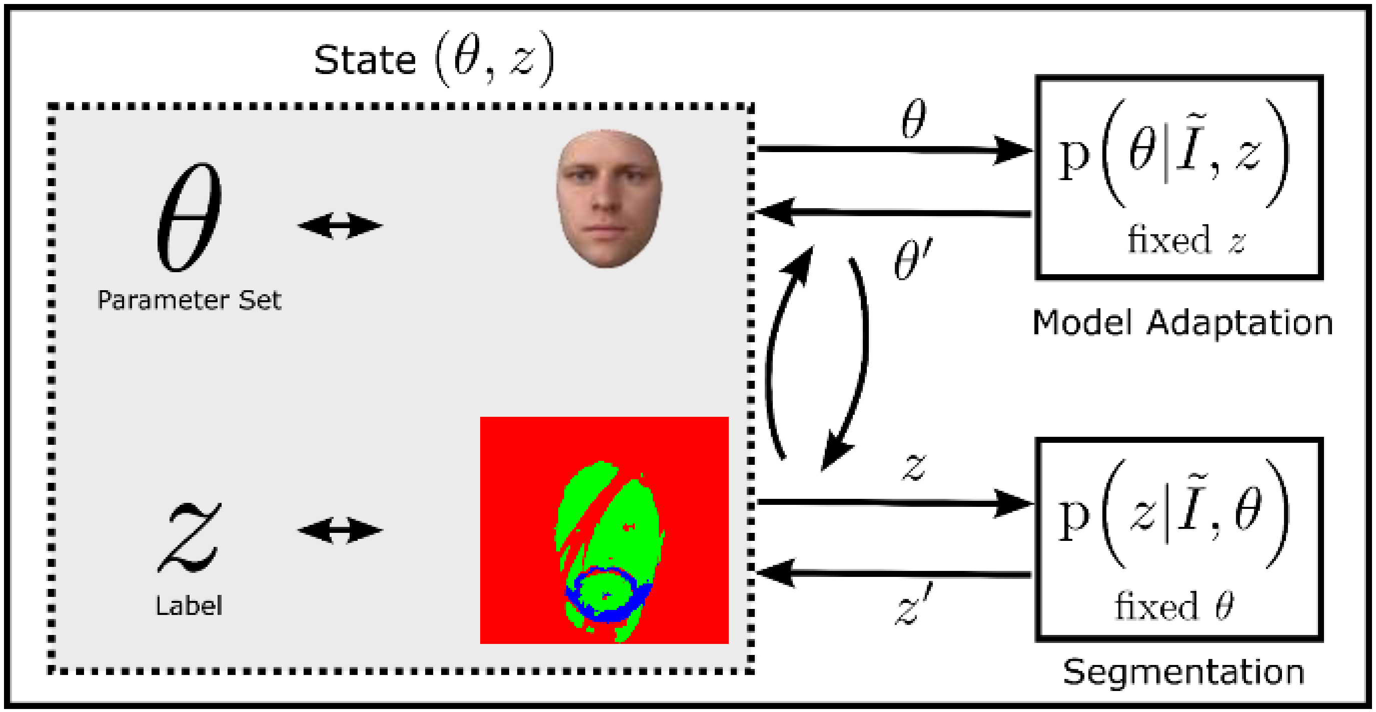
Inference

$$l(\theta; \tilde{I}, z) = \prod_i \prod_k l_k(\theta; \widetilde{I_i})^{z_{ik}}$$

$$P(z|\tilde{I}, \theta) \propto \prod_i \prod_k l_k(\theta; \widetilde{I_i})^{z_{ik}} P(z_{ik}|\theta) P(c) \prod_{j \in n(i)} P(z_{ik}, z_{jk})$$

Egger, Schönborn, Schneider, Kortylewski, Morel-Forster, Blumer, Vetter (2017).
Occlusion-aware Morphable Models and an Illumination Prior for Face Image Analysis, IJCV (invited/under revision)

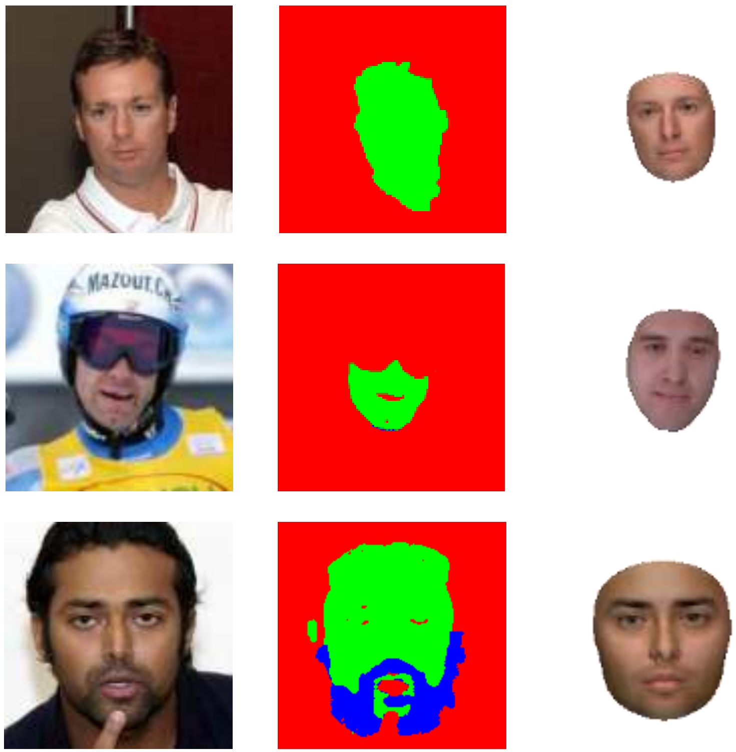
Inference



Egger, Schönborn, Schneider, Kortylewski, Morel-Forster, Blumer, Vetter (2018).
Occlusion-aware Morphable Models and an Illumination Prior for Face Image Analysis, IJCV

Results

Target $\tilde{I}$ | Segmentation z | Fit $I(\theta)$

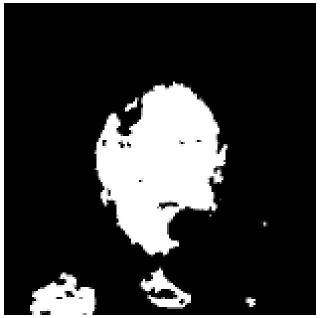


Targets: LFW Face Database

Target $\tilde{I}$ | Segmentation z | Fit $I(\theta)$

Egger, Schönborn, Schneider, Kortylewski, Morel-Forster, Blumer, Vetter (2018).
Occlusion-aware Morphable Models and an Illumination Prior for Face Image Analysis, IJCV

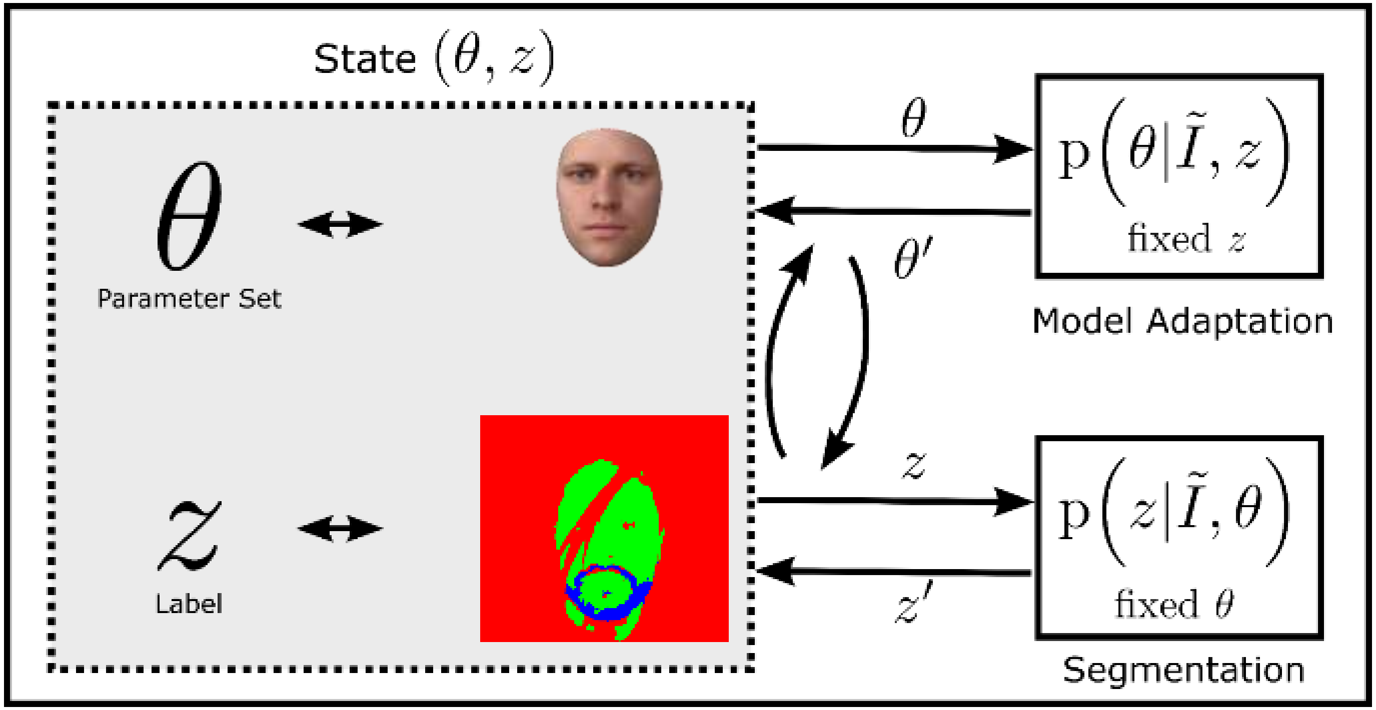
Application: Image Manipulation



Source: LFW Database

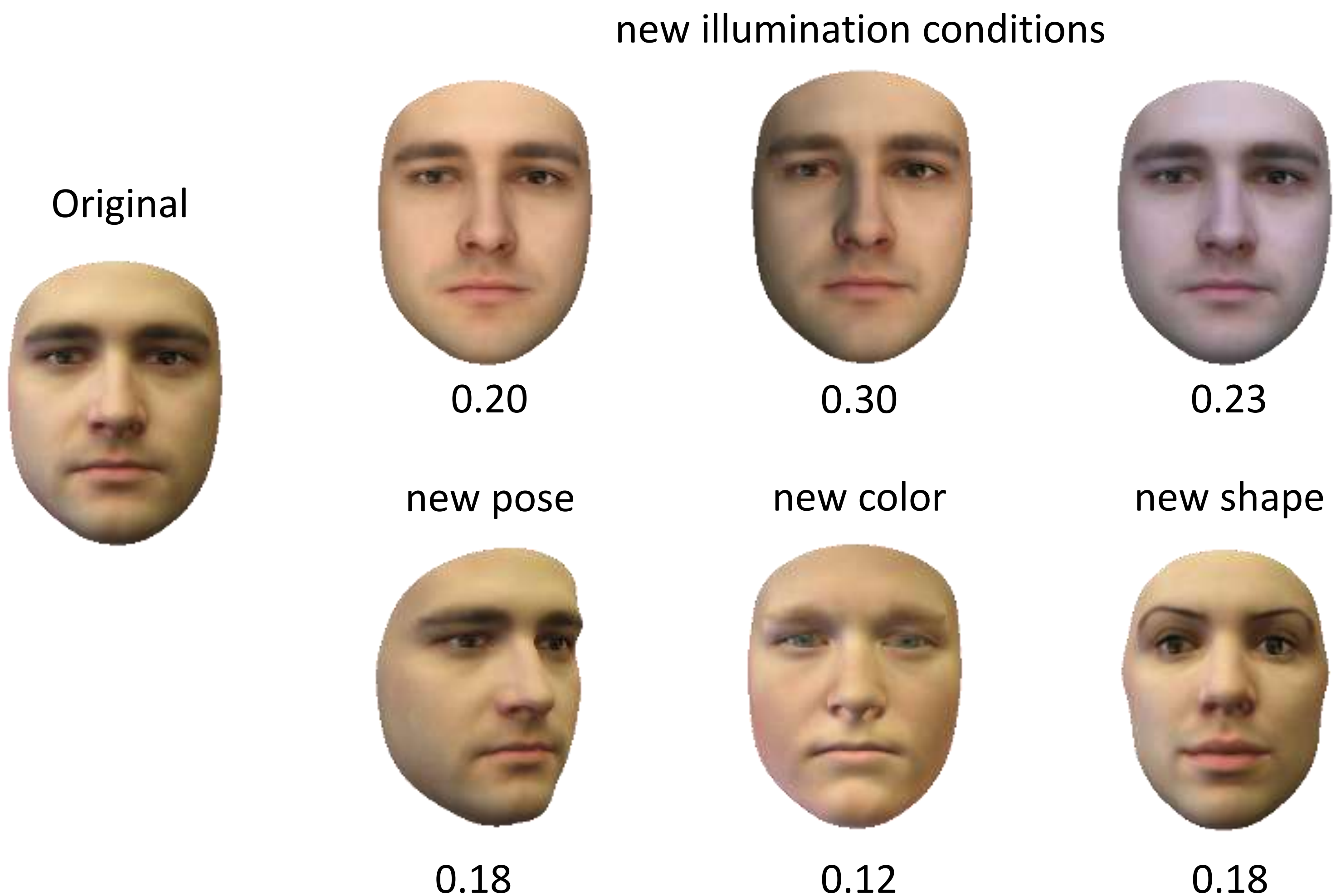
Egger, Schönborn, Blumer, Vetter (2017). Probabilistic Morphable Models in Statistical Shape and Deformation Analysis, Elsevier

How to initialize?

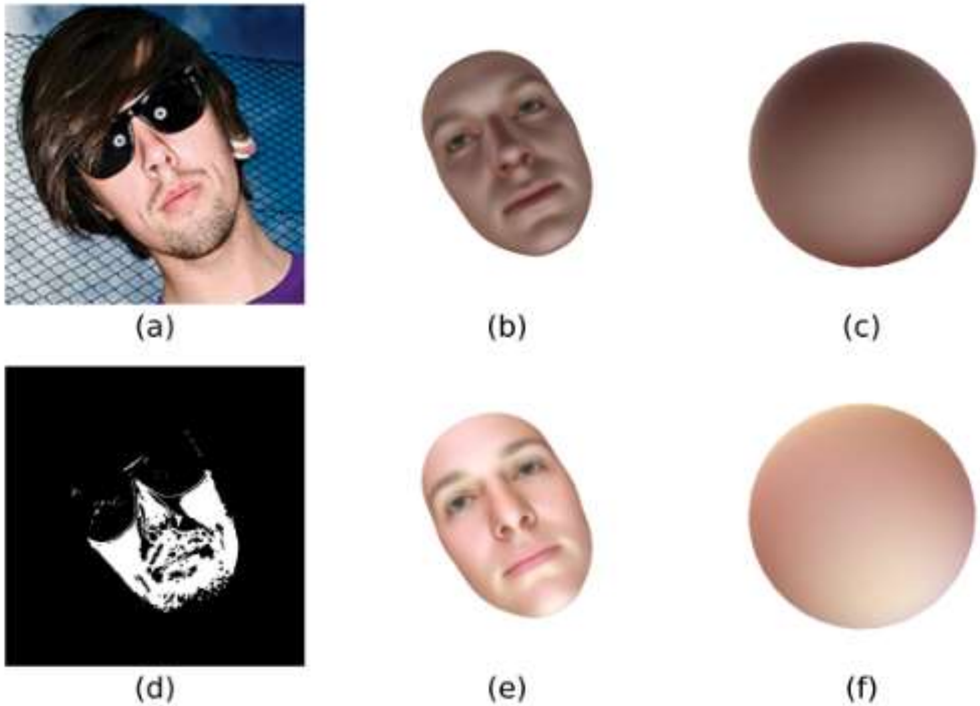


Egger, Schönborn, Schneider, Kortylewski, Morel-Forster, Blumer, Vetter (2018).
Occlusion-aware Morphable Models and an Illumination Prior for Face Image Analysis, IJCV

Illumination Dominates Appearance



Robust Illumination Estimation



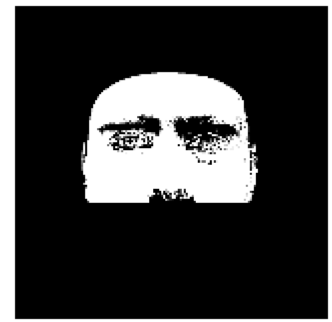
Egger, Schönborn, Schneider, Kortylewski, Morel-Forster, Blumer, Vetter (2018).
Occlusion-aware Morphable Models and an Illumination Prior for Face Image Analysis, IJCV

Initialization: Robust Illumination Estimation

Sampled points

Estimate illumination

Consensus set: Init z



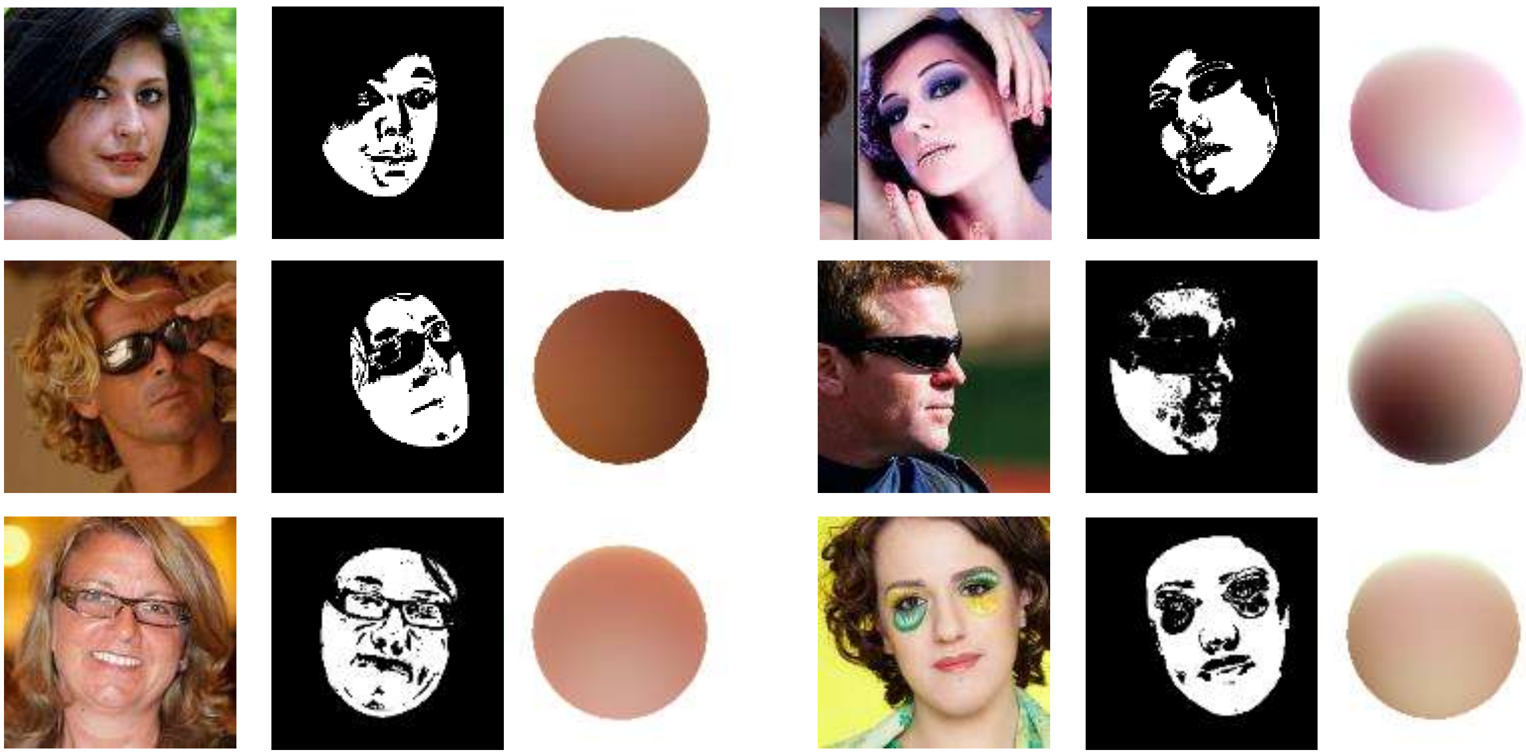
Init θ_{camera}

Init θ_{light}

Egger, Schönborn, Schneider, Kortylewski, Morel-Forster, Blumer, Vetter (2018).
Occlusion-aware Morphable Models and an Illumination Prior for Face Image Analysis, IJCV

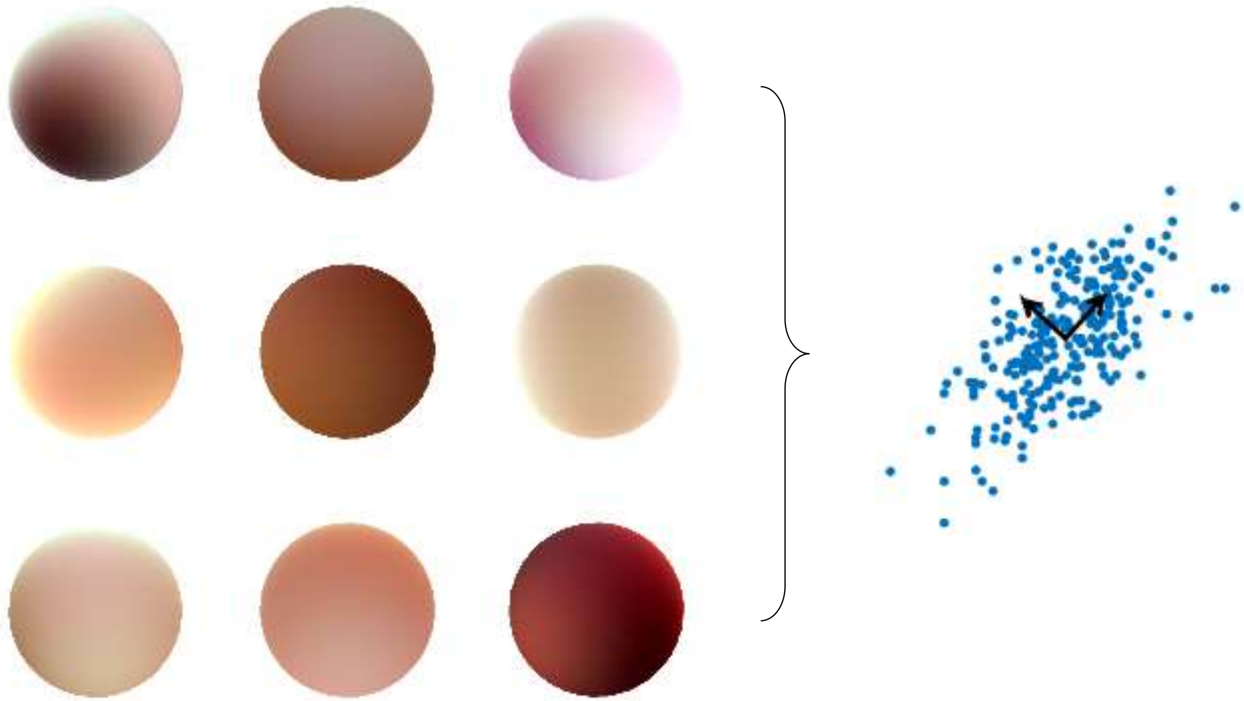
Robust Illumination Estimation «in the Wild»

Source: AFLW Database



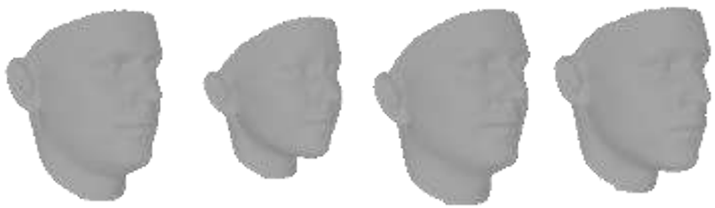
Egger, Schönborn, Schneider, Kortylewski, Morel-Forster, Blumer, Vetter (2018).
Occlusion-aware Morphable Models and an Illumination Prior for Face Image Analysis, IJCV

Illumination Prior from «in the Wild» data

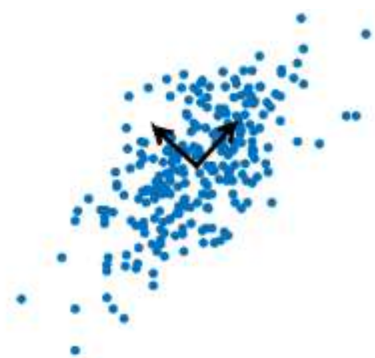


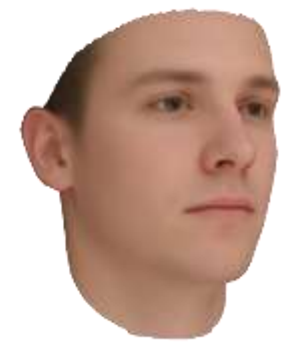
Egger, Schönborn, Schneider, Kortylewski, Morel-Forster, Blumer, Vetter (2018).
Occlusion-aware Morphable Models and an Illumination Prior for Face Image Analysis, IJCV

Joint Color, Shape and Attributes Model



age, height, weight, sex



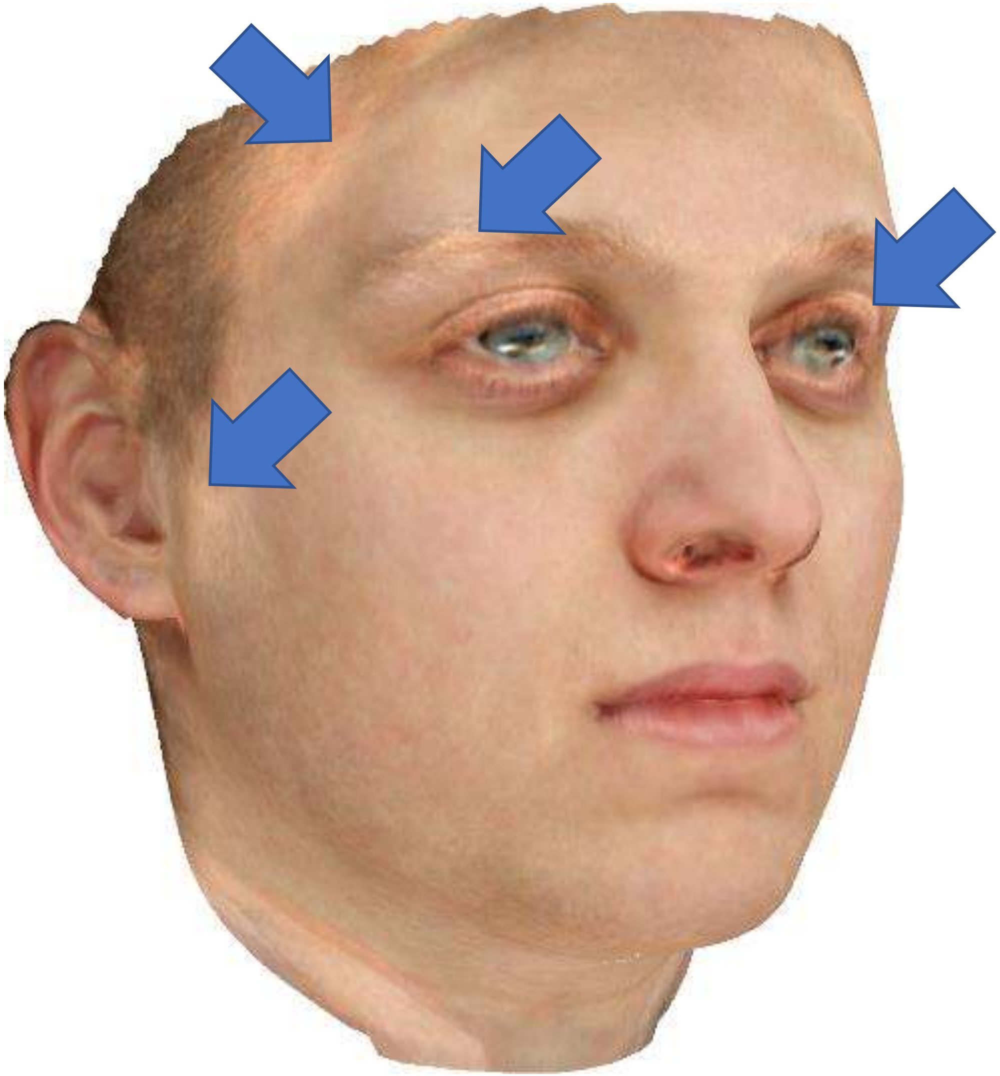


23.8 years, 182 cm, 77 kg, male

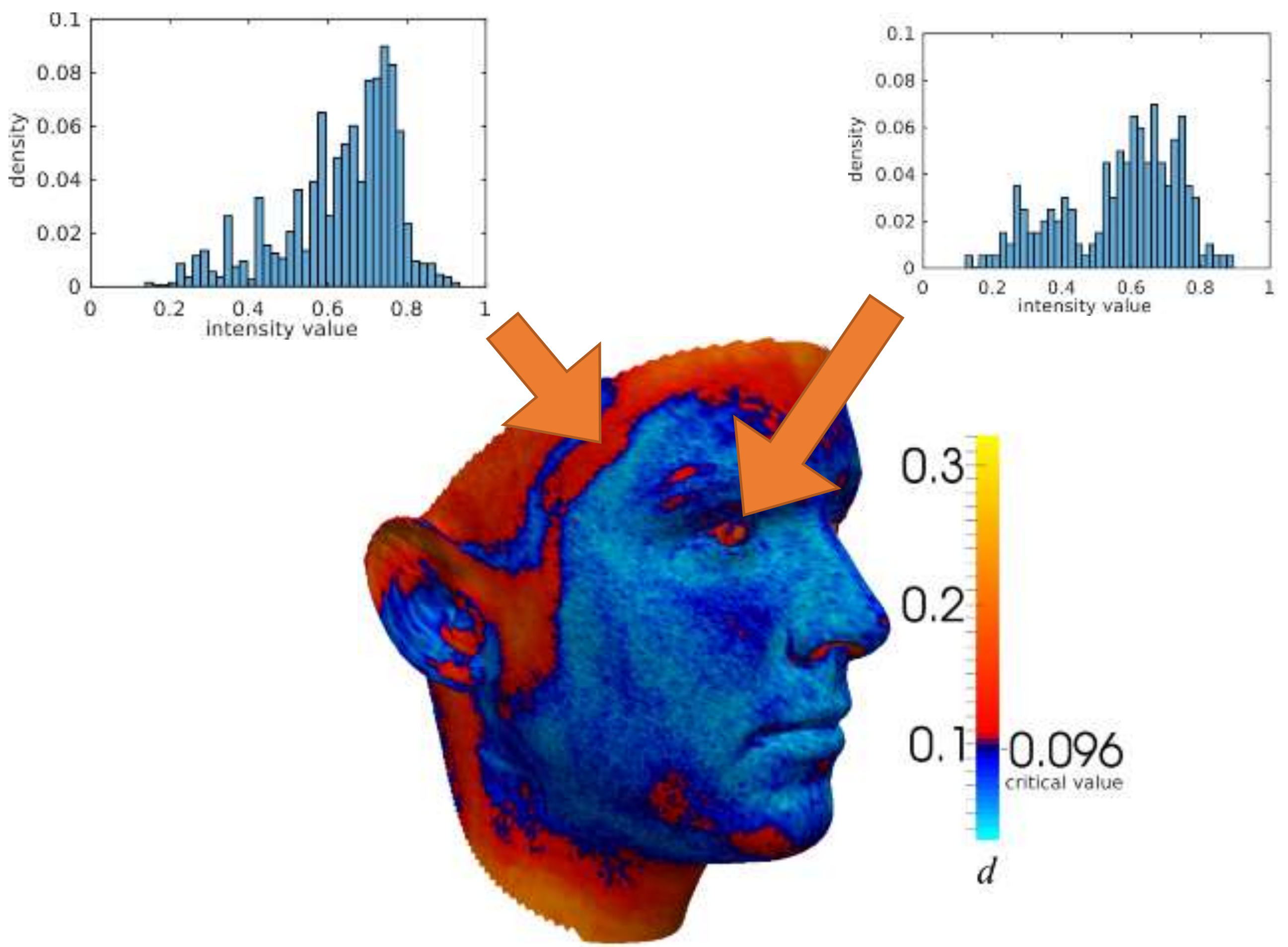
21.7 years, 165 cm, 54 kg, female

Egger*, Kaufmann*, Schönborn, Roth and Vetter (2016). (* equal contribution)
Copula Eigenfaces with Attributes, CCIS

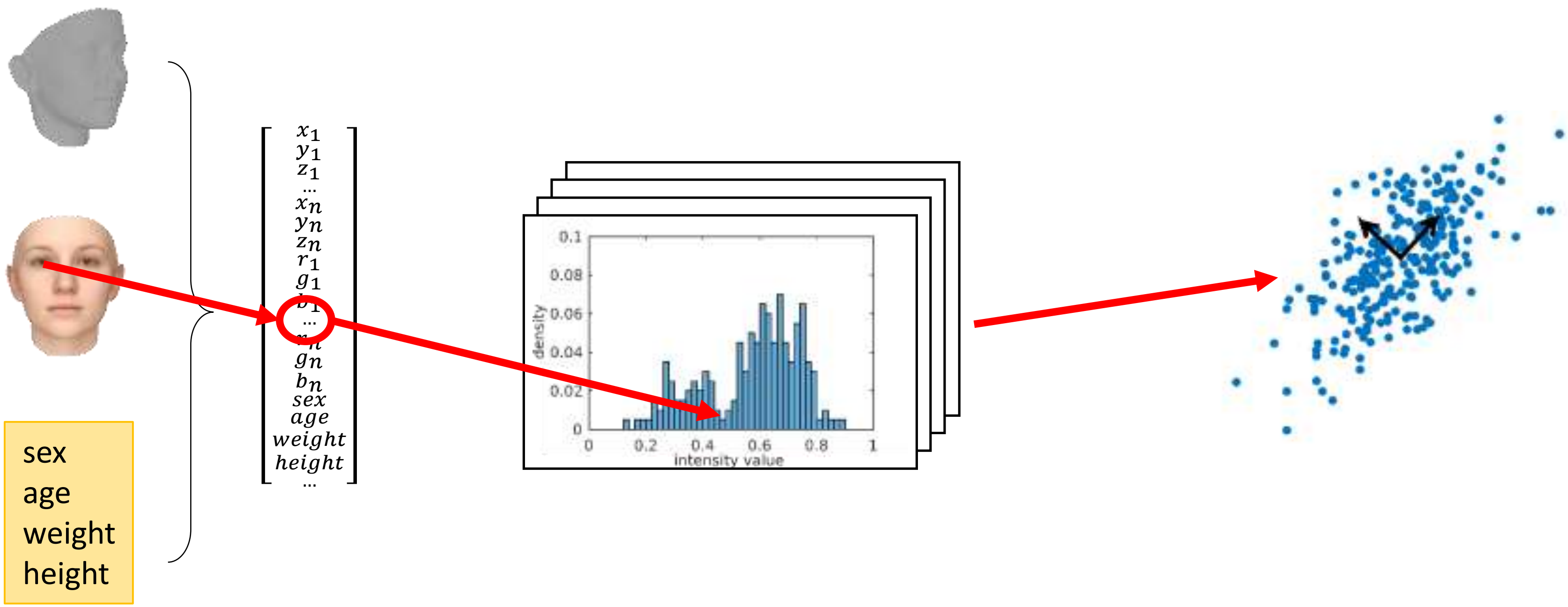
Unnatural artifacts



Marginal Distributions: Color Model



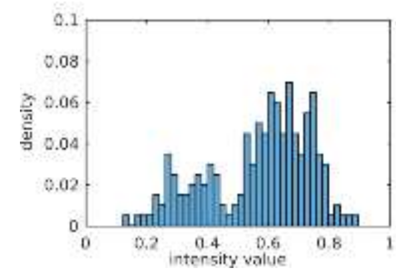
Copula Morphable Model



Egger*, Kaufmann*, Schönborn, Roth and Vetter (2016). (* equal contribution)
Copula Eigenfaces - Semiparametric Principal Component Analysis for Facial Appearance Modeling, GRAPP

Copula Component Analysis benefits

- **Dependency and marginals modeled seperately**
    - Additional flexibility
- **Non-Gaussian** marginals can be modeled



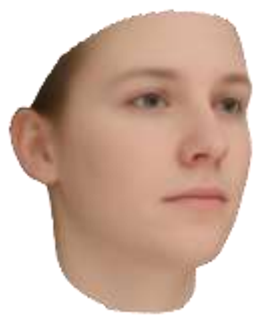
- **Scale-invariant**
    - Combined shape, color and attribute models

sex
age
weight
height

- Robust to outliers
- Pre- and postprocessing

Including Attributes

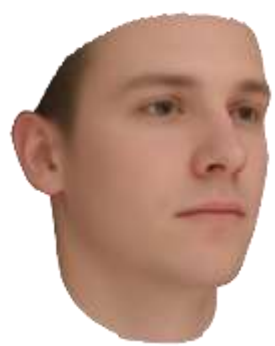
1st PC



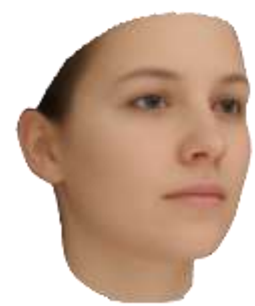
21.4 years, 172 cm, 62 kg

24.7 years, 175 cm 68 kg

2nd PC



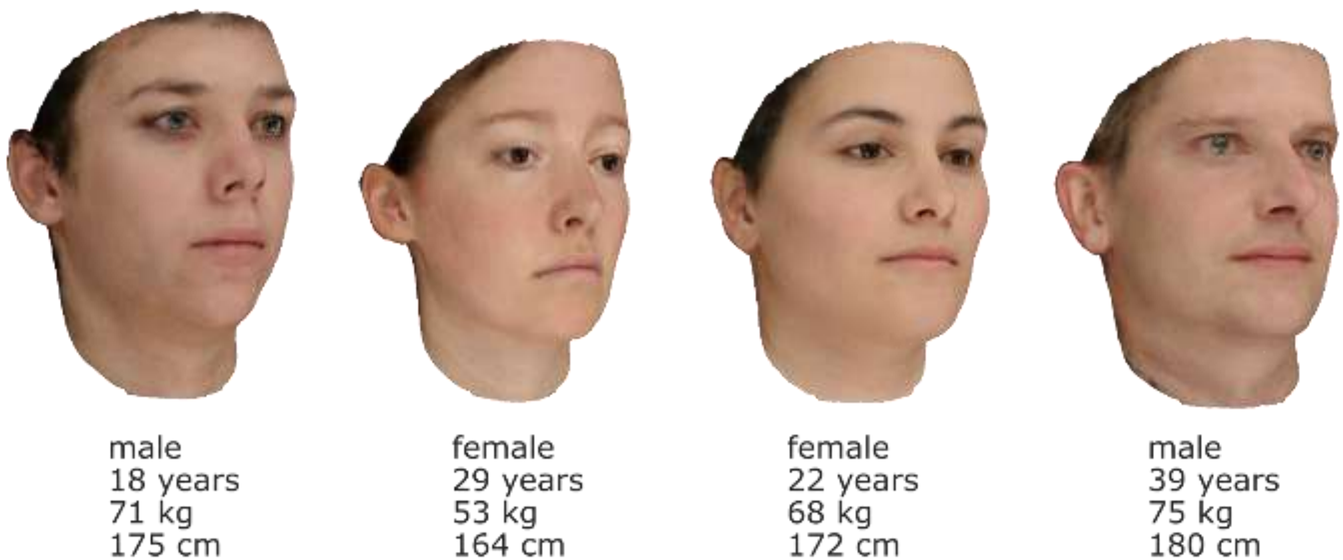
23.8 years, 182 cm, 77 kg



21.7 years, 165 cm, 54 kg

-2σ $+2\sigma$

Random Samples



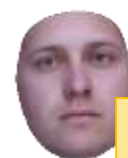
Egger*, Kaufmann*, Schönborn, Roth and Vetter (2016). (* equal contribution)
Copula Eigenfaces with Attributes, CCIS

Copula Posterior model

male

female

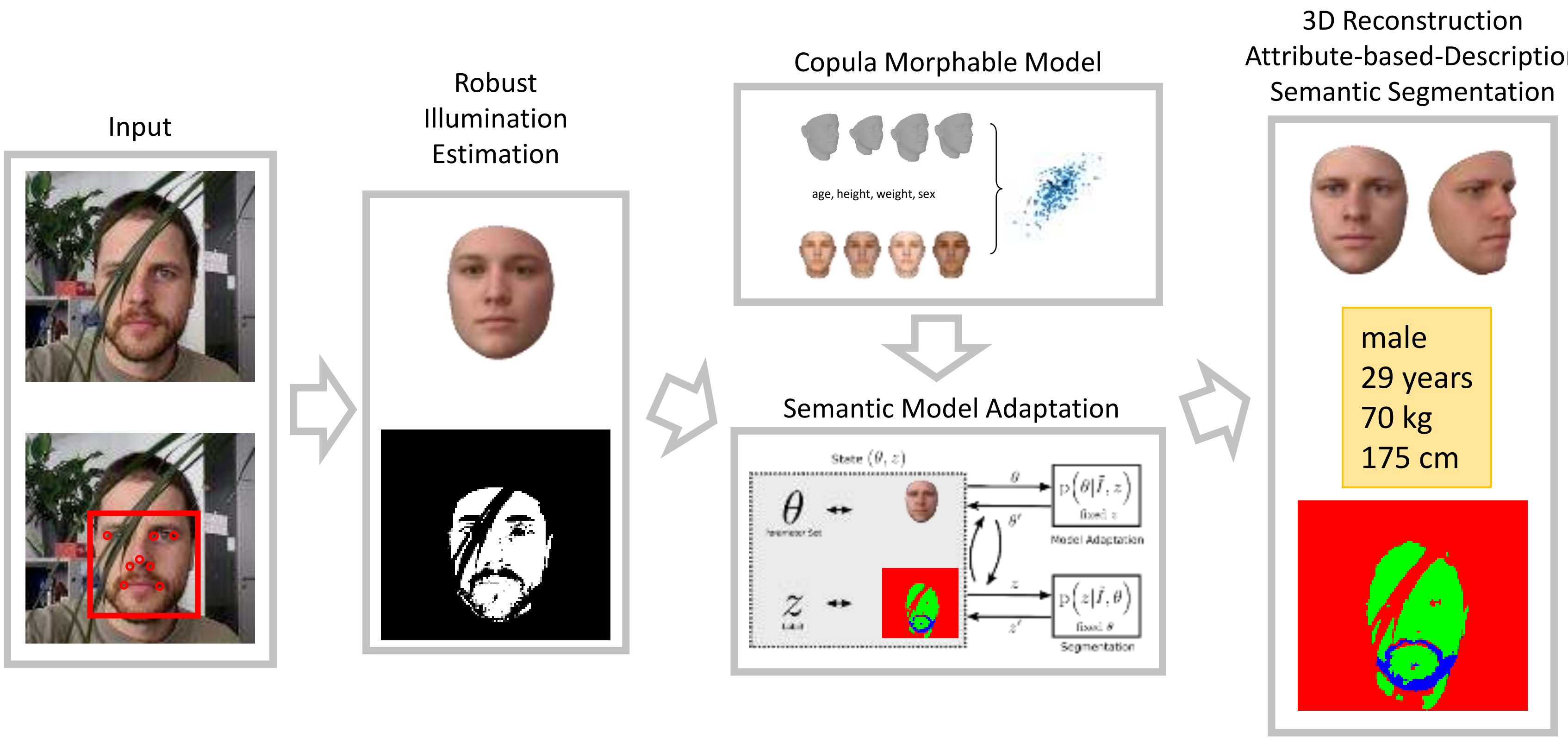
Face Image Analysis: Sex prediction



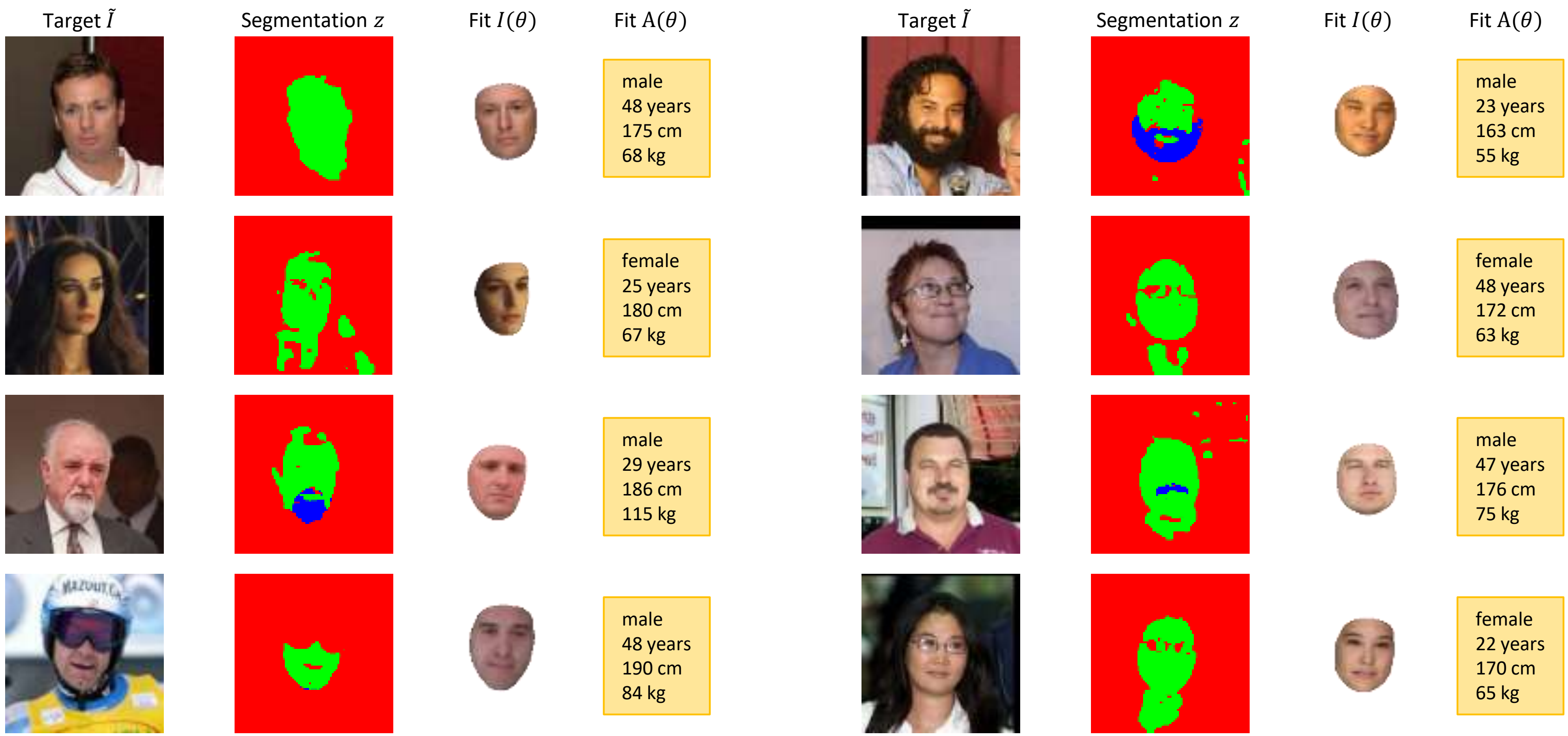
male
28 years
74 kg
175cm

Model / Feature	PCA coefficients + Random forests	Copula Morphable Model	Copula Morphable Model (only caucasian)
Prediction performance	76,2 %	82,5%	88,7%
Additional training data	✓	✗	✗

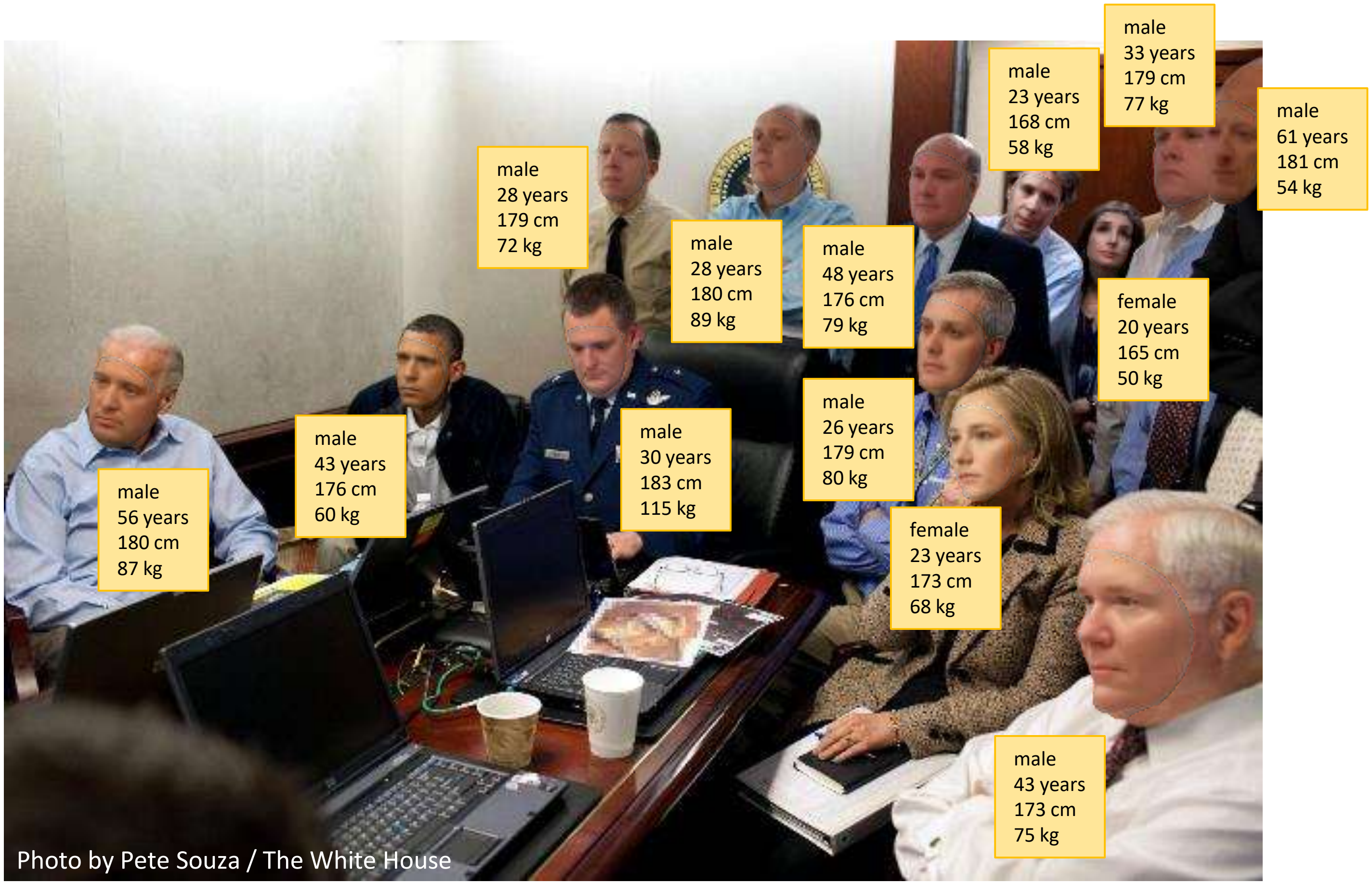
Semantic Morphable Model: Overview



Semantic Image Description: Results



Targets: LFW Face Database

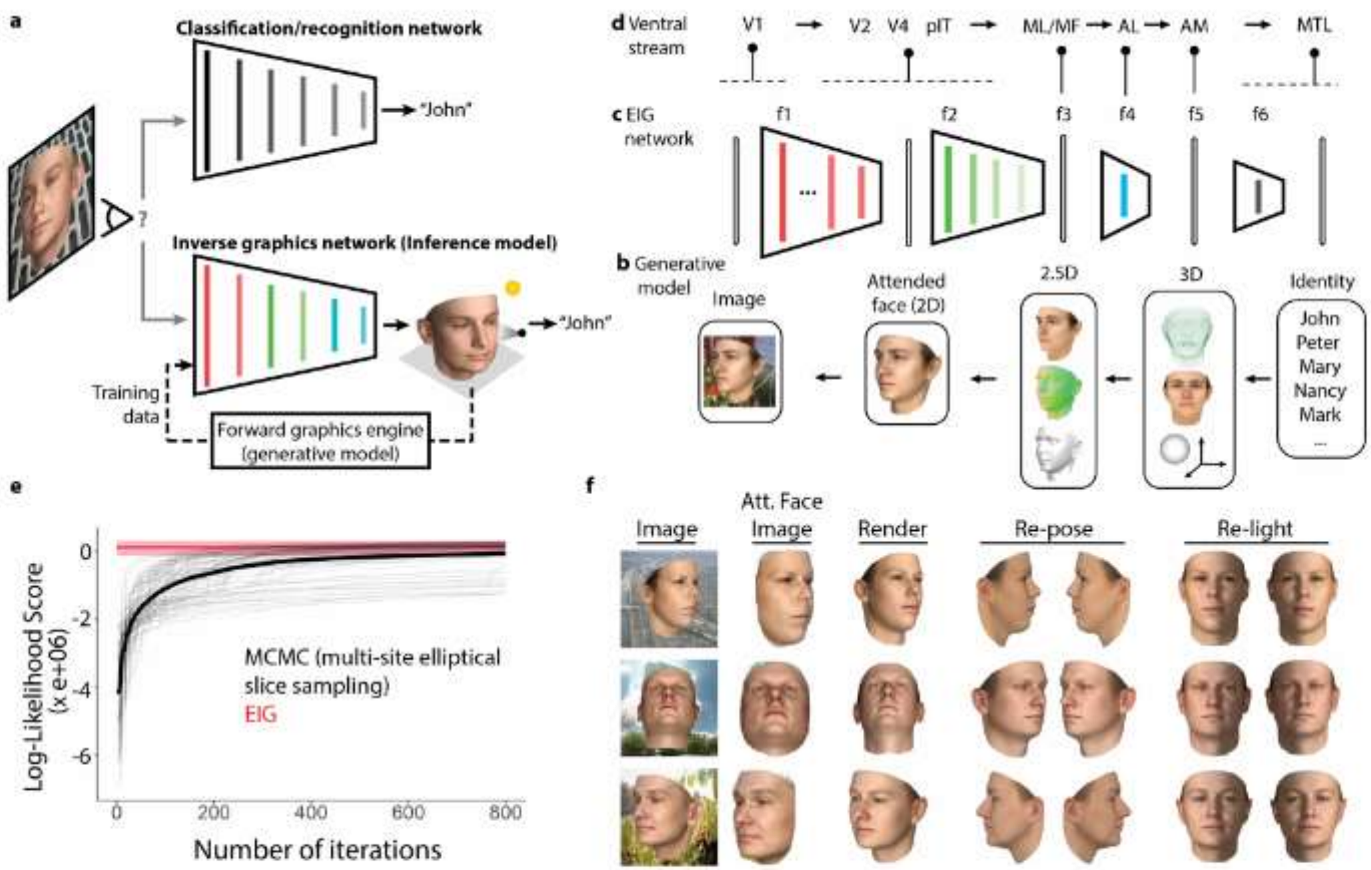

male 28 years 179 cm 72 kg
male 28 years 180 cm 89 kg
male 48 years 176 cm 79 kg
male 23 years 168 cm 58 kg
male 33 years 179 cm 77 kg
male 61 years 181 cm 54 kg
female 20 years 165 cm 50 kg
male 26 years 179 cm 80 kg
male 56 years 180 cm 87 kg
male 43 years 176 cm 60 kg
male 30 years 183 cm 115 kg
female 23 years 173 cm 68 kg
male 43 years 173 cm 75 kg
Photo by Pete Souza / The White House

Application: Image Manipulation

https://gravis.dmi.unibas.ch/PMM/demo/face-manipulation/

Schönborn, Forster, **Egger**, Schneider (2014). Robust Image Analysis by fitting a 3DMM for Portrait Manipulation, Shape Symposium
Walker, Vetter (2009). Portraits made to measure: Manipulating social judgments about individuals with a statistical face model, JoV

Efficient inverse graphics in biological face processing



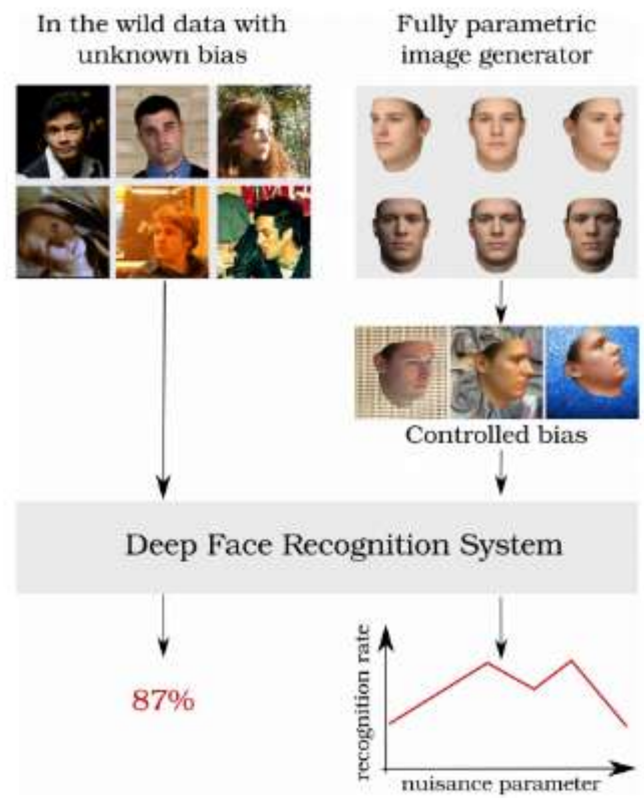
Ilker Yildirim, Mario Belledonne, Winrich Freiwald, Joshua Tenenbaum (2018) Efficient inverse graphics in biological face processing

Study Limitations with Controlled Training Data

- Full control over training data
- Synthetic but similar challanges

- Generalization
- Dataset Bias
- Bootstrapping
  - Less real training data

- Data generator available



Kortylewski, Egger, Schneider, Gerig, Morel-Forster and Vetter (2018), Empirically Analyzing the Effect of Dataset Biases on Deep Face Recognition Systems, CVPR Workshop

Questions