3D Morphable Face Models

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IPAM Workshop I: Geometric Processing
3D morphable model face animation

1,891,903 Aufrufe
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gravis.unibas.ch
Probabilistic 3D Morphable Model

Paysan et al (2009). A 3D Face Model for Pose and Illumination Invariant Face Recognition, AVSS
Gaussian Process Registration

(a) $s = 100, \sigma = 100 \text{ mm}$

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

Image Formation Process

1 principal component = 0.0
Goal: 3D Reconstruction from a Single Image

Source: KEYSTONE
Approach: Analysis by Synthesis
Analysis by Synthesis

parametrized representation

changing camera and illumination

Source: KEYSTONE
Classical Face Model Adaptation

Target $\tilde{I}$

- Probabilistic Framework

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

- Markov chain Monte Carlo-Sampling

Fit $I(\theta)$

$$= R_p (\alpha_1 \cdot \tilde{I} \ + \alpha_2 \cdot \tilde{I} \ + \cdots + \alpha_n \cdot \tilde{I})$$

Markov Chain Monte Carlo for Automated Face Image Analysis IJCV
Color Illumination Ambiguity

\[ \theta \quad \theta_{\text{color}} \quad \theta_{\text{light}} \]

(a) ambient light  (b) mean color  (c)

(d) 0.075  (e) 0.128  (f) 0.097
Results: Qualitative

Source: LFW Database

Classical Morphable Model

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

Markov Chain Monte Carlo for Automated Face Image Analysis IJCV
Background model

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

• Shrinking and the hacks

• Simple generic model is enough
The good

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

MoFA: Model-based Deep Convolutional Face Autoencoder for Unsupervised Monocular Reconstruction arXiv
The bad
Semantic Morphable Model
Semantic Model Adaptation

\[ l(\theta; \tilde{I}, z) = \prod_i \prod_k l_k(\theta; \tilde{I}_i)^{z_{ik}} \]

with \( z_{ik} \in \{0,1\} \) and \( \sum_k z_{ik} = 1 \ \forall i \)

\textbf{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

\[ P(z|\tilde{I}, \theta) \propto \prod_{i} \prod_{k} l_k(\theta; \tilde{I}_i)^{z_{ik}} P(z_{ik}|\theta) P(c) \prod_{j \in n(i)} P(z_{ik}, z_{jk}) \]

Prior \( c \)

Label \( z_i \)

Pixels \( \tilde{I}_i \)

\( l_k(\theta; \tilde{I}_i) \) represents the likelihoods, \( P(z_{ik}|\theta) \) is the prior, and \( P(z_{ik}, z_{jk}) \) captures smoothness.

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

\[ l_{\text{face}}(\theta; \tilde{I}_i) = \begin{cases} 
\tilde{I} \\
I(\theta) 
\end{cases} \]

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

\[
l(\theta; \tilde{I}, z) = \prod_i \prod_k l_k(\theta; \tilde{I}_i)^{z_{ik}}
\]

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

Inference

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

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

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

Original

new illumination conditions

new pose
0.20
0.18

new color
0.30
0.12

new shape
0.23
0.18
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 $\theta_{camera}$

Init $\theta_{light}$

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

Copula Eigenfaces with Attributes, CCIS

21.7 years, 165 cm, 54 kg, female

23.8 years, 182 cm, 77 kg, male
Unnatural artifacts
Marginal Distributions: Color Model
Copula Morphable Model

Copula Eigenfaces - Semiparametric Principal Component Analysis for Facial Appearance Modeling, GRAPP
Copula Component Analysis benefits

- **Dependency and marginals modeled separately**
  - Additional flexibility

- **Non-Gaussian** marginals can be modeled

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

- 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

+2σ
Random Samples

Copula Eigenfaces with Attributes, CCIS
Copula Posterior model

male

female
Face Image Analysis: Sex prediction

<table>
<thead>
<tr>
<th>Model / Feature</th>
<th>PCA coefficients + Random forests</th>
<th>Copula Morphable Model</th>
<th>Copula Morphable Model (only caucasian)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prediction performance</td>
<td>76,2 %</td>
<td>82,5%</td>
<td>88,7%</td>
</tr>
<tr>
<td>Additional training data</td>
<td>✔️</td>
<td>✗</td>
<td>✗</td>
</tr>
</tbody>
</table>

Male
28 years
74 kg
175 cm
Semantic Morphable Model: Overview

Input

Robust Illumination Estimation

Copula Morphable Model

Semantic Model Adaptation

3D Reconstruction
Attribute-based-Description
Semantic Segmentation

male
29 years
70 kg
175 cm
Semantic Image Description: Results

Targets: LFW Face Database
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 challenges
- 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