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A Minor Project -2 Report

On

Human 3D avatar generation from an image

submitted in partial fulfillment of the requirement for the degree of

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In

School of Computer Science and Engineering

Submitted By

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SCHOOL OF COMPUTER SCIENCE & ENGINEERING

CERTIFICATE

This is to certify that Minor Project -2 entitled “Human 3D avatar generation from an image” is a bonafied work carried out by the student team Guruprasad Pattar 01FE21BCS226, Saisamarth Udikeri 01FE21BCS031, Deepak Baligar 01FE21BCS041 in partial fulfillment of completion of Sixth semester B. E. in School of Computer Science and Engineering during the year 2023-2024. The project report has been approved as it satisfies the academic requirement with respect to the project work prescribed for the above said program.

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ABSTRACT

This report presents a comprehensive system for body and pose-guided normal prediction, integrating SMPL body models with neural network-based predictions to generate detailed and accurate normal maps for clothed human bodies. The system begins by estimating the SMPL body mesh from an RGB image, which is used to render initial SMPL-body normal maps. These normal maps, combined with the RGB image, are used to predict clothed-body normal maps through a neural network, refined iteratively for enhanced accuracy. The methodology demonstrates significant potential for applications in virtual reality, fashion, and animation by ensuring the predicted normal maps closely match the actual surface geometry of the clothed body. Additionally, the implementation details, including hardware and software requirements, provide a clear pathway for replication and further development.

Keywords: *SMPL body model, normal prediction, neural networks, 3D reconstruction, RGB image, virtual reality, fashion, animation, iterative refinement, surface geometry.*

CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

INTRODUCTION

The field of computer vision has made significant strides with the advent of image-to-3D reconstruction technology. This innovation converts 2D images into detailed 3D models, capturing the spatial and structural nuances of the objects within the images. The rapid development of deep learning and neural networks has been instrumental in driving this progress, enhancing both the precision and efficiency of 3D reconstructions. Leveraging vast datasets and advanced algorithms, modern reconstruction models are capable of inferring intricate details of shapes and textures, resulting in highly realistic three-dimensional representations.

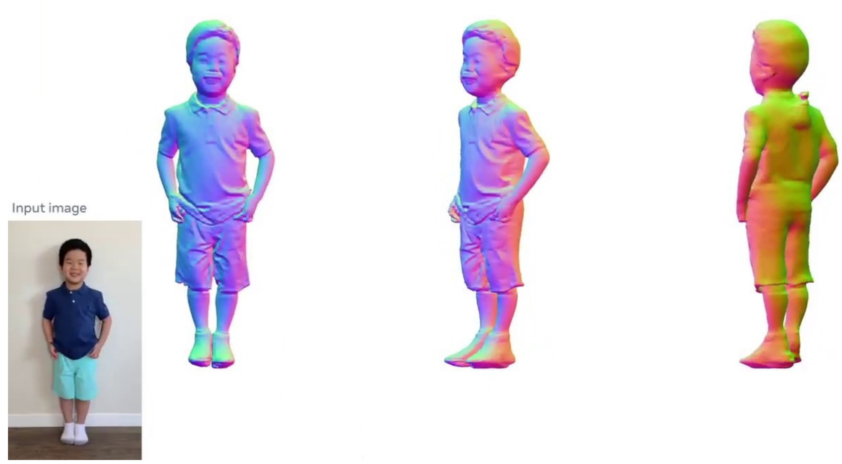

Figure 1.1: Demo of image to 3D generation

These models employ a variety of techniques, including convolutional neural networks (CNNs) and generative adversarial networks (GANs), to predict depth and reconstruct surfaces from single or multiple images. By integrating geometric(pose and shape) and photometric information(Image features), these systems can generate accurate 3D models that closely resemble real-world objects. The continuous improvement in computational power and algorithmic sophistication has significantly reduced the computational complexity and processing time required for these reconstructions.

As the technology evolves, image-to-3D reconstruction models are expected to become more robust and versatile, pushing the boundaries of what can be achieved in digital modeling and simulation. This ongoing research and development promise to further enhance the fidelity and applicability of 3D reconstruction techniques

1.0.1 Motivation

- Converting 2D medical scans like MRI or CT scans into 3D models helps healthcare professionals analyze the anatomical structures of human body.
- Gaming and VR industries leverage 2D to 3D human avatar generation to create lifelike and customizable characters for players.
- 2D to 3D human avatar generation is used by animators, filmmakers, and digital artists to create animated characters and digital content.

1.1 Literature Review / Survey

1.1.1 PIFuHD multi-level pixel-aligned implicit function for high-resolution 3d human digitization [1]

The paper "PIFuHD Multi-level pixel-aligned implicit function" for high-resolution 3d human digitization proposes a novel method for high-resolution 3d reconstruction of clothed humans from a single image the method based on the pixel-aligned implicit function pifu processes high-fidelity 3d geometry without explicitly discretizing the output space this approach leverages a coarse-to-fine framework that refines implicit surface learning enhancing detail retention and handling uncertainties in unobserved regions such as the back extensive experiments demonstrate that pifuhd significantly improves the quality of reconstructions outperforming existing methods by better preserving details and achieving a consistent level of detail throughout the 3d mode[?]

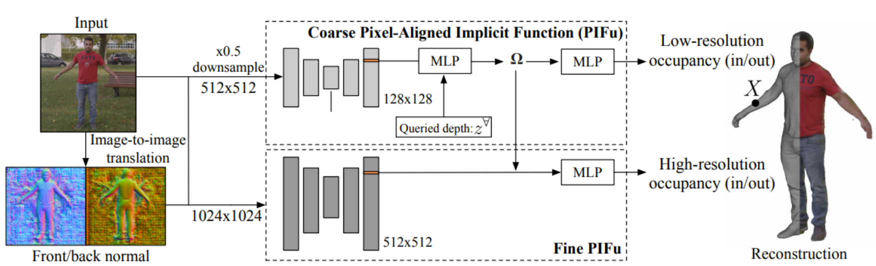

Figure 1.2: 3D Reconstruction of human using Coarse level and Fine level features

1.1.2 PyMAF: 3D Human Pose and Shape Regression with Pyramidal Mesh Alignment Feedback Loop[2]

The literature survey of the paper "PyMAF: 3D Human Pose and Shape Regression with Pyramidal Mesh Alignment Feedback Loop "[2]can be summarized as follows:

In recent research on 3D human pose and shape regression from monocular images, two predominant approaches have been explored: optimization-based[2] and regression-based methods. Optimization-based techniques focus on fitting parametric models directly to 2D image evidence, ensuring precise alignment but often at the cost of computational efficiency and sensitivity to initialization. In contrast, regression-based methods use neural networks to predict model parameters directly from pixels, promising faster inference but struggling with coarse alignment between predicted meshes and image evidence[2]. To address this challenge, approaches such as the Iterative Error Feedback (IEF) loop have been employed, though they may overlook fine-grained alignment details in testing. More recent innovations, exemplified by PyMAF (Pyramidal Mesh Alignment Feedback), propose leveraging a feature pyramid and mesh-aligned evidences to rectify parameter predictions progressively based on alignment status. These advancements aim to enhance the accuracy and alignment fidelity of reconstructed 3D meshes, as validated across benchmarks like Human3.6M and COCO datasets.

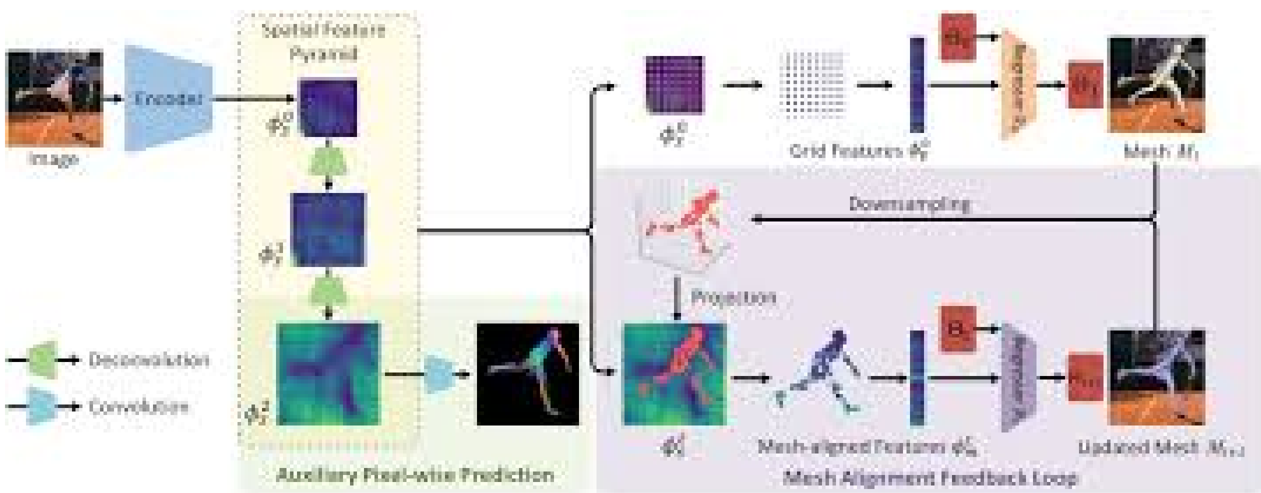

Figure 1.3: Architecture of the Pyramidal Mesh Alignment Feedback (PyMAF)

1.1.3 PaMIR: Parametric Model-Conditioned Implicit Representation for Image-based Human Reconstruction [3]

This paper examines recent advancements in reconstructing 3D human models from single RGB images [3]. Earlier approaches focused on parametric methods using statistical body models or non-parametric methods with various 3D representations. Recent work has explored deep implicit functions for 3D reconstruction, showing promise for high-resolution results [3]. However, challenges remain in handling complex poses and occlusions. Some methods have attempted to combine parametric and non-parametric approaches. This paper proposes a novel method called PaMIR that integrates a parametric SMPL body model with an implicit surface representation [3]. It aims to leverage the strengths of both approaches to achieve detailed reconstruction while maintaining robustness to challenging poses and clothing styles.

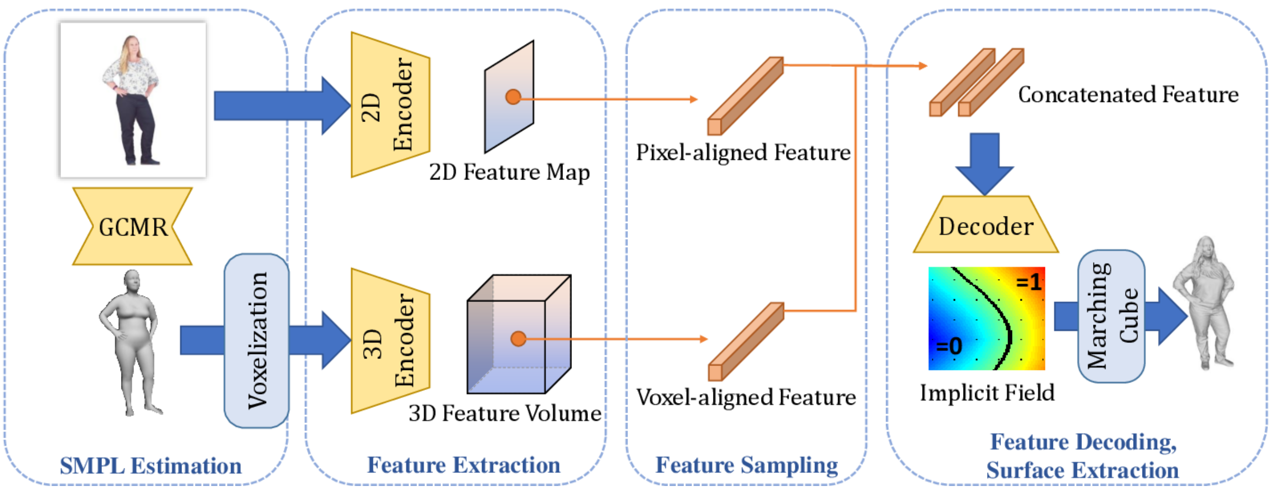

Figure 1.4: Architecture of the Parametric Model-Conditioned Implicit Representation PaMIR

1.1.4 ECON: Explicit Clothed humans Optimized via Normal integration [4]

This paper addresses the challenge of reconstructing detailed 3D human models from single RGB images. Previous approaches have used either parametric methods with statistical body models or non-parametric methods with various 3D representations. Recent work has explored deep implicit functions, showing promise for high-resolution results but struggling with complex poses and occlusions. Some methods have attempted to combine parametric and non-parametric approaches[4]. This paper proposes a novel method called ECON that integrates a parametric SMPL-X body model with an implicit surface representation. It aims to leverage the strengths of both approaches to achieve detailed reconstruction while maintaining robustness to challenging poses and clothing styles. The method uses normal map prediction, depth-aware surface reconstruction, and learned shape completion to produce high-quality results[4].

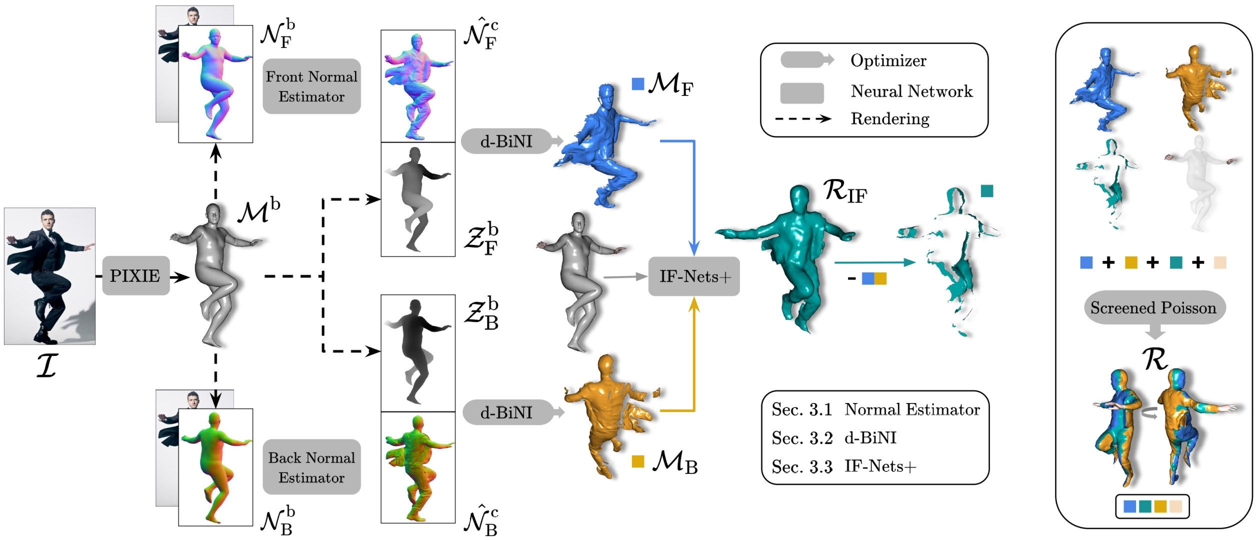

Figure 1.5: Architecture of the Explicit Clothed humans Optimized via Normal integration:(ECON)

1.2 Problem Statement

To develop a framework for generating realistic 3D human avatars from images, integrating advanced computer vision techniques with 3D modeling and rendering for accurate and expressive virtual representations.

1.3 Applications

- **Virtual Avatars and Social VR:** By uploading a photo, users may easily build customized 3D avatars. This makes it possible to engage in networking, gaming, and virtual meetings in virtual settings that are more immersive and adaptable.
- **Personalized Memorabilia and Gifts:** People can design 3D models of cherished pictures, such pictures of their pets or families, to make one-of-a-kind personalised gifts like VR experiences or 3D-printed sculptures.
- **Increased Interaction on Social Media:** By enabling users to turn their images into interactive 3D sceneries or augmented reality filters, social media platforms might incorporate 3D object production, which would increase the engagement and shareability of posts.
- **Accessible Design and Creativity:** Without specialized knowledge in any area, non-designers might effortlessly generate 3D models of commonplace items or prototypes from photos, encouraging creativity and innovation in a variety of sectors.

1.4 Objectives and Scope of the project

1.4.1 Objectives

- **Objective 1:** Using a learning-based architecture to generate a 3D human avatar from a given image.

  The objective involves developing and implementing a deep learning model that can take a 2D image of a human and produce a corresponding 3D avatar. This avatar should capture the realistic appearance and pose of the person depicted in the image.

- **Objective 2:** Refinement of the generated 3D human avatar.

  After generating the initial 3D human avatar from the image, this objective focuses on improving its fidelity and accuracy. Techniques such as geometry refinement, texture enhancement, and pose adjustment may be employed to achieve a more detailed and realistic representation.

1.4.2 Scope of the project

Give the description of the boundaries of the method will work correctly.

- Creating a novel algorithm, that utilizes a 3D body model as a regularizer and employs local image features for reconstruction.
- Evaluating the performance of the model using various metrics and datasets.
- Investigating the method's robustness to different poses, clothing types, and image conditions.

Chapter 2

REQUIREMENT ANALYSIS

2.1 Functional Requirements

- **Image Input Processing:** The system must accept and process single RGB images of clothed humans in various poses and environments.
- **3D Mesh Generation:** The method should produce detailed 3D mesh reconstructions of the clothed human, including clothing details and body shape.
- **Body Model Integration:** The system must incorporate and iteratively refine a parametric 3D body model (SMPL-X) as part of the reconstruction process.
- **Local Feature Extraction:**The system needs to extract and utilize local image features for implicit surface reconstruction, independent of global body pose.
- **Multi-view Rendering:** The system should be capable of rendering the reconstructed 3D model from multiple viewpoints for evaluation and visualization.

2.2 Non-Functional Requirements

- **Accuracy:**The system must achieve higher reconstruction accuracy than current state-of-the-art methods, as measured by Chamfer distance, Point-to-Surface distance(P2S).
- **Generalization:** The system should perform well on diverse, unseen poses and in-the-wild images not present in the training data.
- **Efficiency:** ICON must be able to produce results with less training data compared to existing methods, demonstrating data efficiency.
- **Robustness:** The system should maintain performance quality across various clothing types, body poses, and image conditions.
- **Scalability:**The method must be capable of processing and generating reconstructions for large datasets and potentially in real-time applications.

The functional and non-functional requirements outlined above define the capabilities and performance expectations for the ICON algorithm in 3D human reconstruction from single RGB images.

2.2.1 Hardware Requirements

- Operating System: Ubuntu 20 / 18 - A popular Linux distribution known for its stability and support for deep learning applications.
- GPU Memory: Greater than 12GB - Sufficient memory required for handling large 3D models and complex computations.

2.2.2 Software Requirements

- GCC: 7.5.0 - GNU Compiler Collection version for compiling and building C/C++ applications.
- CUDA: 11.3 - A parallel computing platform and API model by NVIDIA, essential for GPU acceleration.
- Python: 3.8 - A versatile programming language widely used for machine learning and AI development.
- PyTorch: 1.13.0 - An open-source machine learning library for Python, known for its flexibility and dynamic computation graphs.
- PyTorch3D: A library providing efficient, reusable components for 3D deep learning, recommended to install from a local clone.

Chapter 3

SYSTEM DESIGN

The system design for body and pose-guided normal prediction begins with estimating the SMPL body mesh from an RGB image, creating a 3D model of the human body using shape and pose parameters. This mesh generates initial SMPL-body normal maps. These normal maps, along with the RGB image, are used to predict clothed-body normal maps through a neural network. The network is trained with pixel-wise and VGG losses to enhance detail accuracy. An iterative refinement process adjusts the SMPL parameters to minimize the difference between the predicted and actual normal maps, ensuring accurate and detailed representation of the clothed body surface.

3.1 Architecture Design

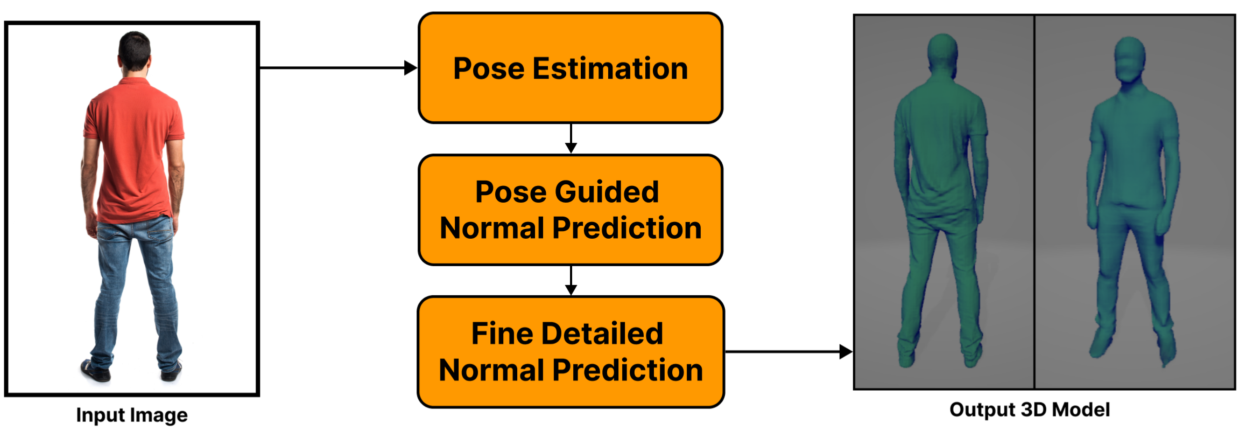

Figure 3.1: Flowchart of methodologies involved in generation of 3D object

The system design of our model integrates pose-guided features and fine detail extraction for enhanced 3D human reconstruction. It utilizes a SMPL-X body model to guide overall shape prediction, while employing a point-based sampling method for capturing fine-grained local details. This dual approach allows our method to maintain anatomical consistency while accurately reconstructing clothing and surface details, resulting in high-quality 3D models from single images across diverse poses and scenarios.

3.1.1 Pose guided normal Prediction

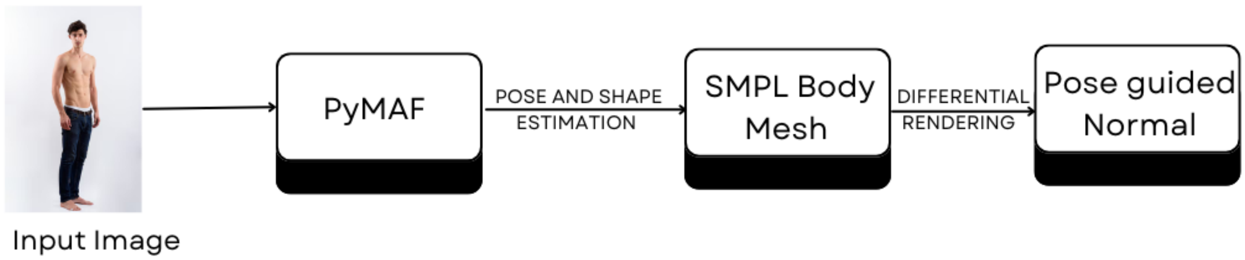

Figure 3.2: Architecture uses SMPL and differential rendering for the pose guided normal Prediction

The Pose-guided normal prediction is a critical component of the our method, which addresses the challenge of reconstructing detailed 3D models of clothed humans from 2D images, even in varied and unconstrained poses.

Overview of Pose-Guided Normal Prediction Pose-guided normal prediction involves estimating the normal maps of a clothed human body, using an underlying SMPL (Skinned Multi-Person Linear) model as a reference. The SMPL model represents the body under the clothing and helps in predicting the normal maps for both the visible and occluded parts of the body from a single RGB image. This process is split into two main parts: front and back normal prediction.

Our Model employs a novel pose-guided approach to enhance the reconstruction of clothed humans. This method leverages the SMPL-X body model as a prior, using it to guide the inference of clothed-body normal maps. The system takes as input both the original image and the pose model's normal map, allowing it to better understand the underlying body structure. This guidance is particularly beneficial for occluded or challenging body regions, where the algorithm can infer more accurate surface details. The process involves a specialized network that learns to predict clothed-body normals while considering the body shape prior. This approach helps maintain anatomical consistency and improves the overall quality of the reconstruction, especially in areas where direct image information might be ambiguous or incomplete. By incorporating this pose-guided feature, our method achieves a more robust and anatomically plausible reconstruction, bridging the gap between bare pose models and fully clothed 3D reconstructions.

3.1.2 Fine detailed implicit 3D representation

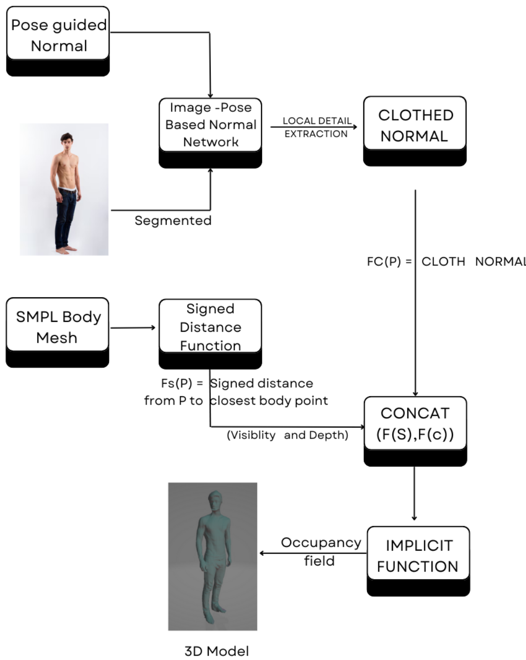

Figure 3.3: Architecture of fine detailed implicit 3D reconstruction

Our method introduces a local feature-based approach for implicit surface reconstruction, departing from global feature methods used in previous works. This technique focuses on extracting and utilizing local image features, which are independent of the overall body pose. By doing so, our method achieves better generalization to diverse and previously unseen poses. The system employs a point-based feature extraction method, where features are sampled at specific 3D locations projected onto the image plane. This local approach allows the model to capture fine-grained details and textures without being overly influenced by the global body configuration. The feature extractor is designed to have a limited receptive field, ensuring that each feature primarily represents local information. This strategy helps in avoiding spurious correlations with global pose that can occur in methods using large convolutional filters or global encoders. The local nature of these features contributes to our method's data efficiency, as it can learn generalizable representations from fewer examples. This approach enables our method to maintain high reconstruction quality across a wide range of poses, including those not well-represented in the training data.

3.1.3 Final architecture of integrated pose guided and fine detailed 3D implicit reconstruction

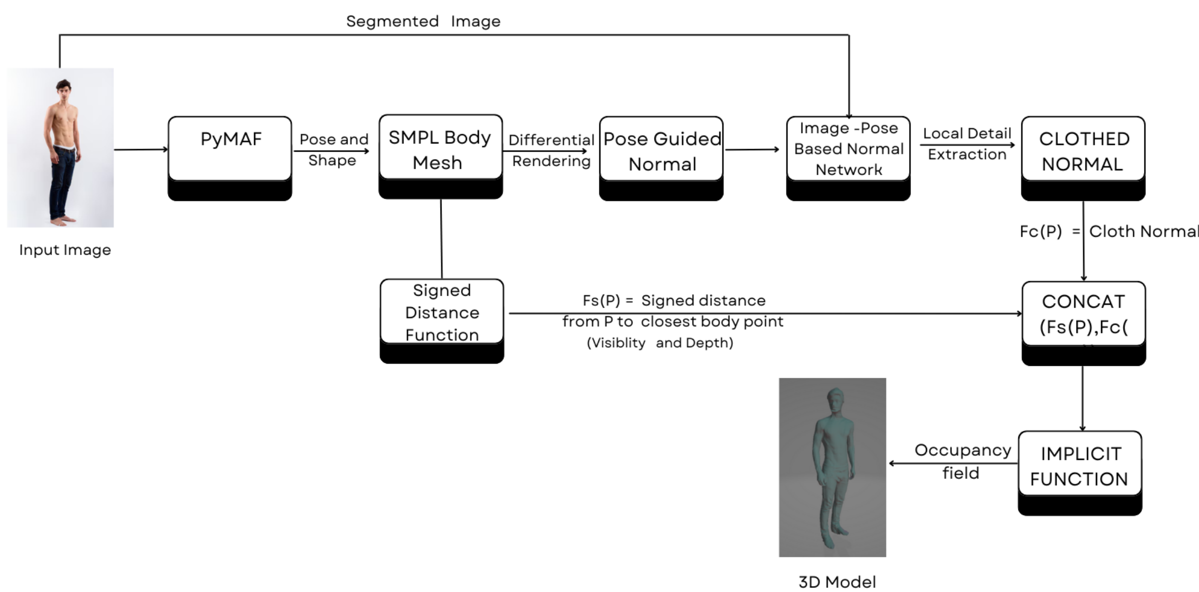

Figure 3.4: Region level feature extraction

The architecture then integrates these local image features with the body-guided features, including a specialized body-normal feature. This amalgamation feeds into an implicit function network, which predicts occupancy or signed distance at 3D query points, enabling detailed surface reconstruction. The final output is a 3D mesh that incorporates both the overall body shape and intricate clothing details. Our model's ability to render this reconstruction from multiple viewpoints further demonstrates its versatility.

3.2 Data Design and Description

The dataset includes high-quality 3D scans with corresponding SMPL-X body model fits. Synthetic renderings provide additional training data with multiple views per scan. The testing sets (CAPE and AGORA-50) are used for quantitative evaluation, while the Pinterest collection allows for qualitative assessment on real-world images.

Characteristic	**Details**
Primary Training Set	450 AGORA and THuman scans
Testing Set	Both AGORA and CAPE-FP
Training Samples	450 scans (main), up to 3,709 (extended)
Testing Samples	113 scans dataset (CAPE, AGORA-50)
Resolution	Not specified, likely high-resolution 3D scans
Scenes	Fashion poses, clothing, and body shapes

Table 3.1: Dataset description

Chapter 4

IMPLEMENTATION

This chapter gives a brief description about implementation details of the Human 3D avatar generation from an image by describing each component and its refinement with its code skeleton in terms of algorithm.

4.1 Pose-Guided Normal Prediction

Algorithm 1 shows the implementation details for generating Pose normal prediction from an 2D RGB image.

The Pose-Guided Normal Prediction algorithm predicts normal maps from an RGB image. The process begins by estimating the SMPL (Skinned Multi-Person Linear) body mesh, which captures the human body's shape and pose using a set of parameters $M(\beta, \theta)$ .his SMPL mesh consists of 6890 vertices forming a detailed 3D model of the human body. The estimated SMPL body mesh is then used to render the SMPL-body normal maps, which provide a coarse but detailed representation of the body's surface normals from the front and back views. These normal maps serve as the foundation for further predictions.

Algorithm 1 Body-Guided Normal Prediction

Require: RGB image I

Ensure: Predicted Posed normal maps $N_{pose} = \{N_{pose}^{\text{front}}, N_{pose}^{\text{back}}\}$

1: Estimate SMPL body mesh $M(\beta, \theta) \in \mathbb{R}^{N\times 3}$, where $\beta \in \mathbb{R}^{10}$ and $\theta \in \mathbb{R}^{3\times 24}$

2: Render SMPL-body normal maps $N_Pose = \{N_Pose^{\text{front}}, N_Pose^{\text{back}}\}$ from $M(\beta, \theta)$

return Predicted Pose normal maps $N_{pose} = \{N_{pose}^{\text{front}}, N_{pose}^{\text{back}}\}$

4.2 Training Refining Loop of Predicted Normal

Algorithm 2 shows the implementation details for Training Refining Loop of Predicted Normal These normal maps, along with the RGB image, are used to predict clothed-body normal maps. The process involves training a neural network with pixel-wise and VGG losses. Optionally, the SMPL parameters are refined iteratively to minimize differences between SMPL and clothed-body normals and silhouettes, improving the accuracy and alignment of the predicted normals.

Algorithm 2 Training Refining Loop of Predicted Normal Maps

Require: RGB image I

Ensure: Predicted Posed normal maps $N_{pose} = \{N^{\text{front}}_{pose}, N^{\text{back}}_{pose}\}$

1: Predict clothed-body normal maps $N_{bc} = \{N^{\text{front}}_{clothed}, N^{\text{back}}_{clothed}\}$ using N_b and I
2: Train normal networks with loss function $L_N = L_{\text{pixel}} + \lambda_{\text{VGG}} L_{\text{VGG}}$
3: $L_{\text{pixel}} = \|N^v_c - N^v_{clothed}\|_1, \quad v = \{\text{front}, \text{back}\}$ (N^v_c is the ground-truth normal for view v)
4: **Optional:** Refine SMPL parameters β, θ, t
5: Objective: $L_{\text{SMPL}} = \min_{\beta,\theta,t}(\lambda_{\text{Ndiff}} L_{\text{Ndiff}} + \lambda_{\text{Sdiff}} L_{\text{Sdiff}})$
6: $L_{\text{Ndiff}} = \|N_b - N_{clothed}\|_1$
7: $L_{\text{Sdiff}} = \|S_b - S_c\|_1$ (S_b is the SMPL body silhouette)
8: Re-render SMPL-body normal maps N_b from refined $M(\beta, \theta)$
9: Re-predict clothed-body normal maps $N_{clothed}$ using updated N_b and I
return updates clothed normal maps $N_{clothed} = \{N^{\text{front}}_{clothed}, N^{\text{back}}_{clothed}\}$

4.3 Fine Detailed 3D Implicit Function

Algorithm 3 shows the implementation details for fine detailed 3D implicit representation.

The Fine detailed 3D Implicit Function algorithm reconstructs a 3D occupancy field of a clothed human body from an RGB image and normal maps. Local features are extracted from the image and normal maps and used by an implicit function network to predict the 3D occupancy field. The network is trained to minimize the difference between the predicted and ground-truth occupancy fields. Optionally, the local features are refined iteratively to enhance the accuracy of the 3D reconstruction, capturing detailed surface geometry of the clothed human body.

Algorithm 3 Local Feature-Based 3D Implicit Function

Require: RGB image I, Clothed-body normal maps $N_{clothed} = \{N^{\text{front}}_{clothed}, N^{\text{back}}_{clothed}\}$, SMPL body mesh $M(\beta, \theta)$

Ensure: 3D occupancy field O

1: Extract local features from RGB image I and normal maps $N_{clothed}$
2: Predict occupancy field O using local features
3: Train implicit function network with loss function $L_O = \|O - O_{\text{gt}}\|_1$ (O_{gt} is the ground-truth occupancy field)
4: **Optional:** Refine local features to improve O iteratively
5: Update implicit function prediction O using refined local features
return Predicted 3D occupancy field O

Chapter 5

RESULTS AND DISCUSSIONS

5.1 Results

5.1.1 Experimental Results on AGORA Dataset

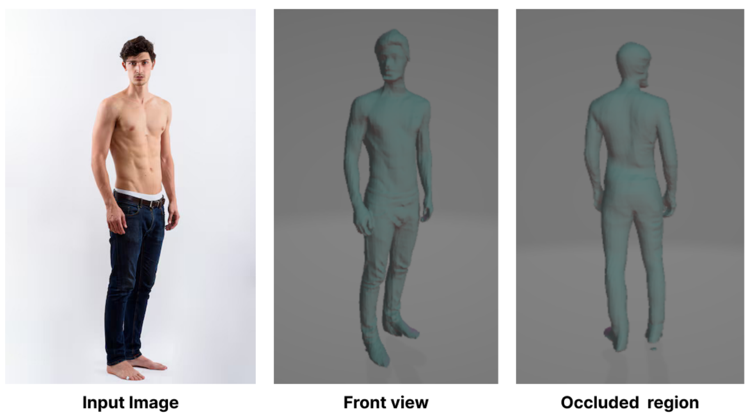

Figure 5.1: enerated 3D mesh from an input image from testing dataset

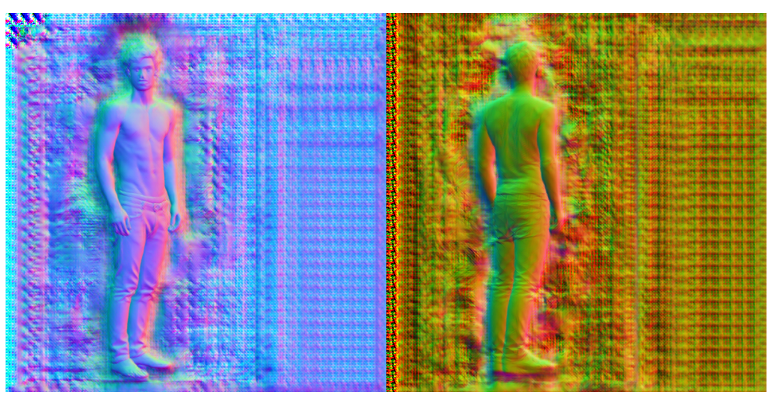

Figure 5.2: Normal maps which is obtained as intermediate results after clothed normal prediction

5.1.2 Experimental Results on THuman Dataset

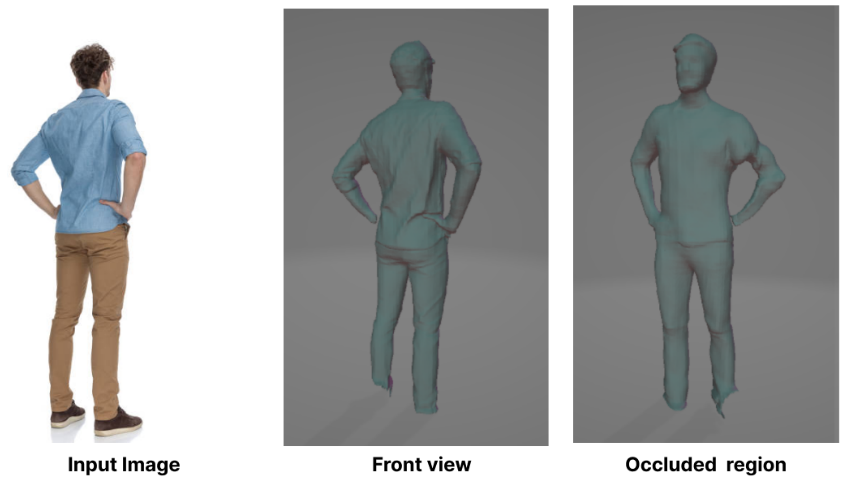

Figure 5.3: Generated 3D mesh from an input image from testing dataset

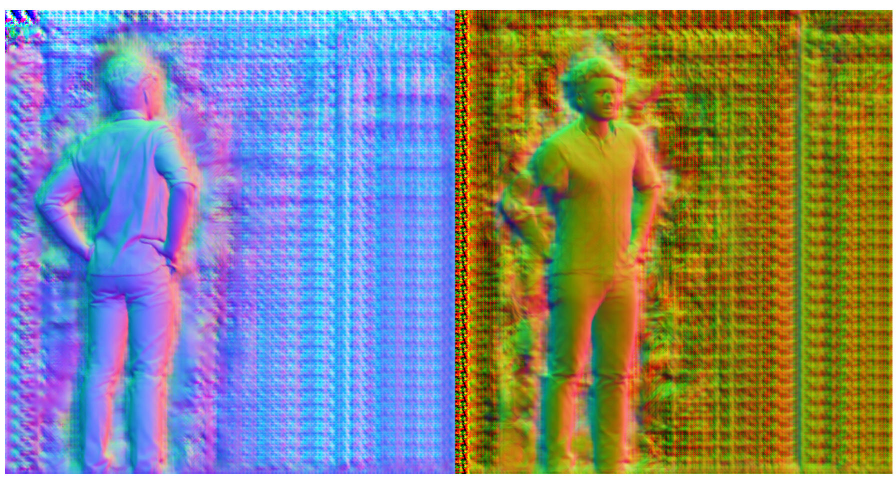

Figure 5.4: Normal maps which is obtained as intermediate results after clothed normal prediction

5.2 Evaluation Metrics

Metrics	Dataset	value
Chamfer Distance	AGORA	1.38
P2S	AGORA	1.8

Table 5.1: Evaluation metrics of Chamfer Distance and P2S on Dataset Of AGORA

Chapter 6

CONCLUSION AND FUTURE SCOPE

Conclusion and Future Scope

6.0.1 Conclusion

The body and pose-guided normal prediction methodology effectively combines SMPL body models with neural network-based predictions to generate detailed and accurate normal maps for clothed human bodies. By leveraging an iterative refinement process, the system ensures that the predicted normal maps closely match the actual surface geometry of the clothed body. This approach demonstrates significant potential in enhancing the realism and accuracy of 3D human body reconstructions from 2D images, making it valuable for applications in virtual reality, fashion, and animation.

6.0.2 Future Scope

Future work could focus on improving the robustness and versatility of the methodology by incorporating more diverse datasets, including varied body types, clothing styles, and poses. Enhancing the neural network architecture to better handle occlusions and complex clothing patterns could further improve prediction accuracy. Additionally, real-time processing capabilities could be developed to enable live applications in augmented reality and gaming. Exploring the integration of this methodology with other computer vision tasks, such as pose estimation and human motion capture, could broaden its application scope and contribute to more comprehensive and interactive 3D modeling systems.

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Human 3d

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GENERAL COMMENTS

PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9

PAGE 10

PAGE 11

PAGE 12

PAGE 13

PAGE 14

PAGE 15

PAGE 16

PAGE 17

REFERENCES

[1] Shunsuke Saito, Tomas Simon, Jason Saragih, and Hanbyul Joo. Pifuhd: Multi-level pixel-aligned implicit function for high-resolution 3d human digitization, 2020.

[2] Hongwen Zhang, Yating Tian, Xinchi Zhou, Wanli Ouyang, Yebin Liu, Limin Wang, and Zhenan Sun. Pymaf: 3d human pose and shape regression with pyramidal mesh alignment feedback loop, 2021.

[3] Zerong Zheng, Tao Yu, Yebin Liu, and Qionghai Dai. Pamir: Parametric model-conditioned implicit representation for image-based human reconstruction, 2020.

[4] Yuliang Xiu, Jinlong Yang, Xu Cao, Dimitrios Tzionas, and Michael J. Black. Econ: Explicit clothed humans optimized via normal integration, 2023.