University of Basel

An Empirical Comparison of Deep Learning and 3DMM-Based Approaches for Facial Occlusion Segmentation

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10.08.2018

Overview

- Motivation
- Occlusion Segmenation with an FCN
- Experiment: Segmentation Quality
  - Qualitative segmenation results
  - Quantitative segmentation results
- Experiment: Fitting under occlusion
- Application to real-life data and conclusion
- Future Work

The Goal


(a) original


(b) mask


(c) resulting fit

Figure: Fitting with a perfect mask

The Problem (Segmentation under Occlusion)

(a) original

(b) resulting fit

Figure: Fitting without a mask

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Convolutional Neural Network (CNN)

- Artificial Neural Network
- fully connected layers at the end
- makes decisions based on global information

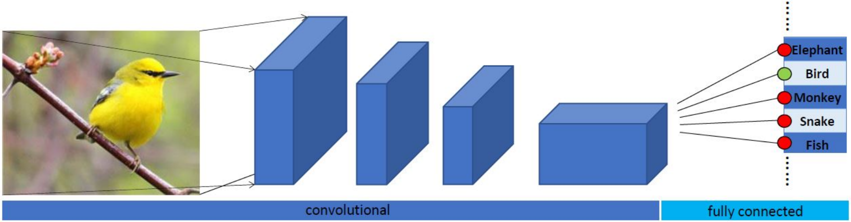

Figure: A classical neural network

Fully Convolutional Network (FCN)

- without fully connected layers at the end
- makes decisions based on spatial information

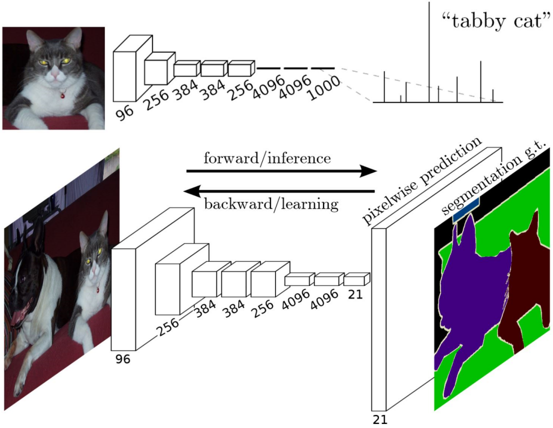

Figure: The transformation from a CNN into a FCN

Training of the FCN

- The FCN was trained by Nirkin et al.
- They used the well known FCN-8s-VGG network
- Training Data: Frames of Videos
- Frame used multiple times (synthetic occlusions)
- Total: 9’818 facial images

Figure: Two images used for training. They are overlaid them with an synthetic occlusion.

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Qualitative Evaluation on the COFW Dataset

- **C**altech **O**ccluded **F**aces in the **W**ild
- used of Nirkin et al themselves

(a) Six segmentations of the FCN

(b) Six segmentations of the approach of Egger et al

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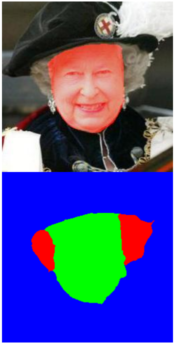
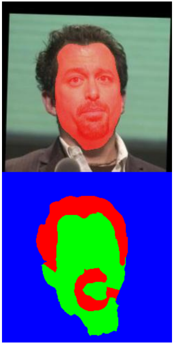
Evaluation on the Parts-LFW Dataset (1)

- **L**abeled **F**aces in the **W**ild
- ground truth labels were provided
- Difficult question: What is an occlusion?



(a) The desired ground truth labels

(b) Face and skin have same label → False negatives



(c) Facial hair is an occlusion → false positives (hair)

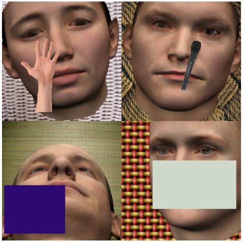
Evaluation on the Parts-LFW Dataset (2)

- statistics with simple pixelwise comparison
- same label for skin parts and face (false negatives)

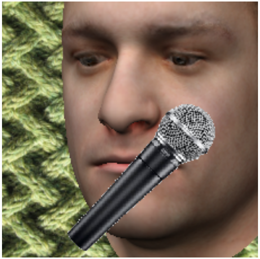
false-positives (hair)	7.04%
false-positives (background)	0.68%
false-negatives (background)	14.13%
right-segmentations	85.87%
right non-sementations	99.32%

Evaluation on Synthetic Data (1)

- Known ground truth labels (c)
- Control of every rotation
- Control of the occluded amount



(a) A synthetic face



(b) A synthetic face with an occlusion

(c) The ground truth mask of (b)

Evaluation on Synthetic Data (2)

- Segmentation is very sensitive to the roll rotation
- Pitch is asymmetric (better recognizable with high angles)
- Yaw rotation has little effect on the segmentation

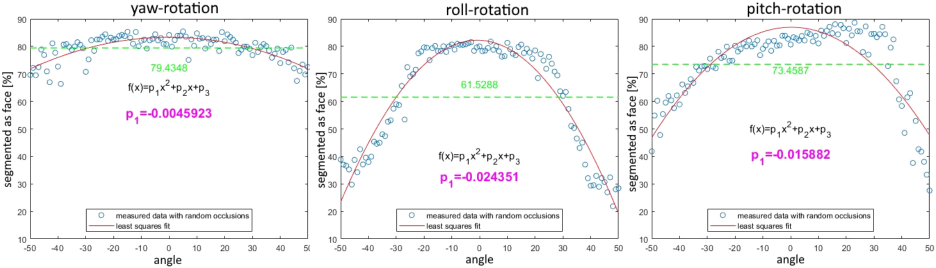


Figure: Plot for every rotation (yaw, roll, pitch). Quadratic fit (red curve/$f(x)$). Average (green). The data for the plot consisted of synthetic facial images with microphones and hands as occlusions.

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Fitting with the FCN segmentation (1)

	ground truth mask	Egger	FCN	no mask
z-labels				
fits				

Fitting with the FCN segmentation (2)

- Calculation of the error (in σ) in each iteration
- In each parameter-space, we used 50 dimensions
- Average over 10 images (only with hands as occlusions)
- In each iteration, 1000 samples were drawn

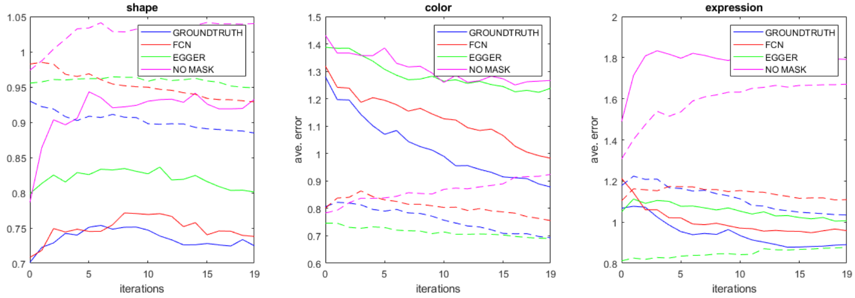


Figure: The average error of the first five (most important) 3DMM parameters is shown with a solid line. The average other 45 parameters is shown with a dashed line.

Oversegmentaion of EGGER

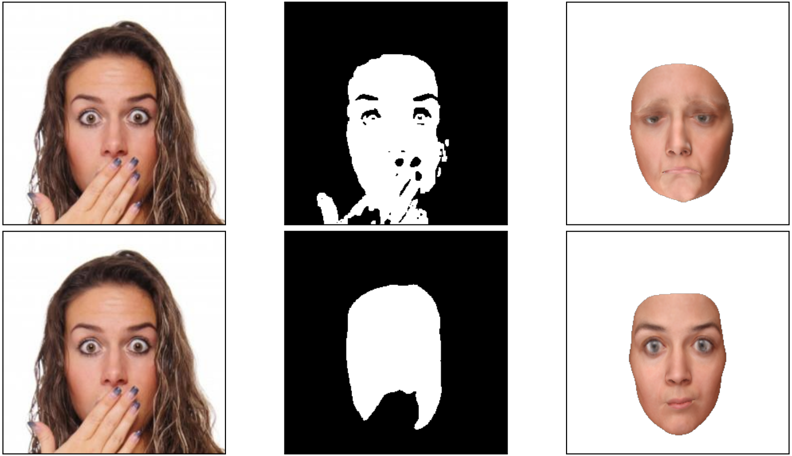
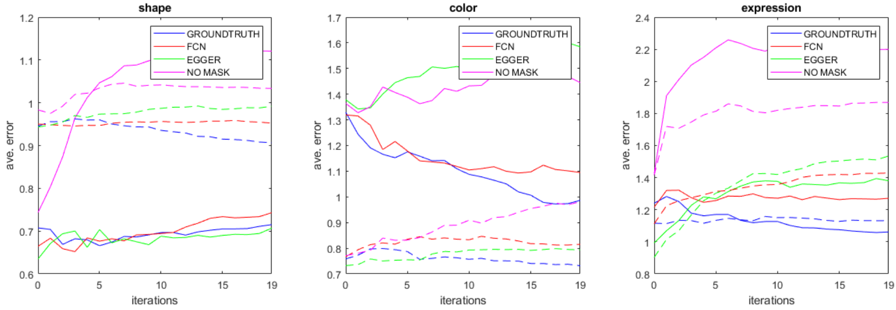


Figure: Fitting with occlusion-aware masks. Mask of Egger et al (top row). Mask of the fully convolution network used in this thesis (bottom row).

Fitting with the FCN segmentation (3)

- Biggest weakness of Egger et al's approach: Oversegmentation
- How can we spread between (FCN and EGGER) bigger?
- Synthetic faces with both, the 'face12' and the 'bfm' version



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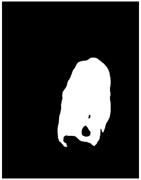
Real-Life data

	masks		**fits**	
original	EGGER	FCN	EGGER	FCN
				
				

Conclusion

	advantages	disadvantages
FCN	• Does not oversegment • Segments only facepixels • Detects known occlusions	• Poor detection of thin and new occlusions • Fitting not much faster • Very sensitive to the rotation of the face
EGGER	• Looks at each pixel individually, therefore can detect any occlusion • Stable on real-life data	• oversegments • excludes important details on the mask • computes the mask iteratively

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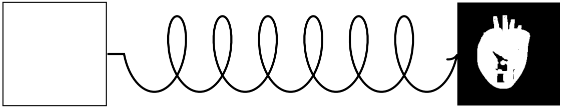
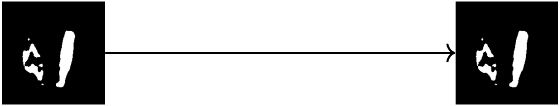
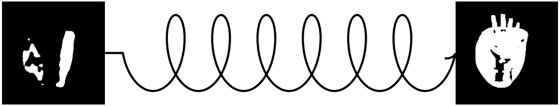
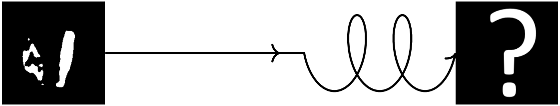
Future Work: Combination of both masks

	initial mask → fitting iterations → final mask
EGGER	
FCN	
Our Combination	
Future Work	

Questions?

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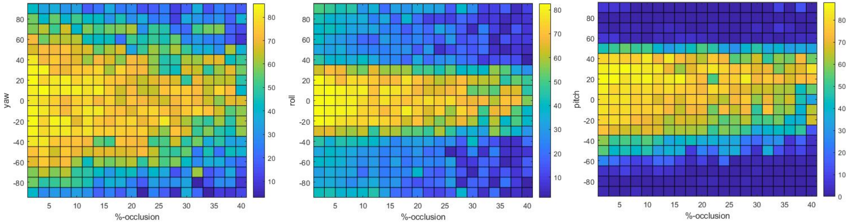
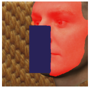
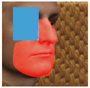
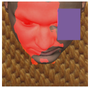
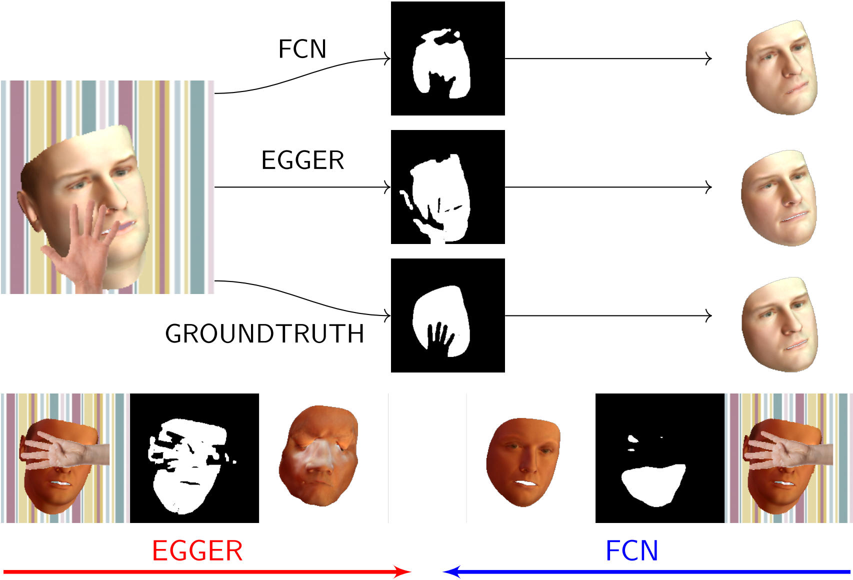
Dependence of the Degree of Occlusion



	yaw	roll	pitch
-40°			
40°			

Wrong Color Choice with the Mask of Egger et al



Related Work (Nirkin et al: On Face Segmentation, Face Swapping, and Face Perception)

- Widespread artificial neural networks can be used for face segmentation
- intra-subject swapped faces remain as recognizable as their sources (a)
- less recognizable inter-subject results (b)

(a) Example of Intra-Subject swapping

(b) Example of Inter-Subject swapping