3DMM Based Face Reconstruction and Makeup Transfer

Christina Tsangouri
Stanford University
xristina@stanford.edu

June 12, 2024

Abstract

This project presents a method for creating personalized virtual makeup try-on experiences. I achieve this by reconstructing a 3D face model from a single 2D image and then transferring makeup styles from a reference image onto the reconstructed model. My 3D reconstruction utilizes a 3D Morphable Model (3DMM), specifically the Basel Face Model (BFM), which is fitted to the input 2D facial image to capture its geometry and texture. For makeup transfer, I segment key facial regions (e.g., lips, eyes) in the reference image and apply the corresponding makeup textures onto the 3D reconstruction. The effectiveness of my approach is evaluated qualitatively through visual comparisons between the final rendered results and the original and reference images. My findings demonstrate the feasibility and potential of this method for generating realistic virtual makeup try-on simulations.

1 Introduction

Virtual try-on experiences have become increasingly popular in various sectors, including fashion, beauty, and retail. In the cosmetics industry, the ability to visualize how different makeup styles would look on one's own face without physically applying them is a valuable tool for both consumers and brands. It allows users to experiment with various looks in a risk-free environment, leading to better purchase decisions and higher customer satisfaction. Brands benefit by providing an engaging and interactive shopping experience, potentially increasing conversion rates and customer loyalty.

However, creating realistic and personalized virtual makeup try-on experiences presents several challenges. The key to a successful virtual try-on system lies in its ability to accurately reconstruct the user's face in 3D from a single 2D image and to seamlessly apply makeup in a manner that looks natural and realistic. This project aims to address these challenges by leveraging 3D Morphable Models (3DMMs) for accurate face reconstruction and advanced image processing techniques for realistic makeup transfer. By combining these approaches, I seek to develop a system that can generate personalized virtual makeup try-on simulations that are both visually appealing and faithful to the user's unique facial features.

One of the primary challenges in 3D face reconstruction is the accurate estimation of 3D facial geometry from a single 2D image. This involves addressing issues such as varying lighting conditions, facial expressions, and occlusions. Traditional methods often rely on dense correspondences between 2D images and 3D models, which can be computationally expensive and prone to inaccuracies. Recent advancements in deep learning, however, have introduced new methods that significantly improve the accuracy and efficiency of 3D face reconstruction.

Makeup transfer is an additional challenging task due to the complexity of human facial features and the variability in makeup styles. Traditional 2D image-based techniques often fail to capture the depth and realistic appearance of facial features, leading to suboptimal results. This project aims to address these challenges by employing 3DMMs for accurate face reconstruction and segmentation for realistic makeup transfer. By focusing on these two core aspects, the project aims to enhance the realism and usability of virtual makeup try-on experiences.

2 Related Work

3D face reconstruction from a single 2D image has been a subject of extensive research, with various approaches being proposed to address its inherent challenges. Traditional methods often rely on complex optimization techniques or require additional input information, such as depth maps or multiple images. However, recent advances in deep learning have led to the development of more efficient and accurate methods for 3D face reconstruction.

The paper ”A Lightweight Monocular 3D Face Reconstruction Method Based on Improved 3D Morphing Models” [5] addresses these challenges by proposing a lightweight and efficient method for 3D face reconstruction. The authors improve the traditional 3DMM approach by introducing novel techniques for better handling of texture and shape variations, resulting in more accurate and robust reconstructions even under challenging conditions.

Makeup transfer involves accurately applying makeup styles from a reference image onto a target face while maintaining the identity and natural appearance of the target. This task is complicated by factors such as differing facial poses, lighting conditions, and skin tones. Traditional methods often struggle with maintaining the consistency of makeup application across different poses and expressions.

This has also seen significant progress. Early methods often relied on simple image warping or color blending, which often resulted in unrealistic or inconsistent results. However, recent research has explored more sophisticated techniques, such as the use of generative models and deep learning architectures.

The paper ”Large-pose Facial Makeup Transfer Based on Generative Adversarial Network Combined Face Alignment and Face Parsing” [2] presents an innovative approach to this problem. The authors combine generative adversarial networks (GANs) with face alignment and face parsing techniques to achieve high-quality makeup transfer. Their method is capable of handling large variations in facial poses, ensuring that the makeup application looks natural and consistent across different views.

The paper ”BareSkinNet: De-makeup and Delighting via 3D Face Reconstruction” [4] presents a novel approach for makeup removal and relighting using 3D face reconstruction. This work highlights the importance of accurate 3D facial geometry for achieving realistic makeup manipulation.

While these existing methods have made significant strides in both 3D face reconstruction and makeup transfer, there are still limitations to be addressed. Many approaches require high-quality input images or rely on complex optimization techniques, which may not be feasible for real-time applications or for users with limited computational resources. Additionally, achieving seamless and realistic makeup transfer remains a challenge, especially when dealing with complex makeup styles or variations in lighting conditions.

This project builds upon the existing research by proposing a method that aims to be both accurate and efficient, utilizing a 3DMM-based approach for face reconstruction and advanced image processing techniques for makeup transfer. I aim to contribute to the field by developing a system that can generate personalized virtual makeup try-on experiences that are accessible and visually compelling but still lightweight and efficient.

3 Approach

My approach to creating personalized virtual makeup try-on experiences consists of two main stages: 3D face reconstruction and makeup transfer. I outline the specific techniques and algorithms employed in each stage below.

3.1 3D Reconstruction

Overview of 3D Morphable Models (3DMMs): 3D Morphable Models [1] are statistical models that represent 3D shapes and textures of human faces.

They are typically built from a set of 3D face scans. The model captures the variations in facial geometry and texture across individuals by using a set of basis vectors. These basis vectors are derived from the principal component analysis (PCA) of the training data, representing the principal modes of variation.

Facial Landmark Detection: In order to establish the correspondences between the 2D image and the 3D model, I use Dlib, a robust machine learning library, to extract 68 facial landmarks. Dlib utilizes a pre-trained model based on extensive facial datasets to accurately identify key points such as the corners of the eyes, the tip of the nose, and the contours of the lips. These landmarks serve as crucial reference points for aligning the 2D image with the 3D face model. These landmarks are then visualized on the input image to verify their accuracy.

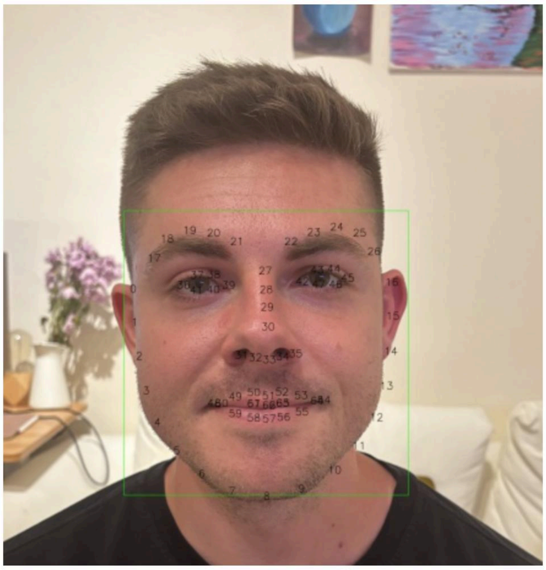

Figure 1: Facial landmarks

3D Morphable Model (3DMM) Fitting: I leverage the Basel Face Model (BFM), a widely used 3DMM, to represent the underlying structure of human faces. The BFM comprises a vast collection of 3D face scans, from which I extract shape and texture basis vectors.

The shape $\mathbf{S}$ and texture $\mathbf{T}$ of a face can be represented as:

$$\mathbf{S} = \bar{\mathbf{S}} + \sum_{i=1}^{N} \alpha_i \mathbf{S}_i$$

$$\mathbf{T} = \bar{\mathbf{T}} + \sum_{i=1}^{N} \beta_i \mathbf{T}_i$$

where $\bar{\mathbf{S}}$ and $\bar{\mathbf{T}}$ are the mean shape and texture, $\mathbf{S}_i$ and $\mathbf{T}_i$ are the basis vectors, and α_i and β_i are the coefficients.

By fitting the BFM to the detected 2D landmarks, I optimize the model's parameters to accurately capture the unique geometry and texture of the individual's face. Fitting the 3DMM to the detected 2D landmarks involves optimizing the model's parameters to minimize the reprojection error. This error is defined as the difference between the projected 3D landmarks and the corresponding 2D landmarks in the input image. The reprojection error E_{proj} can be calculated as:

$$E_{\text{proj}} = \sum_{i=1}^{M} \|\mathbf{p}_i - \Pi(\mathbf{S}(\alpha, \mathbf{S}_i))\|^2$$

where $\mathbf{p}_i$ are the 2D landmarks, Π is the projection function, and $\mathbf{S}(\alpha, \mathbf{S}_i)$ are the 3D landmarks.

In order to create the correspondences between the 2d image 68 facial landmarks from Dlib and the 3D model, I manually mark the points in MeshLab and export their x, y, z coordinates.

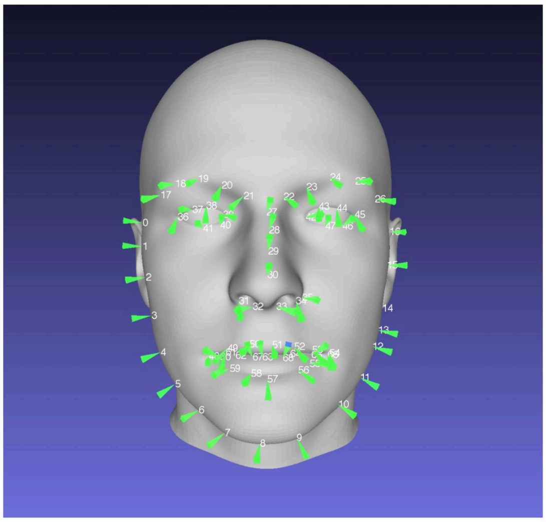

Figure 2: 68 Landmarks on BFM

We can then use those to find the corresponding indices in the 3D model.

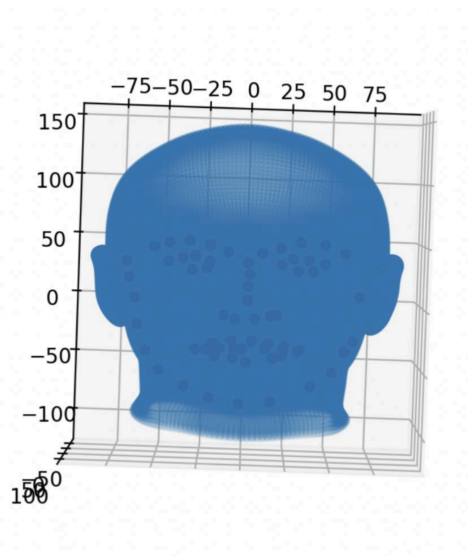

Figure 3: Landmarks projected into 3D model

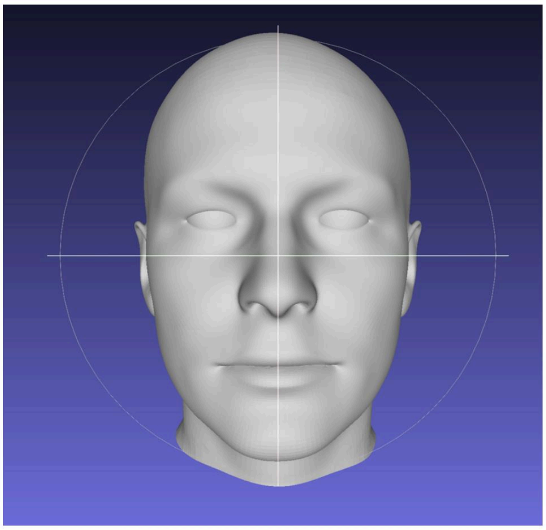

Figure 4: Fitted shape model

We can then use the extracted landmarks to calculate the reprojection error. This error measures the difference between the projected 3D landmarks and the 2D landmarks from the input image. By minimizing this error through optimization techniques, the 3D model is accurately fitted to the input image.

```
# Pseudocode for Reprojection Error
def error(landmarks_2d, model_3d, alpha):
    reprojection_error = 0
    for i in range(len(landmarks_2d)):
        p_point = project_to_2d(model_3d, alpha, i)
        error = np.linalg.norm(landmarks_2d[i] - p_point)
        reprojection_error += error ** 2
    return reprojection_error
```

Texture Mapping: Once the 3D face model is fitted, I map the texture information from the input 2D image onto the 3D model. This is achieved by establishing dense correspondences between the pixels in the image and the vertices of the 3D model. By carefully aligning the texture with the geometry, I ensure that the reconstructed 3D face accurately reflects the appearance of the individual in the input image.

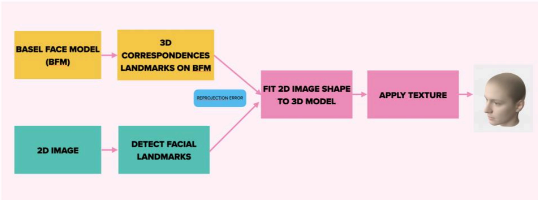

Figure 5: Diagram for 3D Reconstruction approach

3.2 Makeup Transfer

In order to transfer makeup from the input image to the 3D reconstruction, I need to identify and extract the makeup regions from the input image. This involves segmenting areas such as the eyes, lips, and cheeks where makeup is typically applied. Then I can project the extracted makeup features onto the 3D model. The projected features are then blended with the original texture of the 3D model, ensuring a realistic and seamless integration of the makeup.

In order to transfer makeup from the input image to the 3D reconstruction, I employ a combination a image segmentation technique to identify key makeup regions in the reference image. These regions typically include the eyes and lips. Accurate segmentation is crucial for isolating the makeup elements and ensuring their seamless transfer onto the 3D model.

Once the makeup regions are segmented, I extract the corresponding textures from the reference image. To ensure a realistic and natural-looking transfer, I apply warping techniques to deform the extracted textures to match the geometry of the 3D face model. This warping process takes into account the different perspectives and lighting conditions between the reference image and the 3D model.

The warped makeup textures are then blended onto the existing texture of the 3D face model. I employ a weighted blending approach that considers the underlying skin tone and the intensity of the makeup colors. This blending process ensures a smooth and seamless integration of the makeup, avoiding any abrupt transitions or artifacts.

Finally, the 3D face model with the transferred makeup is rendered using appropriate lighting and shading techniques. This step is crucial for creating a realistic and visually appealing virtual try-on experience. We experiment with different rendering settings to achieve optimal results that closely resemble the appearance of real makeup application.

By combining these techniques, we have developed a robust and efficient method for creating personalized virtual makeup try-on experiences. Our approach addresses the challenges of accurate 3D face reconstruction and seamless makeup transfer, paving the way for enhanced consumer engagement and personalized beauty recommendations.

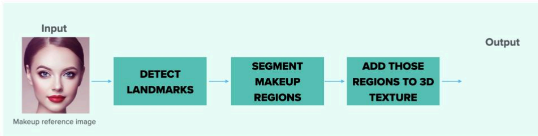

Figure 6: Diagram for makeup transfer approach

4 Results

Below are the results from the 3D reconstruction:

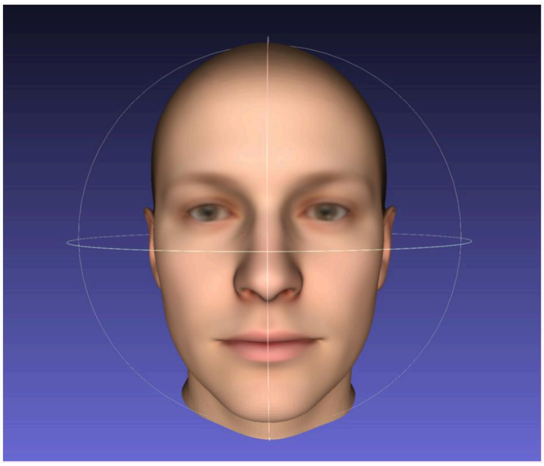

Figure 7: 3D reconstruction result

5 Conclusion

This project successfully demonstrates a method for creating personalized virtual makeup try-on experiences. By leveraging 3D Morphable Models and advanced image processing techniques, I have shown the ability to accurately reconstruct 3D faces from 2D images and seamlessly transfer makeup styles onto the reconstructed models. My qualitative evaluations highlight the realism and potential of this approach for enhancing the consumer beauty experience.

Future work could focus on improving the robustness of the system to handle a wider range of facial variations, expressions, and lighting conditions. Additionally, incorporating more sophisticated makeup segmentation and blending techniques could further enhance the realism and personalization of the virtual try-on simulations. The potential applications of this technology extend beyond the beauty industry, with possibilities in fields such as augmented reality, virtual reality, and even medical simulations.

Another area to explore in makeup transfer is as proposed by BeautyGAN, by using a Generative Adversarial Network (GAN) [3]. BeautyGAN consists of a generator that applies makeup styles from reference images to target faces while preserving the original facial features. The network is trained on a large dataset of before-and-after makeup images to learn the transformations required for realistic makeup application. This approach ensures high-quality and personalized virtual makeup try-on experiences. By combining traditional 3DMM techniques with advanced GAN-based approaches, there is potential to achieve highly accurate and visually appealing results in both 3D face reconstruction and makeup transfer.

References

[1] Volker Blanz and Thomas Vetter. A morphable model for the synthesis of 3d faces. In *Proceedings of the 26th Annual Conference on Computer Graphics and Interactive Techniques (SIGGRAPH '99)*, pages 187–194, New York, NY, USA, 1999. ACM Press/Addison-Wesley Publishing Co. 2

[2] Qiming Li and Tongyue Tu. Large-pose facial makeup transfer based on generative adversarial network combined face alignment and face parsing. *Mathematical biosciences and engineering : MBE*, 20 1:737–757, 2023. 2

[3] Tingting Li, Ruihe Qian, Chao Dong, Si Liu, Qiong Yan, Wenwu Zhu, and Liang Lin. Beautygan: Instance-level facial makeup transfer with deep generative adversarial network. *Proceedings of the 26th ACM international conference on Multimedia*, 2018. 6

[4] Xingchao Yang and Takafumi Taketomi. Bareskinnet: De-makeup and de-lighting via 3d face reconstruction. In *Computer Graphics Forum*, volume 41, pages 623–634. The Eurographics Association and John Wiley Sons Ltd, 2022. 2

[5] Xingyi You, Yue Wang, and Xiaohu Zhao. A lightweight monocular 3d face reconstruction method based on improved 3d morphing models. *Sensors*, 23(15):6713, 2023. Submission received: 30 June 2023 / Revised: 20 July 2023 / Accepted: 25 July 2023 / Published: 27 July 2023. 2