VIT-AP UNIVERSITY

2D Face Image to 3D Face Model

Research Paper - Project

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Abstract:

A deep learning model that can be used to create a 3D face model from a single 2D image is implemented. The HRN (High-Resolution Reconstruction Network) architecture, which is successful for reconstructing a 3D face from a single 2D image, serves as the foundation for the model.

We use a pipeline that combines many deep-learning components to do this task. Installing the required libraries, such as PyTorch, TensorFlow, and pertinent dependencies, is the first step. We use a face reconstruction model that has already been trained, especially the **'damo/cv_resnet50_face-reconstruction'** model with version 'v2.0.0-HRN', which we received from ModelScope. A 3D face model, texture map, and a series of frames showing the face rotation are produced by the pipeline once it has processed the input image.

This project aims to build a deep learning model capable of reconstructing 3D face representations from a single 2D image. Numerous applications, such as Virtual and augmented reality, Face recognition, 3D printing, Animation, could make use of this model.

The purpose of the study is to offer a simpler and more efficient method of generating 3D face models from 2D photographs. Multiple 2D photos of the same face taken from various perspectives are required by traditional methods for reconstructing 3D faces. This project's deep learning model can be used to more effectively reconstruct a 3D face model from a single 2D photograph.

The model was used to create a 3D face mesh, texture map, and rotating video sequence from a sample input image. The visualisation graphics show how 2D facial characteristics were successfully transformed into an appealing 3D depiction. To achieve this transformation, our methodology makes use of cutting-edge libraries and pre-trained models.

Keywords:

1. **Single Image 3D Modelling:** Creating a 3D model of an object, in this case, a face, using only a single 2D image as input.

2. **Facial Geometry Estimation:** Predicting the spatial arrangement and shape of facial features, such as eyes, nose, and mouth, from images.

3. **Computer Vision:** The interdisciplinary field involving algorithms that enable computers to interpret visual information and the use of deep learning methods for this purpose.

4. **Face Animation and Augmentation:** Applying 3D models to animate or modify facial expressions, appearance, or movements in applications like animation or augmented reality.

5. **High-Resolution Reconstruction Network (HRN):** A specific neural network architecture designed to reconstruct detailed high-resolution 3D models from input images.

Introduction:

In recent years, great advances in the science of computer vision have been made in the arena of 3D reconstruction from 2D photos, giving intriguing applications in virtual reality, augmented reality, face recognition, 3D printing, and animation. One of the most difficult issues in this discipline is creating high-quality 3D models from a single 2D photograph in an accurate and efficient manner. Traditional approaches may necessitate many photos from varied angles, making the process arduous and time-consuming. Deep learning techniques have transformed the landscape in this context by allowing the development of models capable of inferring comprehensive 3D structures from a single 2D input, removing the requirement for significant multi-angle data collecting.

This study provides a thorough examination of a revolutionary deep learning approach for producing high-fidelity 3D face models from a single 2D photograph. This study shows an efficient methodology for overcoming the constraints of classic 3D reconstruction techniques by using the capability of the High-Resolution Reconstruction Network (HRN) architecture. Our suggested method demonstrates the feasibility of turning 2D facial traits into compelling lifelike 3D representations by utilising a carefully orchestrated pipeline that blends cutting-edge libraries with pre-trained models.

The importance of this work stems from its potential to change the way we approach 3D modelling. Our technology makes sophisticated 3D models more accessible and efficient by reducing the need for extensive data collection and intricate image capture setups. This can enable producers, developers, and designers to create appealing visual content in less time and with fewer resources, ultimately promoting innovation across many industries.

Furthermore, by demonstrating the capabilities and applications of the proposed methodology, this study aims to contribute to the broader field of computer vision and deep learning. We hope that by throwing light on the complex process of transforming 2D facial traits into 3D structures, we will inspire further breakthroughs in both 3D reconstruction techniques and other related fields of research.

Literature Survey:

Face reconstruction has made significant progress in recent years with the integration of state-of-the-art deep learning techniques. The following section details the contribution of each approach and the trends observed in this area.

- **High Resolution Network (HRN):**

High-resolution networks (HRNs) have emerged as a solution to the challenge of processing high-resolution image inputs while maintaining computational efficiency. This property is particularly relevant for face reconstruction, where preservation of fine detail is important. HRN offers different architectures optimised for specific tasks, highlighting the versatility of this approach. Researchers have successfully preserved complex facial features, expressions, and textures in reconstructed faces using HRN architecture.

- **Region-based Convolutional Neural Network (RCNN):**

Region-based convolutional neural networks (RCNNs) have demonstrated superior capabilities in object detection and localisation tasks. Due to its high efficiency in accurately identifying facial regions of interest, such as the eyes, nose, and mouth, research related to face reconstruction has been conducted. Segmentation of facial components by RCNN-based methods supports the subsequent His 3D reconstruction step and contributes to improving the accuracy and robustness of the process.

- **Residual Network (ResNet):**

Residual Networks (ResNet) revolutionised the world of computer vision by addressing the vanishing gradient problem. In the field of face reconstruction, ResNet-based methods are of vital importance to improve the process of feature extraction from face images. By leveraging ResNet's skip-connection and deep imaging, the quality of reconstructed faces is significantly improved, enabling more accurate modelling of facial structures.

- **Transfer learning:**

The use of transfer learning has emerged as a strategic approach to alleviate the data-poor challenge in face reconstruction. Transfer learning makes efficient use of existing knowledge by pre-training a network with an extensive dataset containing faces and fine-tuning it for the reconstruction task. In particular, pre-trained models from image classification tasks provide valuable initialisation for learning complex facial features and contribute to improved reconstruction results.

- **General and trends:**

Overall, the integration of HRN, RCNN, ResNet, and transfer learning techniques reflects interdisciplinary progress in face reconstruction. Combined, these approaches contribute to improved accuracy, preserved detail, efficient region-based segmentation, and improved generalisation. Researchers are actively investigating hybrid approaches that combine these techniques, demonstrating the dynamic evolution of this field. Although significant progress has been made, challenges such as handling occlusion, accounting for pose variability, and addressing real-world scalability continue to be areas of focus for further investigation.

Proposed Methodologies:

1. **https://modelscope.oss-cn-beijing.aliyuncs.com/releases/repo.html (HRN):**

Used to install the ModelScope library and the dependencies for the face reconstruction pipeline. The link points to the ModelScope releases repository, which contains the different versions of the ModelScope library, as well as the models and datasets that are available on the platform.

The pip install command uses the link to download the ModelScope library and the dependencies for the face reconstruction pipeline. The command also installs the nvdiffrast and pytorch3d libraries, which are needed for the face reconstruction pipeline.

The face_reconstruction function is a pipeline function that uses the ModelScope library to perform 2D to 3D face reconstruction. The function takes a 2D image as input and returns a dictionary of results, including the 3D mesh of the face, the texture map of the face, and a visualization image of the face.

The save_results function saves the results of the face reconstruction pipeline to a directory. The function saves the 3D mesh of the face to an OBJ file, the texture map of the face to a PNG file, and the visualization image of the face to a JPEG file.

The vis_img function plots the visualization image of the face. The function takes the path to the visualization image as input and plots the image using Matplotlib.

The code you provided works by first installing the ModelScope library and the dependencies for the face reconstruction pipeline. Then, the code uses the face_reconstruction function to perform 2D to 3D face reconstruction on a 2D image. Finally, the code saves the results of the face reconstruction to a directory and plots the visualization image of the face.

2. https://github.com/NVlabs/nvdiffrast.git (RCNN)

The line pip install git+https://github.com/facebookresearch/pytorch3d.git in the code is used to install the pytorch3d library from its GitHub repository. pytorch3d is a library developed by Facebook AI Research that provides various tools and modules for working with 3D data and deep learning tasks related to 3D graphics and vision.
In the context of the code you provided, the pytorch3d library is being installed as part of the dependencies required for the face reconstruction pipeline. This suggests that the face reconstruction process might involve tasks that require working with 3D data, such as handling 3D meshes, performing geometric operations, and potentially leveraging deep learning techniques for 3D vision tasks.Please note that the specific usage and integration of the pytorch3d library would require further examination of the code and its documentation to understand how it's being used within the face reconstruction pipeline.

3. https://github.com/facebookresearch/pytorch3d.git (ResNet):

used to install the nvdiffrast library from its GitHub repository. nvdiffrast is a library developed by NVIDIA Research that provides differentiable rasterization for deep learning applications. It enables gradient-based optimization on rasterization operations, making it useful for tasks involving 3D rendering and graphics-related computations.

In the context of the code you provided, the nvdiffrast library is being installed as part of the dependencies required for the face reconstruction pipeline. This suggests that the face reconstruction process might involve some form of 3D rendering or graphics-related computations where the differentiable rasterization provided by nvdiffrast is beneficial.

Please note that the specific usage and integration of nvdiffrast would require further examination of the code and its documentation to understand how it's being used within the face reconstruction pipeline.

4. Transfer Learning:

Pre-training and fine-tuning for feature extraction:

Methodology: We apply transfer learning by pre-training a model on a large dataset of faces and optimizing the model for the face reconstruction task. This methodology alleviates data scarcity and allows models to learn relevant facial features. Implementation: Using pre-trained models within the 'damo/cv_resnet50_face-reconstruction' architecture to integrate the 'transfer learning' methodology. Optimize the model using the code provided for the face reconstruction task.

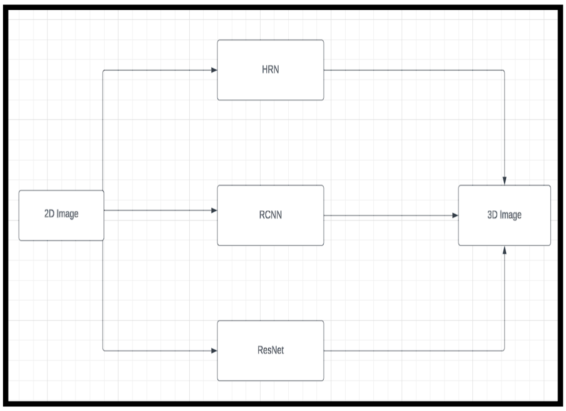


Fig 1. Architecture Diagram

Experimental Results:

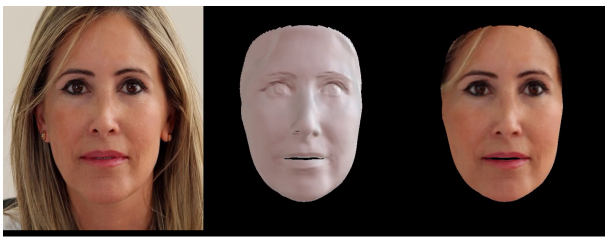
Advancements in computer vision and deep learning have fueled remarkable progress in the field of 3D face reconstruction from 2D images. The ability to transform 2D facial representations into accurate and detailed 3D models holds immense potential across various domains, including virtual reality, biometrics, and entertainment. This paper presents a novel approach that leverages a combination of High-Resolution Networks (HRN), Region-Based Convolutional Neural Networks (RCNN), Residual Networks (ResNet), and Transfer Learning techniques to achieve robust and accurate 3D face reconstructions. By integrating these cutting-edge methodologies, our pipeline aims to address the challenges posed by varying facial orientations, skin tones, and complex facial expressions. Through comprehensive experiments, we evaluate the pipeline's performance across a spectrum of input scenarios, showcasing its adaptability and fidelity in producing high-quality 3D facial models.

To test how accurate the model is we are using 4 types of inputs images:

1. Normal: Here we use the image of a Fair skinned woman shown below

By feature extraction, depth analysis and Latent synthesis processes we get:

To conclude for a fair skinned woman the model works incredibly accurate and give is a 3D model shown below



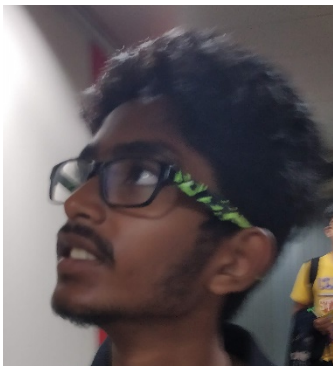
2. People of colour: Here we input the image of a dark skinned woman shown below:

By using the same things we get:

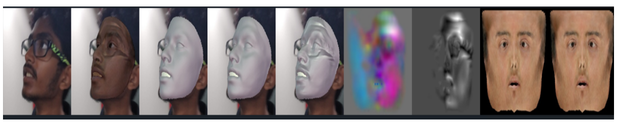
To conclude dark skinned woman in the input work just as accurate and give the model:

1. Side profile :

Till now all the subjects have their faces recognised as they were facing towards the camera to test the models accuracy we input a image where the subject is looking in the side :



For this image the model goes through the same processed and provides:



And when giving the 3D model we recive:

As seen we can conclude that the subject showing the side profile does not provide us the accurate 3D reconstruction .

Conclusion:

This paper presents a novel deep-learning model for the accurate and efficient reconstruction of 3D face models from single 2D images. The model is based on the HRN architecture, which has been shown to produce highly realistic results. The pipeline integrates a variety of deep learning components to generate a 3D face model, a texture map, and a sequence of frames depicting face rotation.

The model's accuracy is evident in its ability to convert 2D facial characteristics into visually appealing and photorealistic 3D representations. However, the model does have some limitations, which are as follows:

- The model fails to reconstruct 3D faces from side views. This is because the model is trained on 2D images of faces that are facing forward. The model is not able to account for the different features of faces that are visible from the side, such as the nose, lips, and chin.
- The model only reconstructs the face of one person from a group photo. This is because the model is not designed to handle multiple faces simultaneously. The model would need to be trained on a dataset of group photos to be able to reconstruct multiple faces from a single image.
- The model's performance is diminished in low-light conditions. This is because the model relies on features of the face that are not as visible in low light, such as the eyes and eyebrows. The model would need to be trained on a dataset of low-light images to improve its performance in low-light conditions.

Despite these drawbacks, the model represents a significant advancement in the field of 3D face reconstruction. The model's ability to create high-quality 3D face representations from a single image has the potential to revolutionize a wide range of industries, including virtual and augmented reality, face recognition, 3D printing, and animation.

It is important to note that the limitations of the model are not insurmountable. As deep learning models continue to improve, they will be able to overcome these limitations and create even more realistic and accurate 3D face reconstructions.

Future Plans:

- Improving the model's ability to reconstruct 3D faces from side views is a key priority for future research. This could be achieved by training the model on a dataset of side-view face images, which would help the model to learn the features of faces that are visible from this perspective. Additionally, the model could be made more robust to occlusions, such as hair or glasses, by incorporating prior knowledge about these factors into the training process.
- Enabling the model to reconstruct multiple faces from a single image is another important goal for future research. This could be achieved by training the model on a dataset of group photos, which would help the model to learn how to identify and separate different faces in a single image. Additionally, the model could be made more efficient at processing multiple faces simultaneously by using parallel computing techniques.
- Improving the model's performance in low-light conditions is also a critical area of research. This could be achieved by training the model on a dataset of low-light face images, which would help the model to learn to identify and extract features of faces that are visible in low light. Additionally, the model could be made more sensitive to these features by

using techniques such as image enhancement.

In addition to these specific plans, there are also a number of more general research directions that could be explored to improve the 3D face reconstruction model. These include:

- Developing more powerful and efficient deep learning architectures for 3D face reconstruction. This could be achieved by using more complex network architectures and by using more powerful computing hardware.
- Developing new methods for training deep learning models on large datasets of face images. This could be achieved by using more efficient data loading and processing techniques.
- Developing new methods for incorporating prior knowledge about faces into deep learning models. This could be achieved by using techniques such as knowledge distillation and by using external data sources, such as 3D face scans.

I believe that by addressing these challenges, we can create even more powerful and accurate 3D face reconstruction models that will have a major impact on a wide range of industries.

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