A Comprehensive Survey on 3D Human Mesh Reconstruction

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***Abstract*—3D human mesh reconstruction has become a pivotal area in computer vision, enabling applications in virtual reality, augmented reality, gaming, healthcare, and human-computer interaction. This survey provides a comprehensive overview of the latest advancements in 3D human mesh reconstruction, categorizing methods based on input modalities, underlying techniques, and application domains. We explore single-view and multi-view approaches, depth-based methods, and neural network-based frameworks, highlighting key innovations such as Neural Radiance Fields (NeRF), implicit functions, and Generative Adversarial Networks (GANs). Additionally, we discuss challenges in achieving real-time performance, handling occlusions, and ensuring high fidelity in reconstructions. Future directions are proposed to address these challenges, emphasizing multi-modal data integration and the advancement of self-supervised learning techniques.**

***Index Terms*—3D Human Reconstruction, Mesh Reconstruction, Neural Networks, Computer Vision, Virtual Reality, Augmented Reality**

I. Introduction

3D human mesh reconstruction has garnered significant attention in the computer vision community due to its wide range of applications, including virtual try-on systems, motion capture for animation, virtual reality (VR), augmented reality (AR), and human-computer interaction [1]–[3]. Traditional methods rely on multiple cameras or depth sensors to capture the human form, but recent advancements leverage single RGB images and deep learning techniques to achieve high-fidelity reconstructions.

A. Historical Development

Historically, 3D human reconstruction evolved from simplistic geometric models to complex, data-driven approaches. Early methods primarily utilized multi-view geometry and photogrammetry to reconstruct human figures, which, while effective, were limited by the need for controlled environments and extensive computational resources [4]. The advent of deep learning revolutionized this field by enabling the learning of complex mappings from 2D images to 3D structures without explicit geometric constraints [5].

This work was supported by Professor Feng Daqian, Shenzhen University.

B. Research Significance

High-quality 3D human mesh reconstruction is not only essential for entertainment and interactive applications but also holds substantial promise in medical rehabilitation, ergonomics, virtual fitting rooms, and social networks. For instance, in healthcare, accurate 3D models can be used for patient rehabilitation training and surgical planning [6]. In virtual try-on systems, consumers can visualize clothing on their personalized avatars, enhancing the shopping experience [7].

C. Current Trends and Challenges

Recent developments focus on overcoming inherent challenges in 3D reconstruction, such as dealing with occlusions, varying lighting conditions, and the high dimensionality of human body poses and shapes [8]. Integrating parametric models like SMPL [9] with neural networks has paved the way for more accurate and flexible reconstruction frameworks. Additionally, the use of implicit representations and generative models has enhanced the ability to capture fine-grained details and generate realistic human meshes [10], [11]. However, challenges such as achieving real-time performance, handling complex clothing and accessories, and

ensuring data diversity and generalization remain significant hurdles [12].

D. Paper Structure

This paper is structured as follows: Section II presents a taxonomy of existing 3D human mesh reconstruction methods. Section III delves into various methodologies, including single-view, multi-view, depth-based, and neural network-based approaches. Section IV discusses key techniques and their mathematical formulations. Section V analyzes current challenges in the field. Section VI outlines future research directions, and Section VII provides a comprehensive discussion of the findings. Finally, Section VIII concludes the paper.

II. Taxonomy of 3D Human Mesh Reconstruction

To systematically analyze the diverse methodologies in 3D human mesh reconstruction, we categorize them based on input modalities and underlying techniques. Figure 1 illustrates the taxonomy of existing approaches, broadly divided into Reconstruction Methods and Generation Methods [13].

- **Reconstruction Methods**: Focus on generating accurate 3D meshes from existing data, such as single-view or multi-view images, depth maps, and sensor data. These methods prioritize fidelity and accuracy in replicating the human form.
- **Generation Methods**: Emphasize creating novel human meshes, often leveraging generative models like GANs and VAEs to synthesize realistic and diverse human shapes and poses. These methods are crucial for applications requiring a wide variety of human forms.

This classification not only helps in organizing the existing research but also highlights the distinct approaches and their respective strengths and limitations.

III. Methodologies

3D human mesh reconstruction methodologies can be broadly categorized into single-view reconstruction, multi-view reconstruction, depth-based methods, neural network-based frameworks, and hybrid approaches. Each category is further divided based on specific techniques and input types.

A. Single-View Reconstruction

Single-view approaches reconstruct 3D human meshes from a single RGB image, addressing depth ambiguity by leveraging prior knowledge about human body shapes and poses. These methods typically utilize deep learning models to infer depth and pose information from 2D inputs [14].

1) Neural Implicit Functions: Neural implicit functions represent 3D geometry as continuous functions, enabling detailed and flexible mesh reconstructions. For instance, [15] employs surface normal predictions to enhance monocular 3D human reconstructions. These methods often use neural networks to learn implicit representations such as Signed Distance Functions (SDFs) or occupancy fields, capturing fine-grained geometric details [16].

2) Generative Adversarial Networks (GANs): GAN-based methods leverage adversarial training to generate realistic 3D human poses from single RGB images [17]. These approaches handle unseen poses through zero-shot learning, enabling plausible 3D mesh generation even for poses not present in the training data. The GAN framework consists of a generator G and a discriminator D, optimizing the objective:

$$\min_G \max_D \mathbb{E}_{\mathbf{x}\sim p_{\text{data}}}[\log D(\mathbf{x})]+\mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}}[\log(1-D(G(\mathbf{z})))] \tag{1}$$

where $\mathbf{z}$ is a noise vector sampled from a prior distribution $p_{\mathbf{z}}$.

While GANs excel in producing visually realistic outputs, they face challenges such as mode collapse and training instability [18]. Ensuring consistency and accuracy across different poses and body types remains an ongoing challenge [12].

3) Parametric Models: Parametric models like SMPL [9] provide predefined human body models with parameters controlling shape and pose. Single-view methods regress these parameters directly from input images, facilitating the reconstruction of 3D human meshes that adhere to human body priors. The SMPL model is defined as:

$$\mathbf{M}(\beta,\theta) = \mathbf{T}(\beta,\theta) + \mathbf{W}(\beta,\theta) \tag{2}$$

where β represents shape parameters, θ represents pose parameters, $\mathbf{T}$ is the global translation, and $\mathbf{W}$ is the pose-dependent deformations.

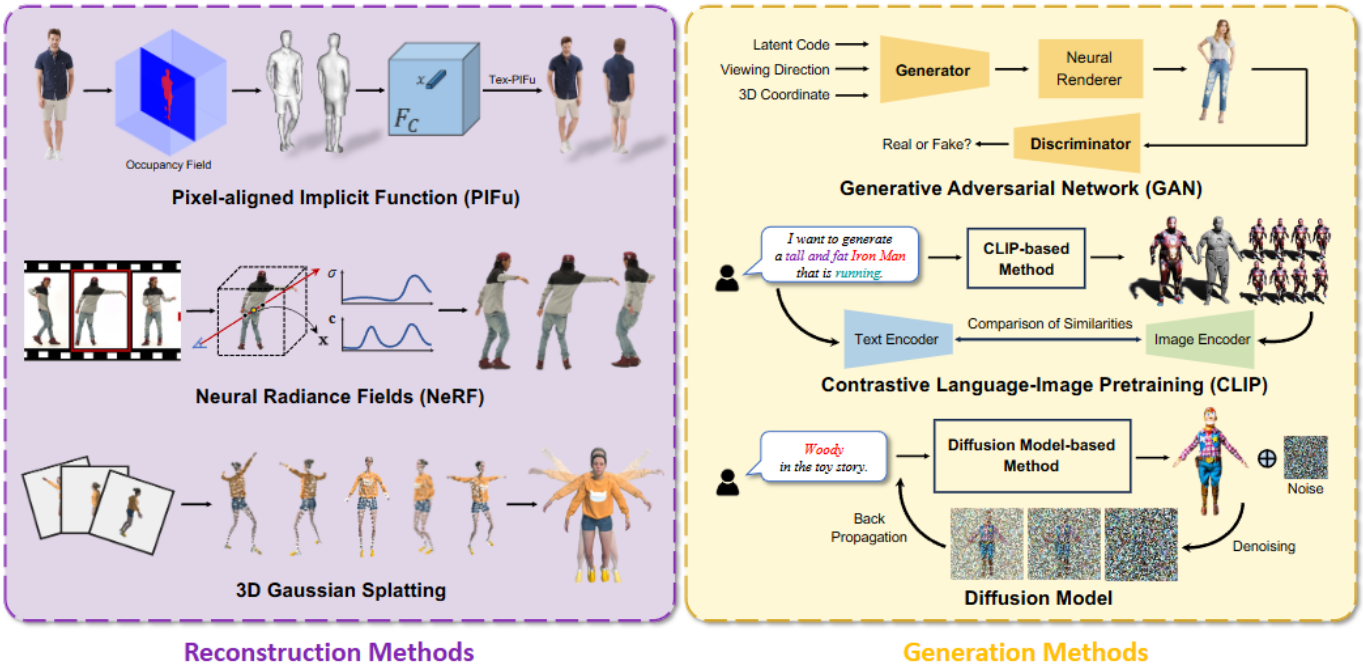

Fig. 1: An overview of typical 3D human avatar modeling approaches [13]

Advantages of parametric models include anatomical consistency and real-time applicability by reducing the problem to parameter estimation [19]. However, they may struggle with capturing highly detailed or unique body shapes and poses, as well as complex clothing and accessories [10].

B. Multi-View Reconstruction

Multi-view approaches utilize images from multiple viewpoints to reconstruct accurate 3D human meshes, benefiting from additional spatial information and resolving ambiguities inherent in single-view methods [20].

1) Multi-View Stereo: Methods like [2] integrate multi-view stereo techniques with deep learning to improve 3D human reconstruction precision. Leveraging geometric constraints from multiple views enhances accuracy, especially under varying lighting conditions and occlusions. The multi-view stereo process involves:

a. **Feature Extraction**: Extracting features from each view using CNNs.
b. **Depth Estimation**: Estimating depth maps by matching features across views.
c. **Point Cloud Generation**: Triangulating corresponding points to generate a point cloud.
d. **Mesh Reconstruction**: Refining the point cloud into a coherent mesh using surface reconstruction algorithms.

While effective, these methods require synchronized multiple cameras and are computationally intensive, limiting their use in real-time applications [8].

2) Sensor Fusion: Sensor fusion techniques combine data from multiple sensors, including RGB and depth cameras, to achieve robust reconstructions. For example, [21] introduces BodyNet, integrating multi-view data for real-time, high-resolution 3D human body reconstructions. The sensor fusion process involves:

a. **Data Alignment**: Aligning data from different sensors to a common coordinate system.
b. **Data Integration**: Combining RGB and depth data using fusion strategies.
c. **Mesh Refinement**: Refining the integrated data to produce a high-quality mesh.

Sensor fusion mitigates individual sensor limitations but increases system complexity and cost [22].

C. Depth-Based Methods

Depth-based methods leverage depth information from RGB-D cameras to facilitate 3D human

mesh reconstruction, often achieving real-time performance suitable for interactive applications [23].

1) RGB-D Cameras: RGB-D based methods, such as those in [17], utilize single RGB-D cameras to reconstruct 3D human bodies in real-time. Depth information provides direct geometric measurements, simplifying the reconstruction process by reducing reliance on complex depth inference from RGB data alone. The RGB-D reconstruction pipeline includes:

a. **Depth Map Acquisition**: Capturing depth maps using RGB-D sensors.
b. **Point Cloud Generation**: Converting depth maps to point clouds.
c. **Point Cloud Registration**: Aligning point clouds from different frames using algorithms like ICP.
d. **Mesh Construction**: Building a mesh from the registered point clouds.

2) Depth Map Fusion: Depth map fusion combines multiple depth maps to create a coherent and complete 3D model. [8] presents a real-time 3D human reconstruction approach using depth map fusion, integrating depth information from multiple frames to handle occlusions and improve mesh quality. The fusion process includes:

a. **Depth Map Registration**: Aligning depth maps using registration algorithms.
b. **Occlusion Handling**: Resolving occlusions by prioritizing depth information based on confidence scores or temporal consistency.
c. **Mesh Refinement**: Enhancing mesh accuracy using surface reconstruction techniques.

Depth map fusion enhances reconstruction completeness and accuracy but demands efficient algorithms for real-time integration [24].

D. Neural Network-Based Frameworks

Neural network-based frameworks have revolutionized 3D human mesh reconstruction by enabling end-to-end learning from data. These frameworks leverage various neural architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based models, to infer 3D structures from 2D inputs [25].

1) Convolutional Neural Networks (CNNs): CNNs are widely used for feature extraction and depth estimation in 3D human mesh reconstruction. They effectively capture spatial hierarchies in images, enabling the extraction of meaningful features that aid in accurate mesh generation [14].

2) Recurrent Neural Networks (RNNs): RNNs are employed in scenarios involving temporal data, such as video sequences. They help in maintaining temporal consistency and improving reconstruction accuracy over time [26].

3) Transformer-Based Models: Transformer-based architectures have recently gained popularity for their ability to model long-range dependencies and handle complex interactions in data. They are particularly useful in multi-modal data integration and large-scale 3D reconstruction tasks [20].

E. Hybrid Approaches

Hybrid approaches combine multiple methodologies to leverage the strengths of each. For example, integrating parametric models with neural implicit functions can enhance both anatomical accuracy and geometric detail [16]. These approaches often achieve a balance between flexibility, accuracy, and computational efficiency [19].

IV. Key Techniques and Formulas

This section delves into influential methods and their mathematical formulations underpinning advancements in 3D human mesh reconstruction.

A. 3D Gaussian Splatting

3D Gaussian Splatting [11] leverages sets of 3D Gaussians for real-time radiance field rendering. Key steps include:

a. **Sparse Point Initialization**: Representing the scene with 3D Gaussians based on sparse points from camera calibration.
b. **Interleaved Optimization**: Optimizing density and anisotropic covariance to accurately represent scene geometry.
c. **Visibility-Aware Rendering**: Rendering accounting for visibility and supporting anisotropic splatting for real-time performance.

Each Gaussian is mathematically represented as:

$$G_i = \mathcal{N}(\mu_i, \Sigma_i) \tag{3}$$

where μ_i is the mean vector and Σ_i is the covariance matrix.

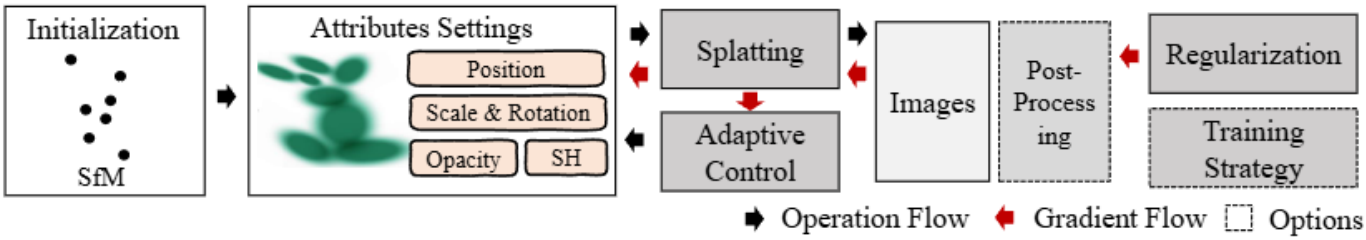

Fig. 2: Pipeline and Related Technologies of 3D Gaussian Splatting [11]

The optimization objective is:

$$\min_{\{\mu_i,\Sigma_i\}} \sum_i \mathcal{L}(G_i, \text{Data}) \tag{4}$$

where $\mathcal{L}$ measures the discrepancy between the Gaussian representation and scene data.

3D Gaussian Splatting enables efficient rendering and reconstruction by approximating complex geometries with a manageable number of Gaussian primitives, balancing detail and computational load [11].

B. Neural Radiance Fields (NeRF)

NeRF represents scenes as continuous volumetric radiance fields using neural networks [24]. The model is defined as:

$$\text{NeRF}(\mathbf{x}, \mathbf{d}) = (c, \sigma) \tag{5}$$

where c is the emitted color and σ is the volume density.

The rendering equation is:

$$C(\mathbf{d}) = \int_{t_n}^{t_f} T(t)\sigma(\mathbf{x}(t), \mathbf{d})c(\mathbf{x}(t), \mathbf{d})dt \tag{6}$$

with accumulated transmittance $T(t)$.

The optimization objective is:

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} \|C(\mathbf{d}_i) - C_{\text{obs}}(\mathbf{d}_i)\|^2 \tag{7}$$

NeRFs excel in high-fidelity reconstructions by accurately modeling light interactions and scene geometry but require significant computational resources for training and rendering [19].

Figure 3 provides an overview of the NeRF framework, illustrating how neural networks are used to model radiance fields for view synthesis.

C. Neural Implicit Functions

Neural implicit functions define 3D surfaces as zero level-sets of continuous functions:

$$f(\mathbf{x}; \theta) = 0 \tag{8}$$

For example, [10] conditions the implicit function on side-view images to reconstruct clothed human figures. The training objective minimizes:

$$\mathcal{L} = \sum_i \|f(\mathbf{x}_i; \theta) - y_i\|^2 \tag{9}$$

where y_i indicates if $\mathbf{x}_i$ is inside or outside the mesh.

Implicit surface models provide smooth, high-resolution reconstructions but require sophisticated optimization and are computationally intensive.

D. Generative Adversarial Networks (GANs)

GANs consist of a generator G and discriminator D, trained adversarially:

$$\min_G \max_D \mathbb{E}_{\mathbf{x}\sim p_{\text{data}}}[\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}}[\log(1 - D(G(\mathbf{z})))] \tag{10}$$

In 3D human mesh reconstruction, GANs generate realistic poses and shapes, enhancing realism and diversity [7]. Conditional GANs (cGANs) can further improve relevance by conditioning on input images [25].

Despite challenges like mode collapse and training instability, GANs demonstrate impressive capabilities in generating high-quality, diverse 3D human meshes [18].

V. Challenges

Despite significant progress, several challenges persist in 3D human mesh reconstruction. Addressing these is crucial for advancing the field and enabling broader applications.

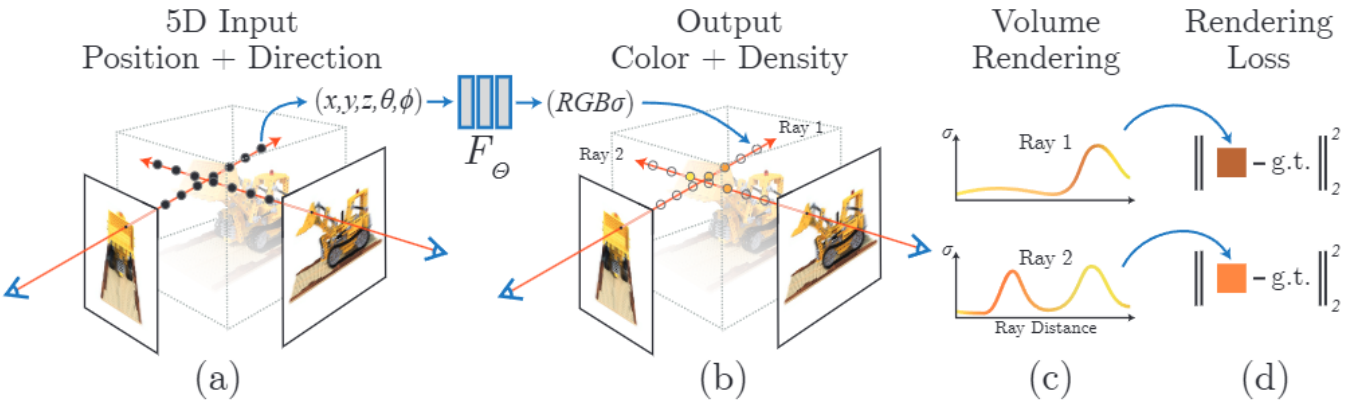

Fig. 3: NeRF Overview [24]

A. Real-Time Performance

Achieving real-time reconstruction with high accuracy remains a technical challenge, especially with high-resolution data and complex poses [21]. Real-time applications like VR and AR require fast processing without compromising mesh quality. Optimization techniques, efficient neural architectures, and hardware acceleration are essential [27].

Current approaches often trade off speed for accuracy, necessitating research into more efficient algorithms. Techniques such as model pruning, quantization, and knowledge distillation can reduce computational overhead [12]. Leveraging specialized hardware like GPUs and TPUs can also accelerate inference [26].

B. Handling Occlusions

Occlusions from clothing, accessories, or object interactions complicate reconstruction. Robust methods are required to accurately infer hidden body parts [13]. Techniques like multi-view integration, depth-based methods, and prior-based inference help mitigate occlusions but may fall short in highly cluttered environments [22].

Future research should develop sophisticated occlusion handling mechanisms, possibly integrating temporal information from video sequences to better infer occluded regions based on previous frames [3]. Context-aware reasoning and leveraging human pose priors can enhance the prediction and reconstruction of occluded body parts.

C. Data Diversity and Generalization

Ensuring models generalize across diverse body types, poses, and environments is essential but challenging due to limited and biased training datasets [12]. Overfitting to specific datasets can result in poor performance on unseen data.

Techniques such as data augmentation, synthetic data generation, and self-supervised learning can improve generalization . Leveraging large-scale datasets capturing a wide range of human shapes and poses is critical [28]. Cross-dataset training and domain adaptation strategies can also enhance model robustness [19].

D. High-Fidelity Reconstruction

Capturing fine-grained details like clothing wrinkles, facial expressions, and subtle body deformations is critical for high-fidelity reconstructions [7]. Balancing reconstruction accuracy and computational efficiency remains challenging.

Enhancing mesh resolution and detail while maintaining real-time performance requires advanced neural architectures and optimization techniques [10]. Incorporating multi-scale representations and attention mechanisms enables models to capture both global structures and local details effectively [29].

E. Integration of Multiple Modalities

Integrating multiple data modalities, such as RGB, depth, and inertial measurements, poses challenges in data synchronization, fusion, and processing. Effective integration requires sophisticated

algorithms to handle heterogeneous data sources and leverage their complementary strengths [22].

Future research should explore seamless integration frameworks that efficiently process and fuse multi-modal data in real-time [25]. Techniques like multi-stream neural networks and sensor fusion algorithms are promising for achieving effective multi-modal integration [7].

F. Ethical and Privacy Concerns

As 3D human mesh reconstruction technologies become pervasive, addressing ethical and privacy concerns is crucial. Reconstructing detailed 3D models of individuals raises significant privacy issues, especially regarding consent and data security [12].

Future research should incorporate privacy-preserving techniques, ensure data security, and develop ethical guidelines for 3D human reconstructions to prevent misuse and protect individual privacy. Techniques like differential privacy, secure multi-party computation, and anonymization strategies can mitigate privacy risks [28].

VI. Future Directions

Future research directions in 3D human mesh reconstruction aim to address current limitations and push the boundaries of what is achievable. Key areas include:

A. Multi-Modal Data Integration

Combining visual, depth, and inertial data can significantly enhance reconstruction accuracy and robustness. Multi-modal integration leverages complementary information from different sensors, improving the handling of occlusions, varying lighting conditions, and diverse poses. Future work should develop seamless integration frameworks capable of real-time multi-modal data processing and fusion [21].

B. Self-Supervised and Unsupervised Learning

Reducing reliance on labeled data is crucial for scaling 3D human mesh reconstruction. Self-supervised and unsupervised learning techniques enable models to learn from vast amounts of unlabeled data, improving generalization and reducing the need for extensive annotations [28]. Techniques such as contrastive learning, generative modeling, and consistency-based training hold promise for enhancing model learning capabilities.

C. Improved Neural Representations

Advancing neural representations like implicit surfaces and radiance fields can capture finer details and dynamic changes in human meshes [30]. Enhanced representations facilitate more accurate and realistic reconstructions, especially in dynamic and real-world environments. Future research should explore novel neural architectures and optimization techniques to better model complex geometries and temporal dynamics [16].

D. Real-Time Optimization Techniques

Developing efficient optimization algorithms and leveraging hardware acceleration can address real-time performance challenges [27]. Techniques such as parallel processing, model compression, and specialized hardware implementations are essential for achieving required processing speeds without sacrificing reconstruction quality. Exploring lightweight neural network architectures that maintain high performance while reducing computational demands is also a key area of interest [12].

E. Enhanced Handling of Clothing and Accessories

Improving the ability to reconstruct detailed clothing and accessories remains important. Future methods should focus on better modeling cloth dynamics and interactions with the environment to achieve more realistic reconstructions [10]. Integrating physics-based models with data-driven approaches can accurately capture clothing deformations and draping, enhancing overall mesh realism [7].

F. Scalability and Portability

Ensuring reconstruction models scale to different devices and environments is essential for widespread adoption. Developing lightweight models that run on mobile and embedded devices without compromising performance is a key future direction [21]. Creating scalable frameworks capable of handling large-scale datasets and diverse environments will enhance applicability across various domains [19].

G. Integration with Human Behavior and Interaction

Integrating 3D human mesh reconstruction with models of human behavior and interaction can lead to sophisticated applications in human-computer interaction, robotics, and social VR/AR. Understanding and predicting human movements and interactions in real-time can enable more natural and intuitive interfaces, enhancing user experience and engagement [3].

H. Ethical and Privacy Considerations

As 3D human mesh reconstruction technologies become pervasive, addressing ethical and privacy concerns is increasingly important. Future research should incorporate privacy-preserving techniques, ensure data security, and develop ethical guidelines for 3D human reconstructions to prevent misuse and protect individual privacy [12]. Techniques like differential privacy, secure multi-party computation, and anonymization strategies can mitigate privacy risks [28].

VII. Discussion

This section provides a comprehensive analysis of the main findings and trends in 3D human mesh reconstruction, discussing their implications and potential impacts on various applications.

A. Technological Integration Trends

With the advancement of different technologies, 3D human mesh reconstruction is moving towards multi-modal, real-time, and high-fidelity solutions. The integration of implicit representations with generative models has enabled precise reconstruction of complex poses and clothing, bridging the gap between accuracy and computational efficiency [10], [11]. Additionally, the combination of neural implicit functions with traditional parametric models like SMPL has resulted in hybrid frameworks that leverage the strengths of both approaches [16].

B. Application Prospects

The maturation of 3D human mesh reconstruction technology is set to significantly advance fields such as VR/AR, entertainment, healthcare, and human-computer interaction. For example, virtual fitting rooms will become more realistic and interactive, enhancing the online shopping experience [7]. In healthcare, personalized 3D models can lead to more effective rehabilitation training and surgical planning [6]. Furthermore, in the entertainment industry, accurate motion capture can improve the realism of animated characters in films and video games [3].

C. Impact on Related Fields

Advancements in 3D human mesh reconstruction also have ripple effects on related fields such as robotics and autonomous systems. Accurate human modeling is crucial for human-robot interaction, enabling robots to understand and predict human movements for safer and more effective collaboration [26]. Moreover, in social VR/AR platforms, enhanced human mesh reconstructions contribute to more immersive and engaging user experiences by providing lifelike avatars.

D. Focus Areas for Future Research

Future research should prioritize enhancing model generalization, optimizing real-time performance, improving the handling of complex clothing and dynamic scenes, and ensuring the ethical and privacy aspects of the technology. Additionally, developing comprehensive and diverse datasets will be crucial for training robust and versatile models. Research into integrating temporal information from video sequences can further improve the robustness of reconstructions in dynamic environments [3].

E. Interdisciplinary Collaboration

Collaboration between computer vision, graphics, machine learning, and other related disciplines is essential for driving innovation in 3D human mesh reconstruction. Interdisciplinary efforts can lead to the development of novel algorithms and models that address the multifaceted challenges of accurate and efficient human reconstruction. Furthermore, partnerships with industry can facilitate the translation of research advancements into practical applications, accelerating the adoption of 3D human mesh reconstruction technologies in various sectors [12].

VIII. Conclusion

3D human mesh reconstruction has made remarkable strides through the integration of deep learning, neural representations, and multi-view techniques. The field has evolved from traditional geometric methods to sophisticated neural network-based frameworks offering high accuracy and flexibility. These advancements enable realistic and detailed reconstructions, facilitating applications in VR, AR, gaming, healthcare, and human-computer interaction [3], [6].

Despite significant progress, challenges such as real-time performance, handling occlusions, ensuring data diversity, and capturing high-fidelity details remain. Addressing these challenges is essential for advancing the field and enabling broader applications of 3D human mesh reconstruction technologies. Innovations in neural implicit functions, generative models, and multi-modal data integration pave the way for more accurate, robust, and versatile 3D human reconstructions [10], [11].

Future directions emphasize the need for improved neural representations, efficient optimization techniques, and enhanced handling of complex real-world scenarios. Additionally, integrating multi-modal data and advancing self-supervised learning techniques hold significant promise for overcoming current limitations. As the field progresses, 3D human mesh reconstruction is expected to play an increasingly vital role in transforming human interactions with digital environments and technologies [24].

Continued collaboration between academia and industry, along with the development of comprehensive and diverse datasets, will drive further advancements. By addressing remaining challenges and exploring innovative solutions, the future of 3D human mesh reconstruction looks promising, unlocking new possibilities across various domains.

Acknowledgment

The authors would like to thank Professor Feng Daqian for his invaluable guidance and support throughout the research and writing of this paper.

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