MoFA: Model-based Deep Convolutional Face Autoencoder for Unsupervised Monocular Reconstruction
— Supplemental Material —

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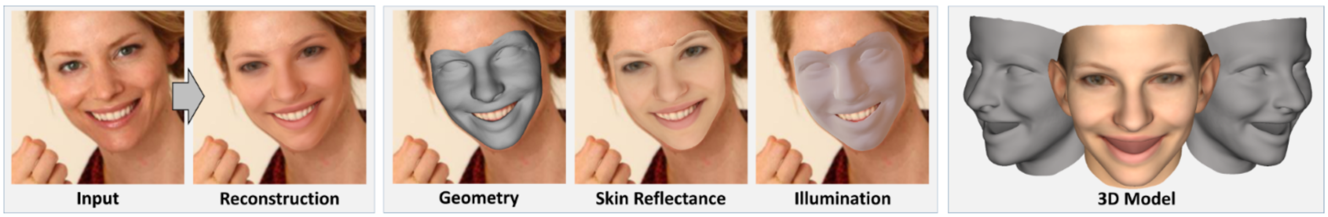

Our model-based deep convolutional face autoencoder enables unsupervised learning of semantic pose, shape, expression, reflectance and lighting parameters. The trained encoder predicts these parameters from a single monocular image, all at once.

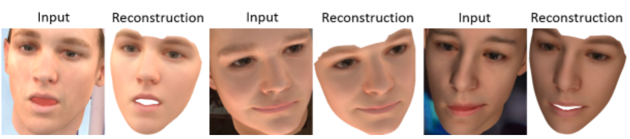

Figure 1. Results on synthetic ground truth data: We obtain good fits for all parameters.

This supplemental document shows more results and evaluations of our novel model-based deep convolutional face autoencoder (MoFA) that allows for unsupervised monocular reconstruction. In particular, we show more images of our real-world training corpus (see Fig. 3), additional qualitative results (see Fig. 4) and additional comparison to optimization-based (see Fig. 2 and 10) and learning based (see Fig. 9) monocular reconstruction approaches. We evaluate the influence of our surrogate task (see Fig. 7) and show reconstruction results based on different encoders (see Fig. 6). We provide a visual evaluation of the convergence (see Fig. 8). In addition, we illustrate the limitations of our approach (see Fig. 5) and show more reconstruction results on our synthetic ground truth test set (see Fig. 1). For a detailed description of these results, please refer to the corresponding sections of the main document.

Additional reconstruction results for images and video sequences are shown in the supplemental video. Note, to obtain temporally coherent video results we generate the 2D bounding box crops, which are the input to our network, using the face tracker of [10]. For all image results we obtain the crops using Haar Cascade Face Detection [1].

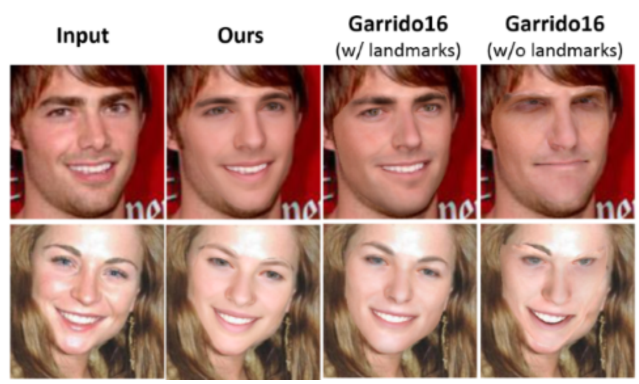

Figure 2. We compare to our implementation of the high quality offline monocular reconstruction approach of [3]. We obtain similar quality without requiring landmarks as input. Without landmarks, [3] often gets stuck in a local minimum.

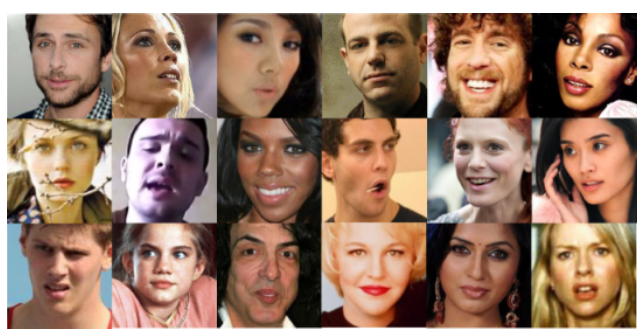

Figure 3. Sample images of our real world training corpus.

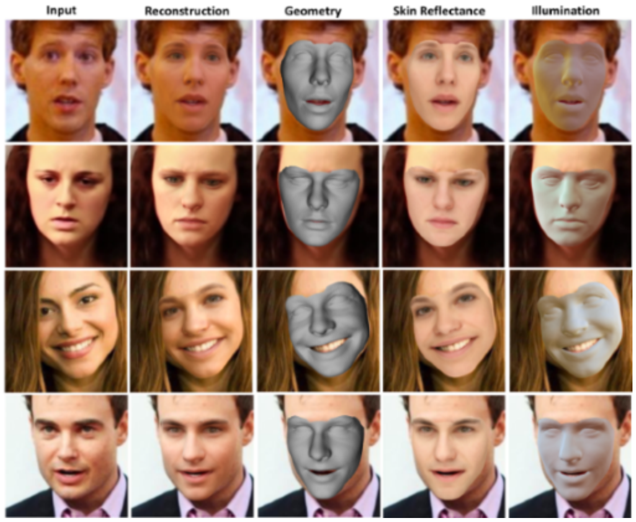

Figure 4. Our approach enables the regression of high quality pose, shape, expression, skin reflectance and illumination from just a single monocular image (images from CelebA [6]).

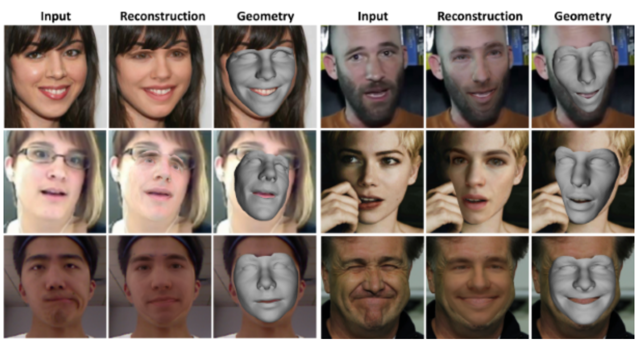

Figure 5. Strong occlusions or pronounced expressions outside the span of training data can lead to inaccurate regression results.

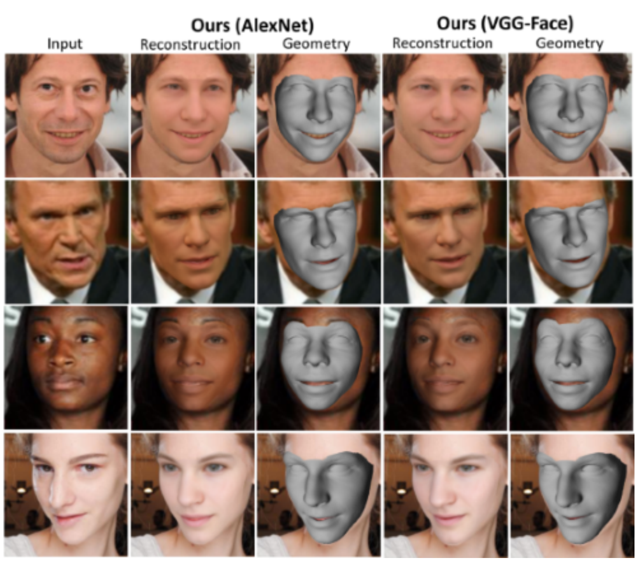

Figure 6. We evaluate different encoders in combination with our model-based decoder. In average VGG-Face [7] leads to slightly better results than AlexNet [5], but the results are comparable.

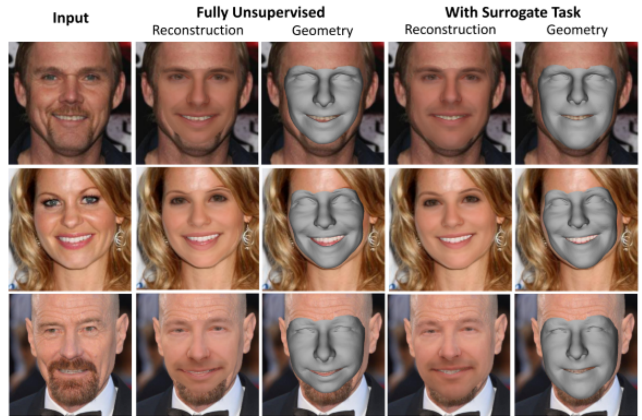

Figure 7. We evaluate the influence of the proposed surrogate task. The surrogate task leads to improved reconstruction quality and increases robustness to occlusions and strong expressions.

References

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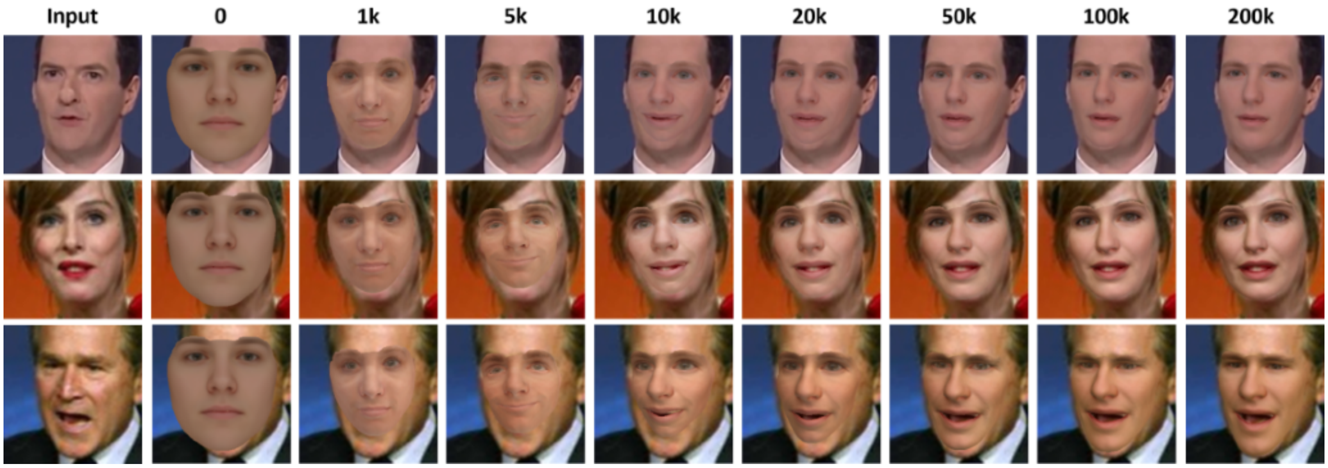

Figure 8. Visual evaluation of the convergence during training. Starting from the average face, our approach learns the variation between faces in an unsupervised manner. This evaluation has been performed on the test set — the CNN has not seen these images during training.

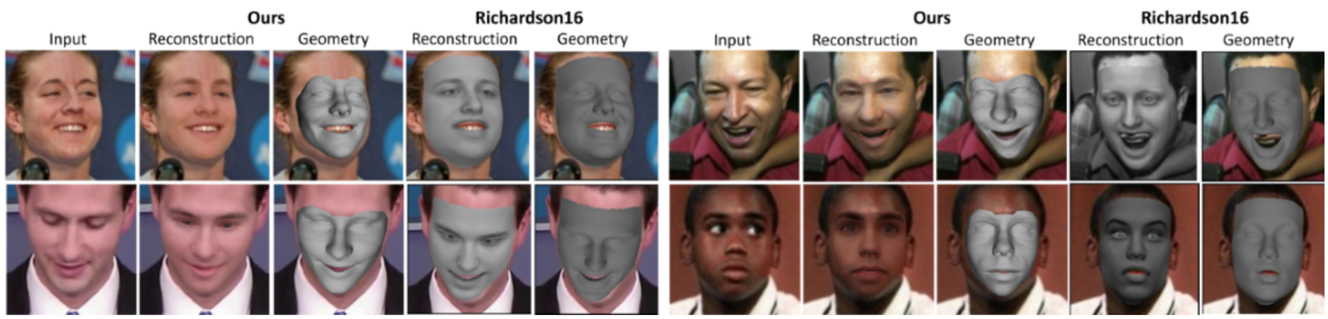

Figure 9. Comparison to Richardson et al. [8, 9] (coarse network without refinement) on 300-VW [2, 11, 13] (left) and LFW [4] (right). Our approach obtains higher reconstruction quality and provides estimates of colored reflectance and illumination. Note, the greyscale reflectance of [8, 9] is not regressed, but obtained via optimization, we on the other hand regress all parameters at once.

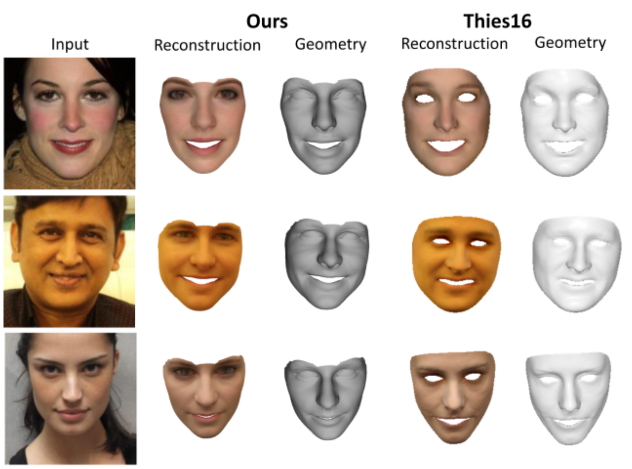

Figure 10. Comparison to the monocular reconstruction approach of [12] on CelebA [6]. Our approach obtains similar or higher quality, while being orders of magnitude faster (4ms vs. $\sim$ 500ms).

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