

LHM: Large Animatable Human Reconstruction Model for Single Image to 3D in Seconds

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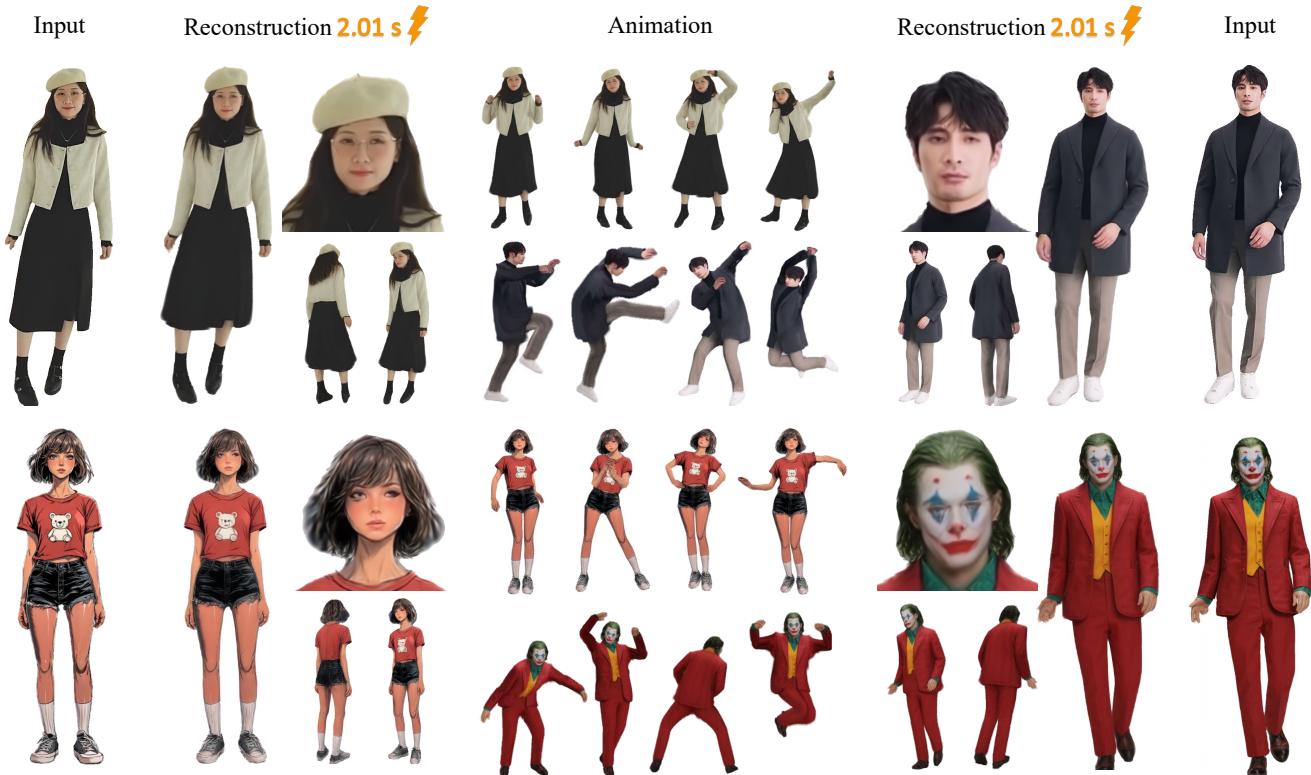


Figure 1. **3D Avatar Reconstruction and Animation Results of our LHM.** Our method reconstructs an animatable human avatar in a single feed-forward pass in seconds. The resulting model supports real-time rendering and pose-controlled animation.

Abstract

Animatable 3D human reconstruction from a single image is a challenging problem due to the ambiguity in decoupling geometry, appearance, and deformation. Recent advances in 3D human reconstruction mainly focus on static human modeling, and the reliance of using synthetic 3D scans for training limits their generalization ability. Conversely, optimization-based video methods achieve higher

fidelity but demand controlled capture conditions and computationally intensive refinement processes. Motivated by the emergence of large reconstruction models for efficient static reconstruction, we propose LHM (Large Animatable Human Reconstruction Model) to infer high-fidelity avatars represented as 3D Gaussian splatting in a feed-forward pass. Our model leverages a multimodal transformer architecture to effectively encode the human body positional features and image features with attention mechanism, enabling detailed preservation of clothing geometry and texture. To further boost the face identity preser-

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vation and fine detail recovery, we propose a head feature pyramid encoding scheme to aggregate multi-scale features of the head regions. Extensive experiments demonstrate that our LHM generates plausible animatable human in seconds without post-processing for face and hands, outperforming existing methods in both reconstruction accuracy and generalization ability. Our code is available on <https://github.com/aigc3d/LHM>.

1. Introduction

Creating 3D animatable human avatars from single images is crucial for immersive AR/VR applications, yet remains challenging due to the coupled ambiguities of geometry, appearance, and deformation.

Recently, diffusion-based human video animation methods [17, 32, 37, 69] have shown the capability to generate photorealistic human videos. However, these methods often suffer from inconsistent views under extreme poses and require long inference times for video sampling. In 3D animatable human reconstruction, early methods rely on parametric models [2, 34] to provide strong human body priors for animation but struggle to capture the fine-grained geometry of loose clothing, and high-fidelity facial details, limiting their expressiveness. While learning-based 3D methods have made considerable progress in static clothed human reconstruction in recent years [50, 51, 59], most existing approaches either fail to produce animatable humans or lack generalization to in-the-wild images [14, 22]. The problem of generalizable 3D animatable human reconstruction from a single image remains underexplored due to the lack of a suitable model architecture and a large-scale 3D rigged human dataset for learning.

Recently, large reconstruction model (LRM) [16] have shown that scalable transformer models trained with large-scale of 3D data can learn generalizable priors for single-image 3D object reconstruction. While promising, extending this success to *animatable human reconstruction* presents unique challenges that demand solutions to two critical problems: 1) designing an effective architecture that combines 3D human representation with animation capabilities, and 2) overcoming the scarcity of high-quality 3D rigged human training data.

In this work, we propose *LHM* (Large Animatable Human Model), a scalable feed-forward transformer model, that produces animatable 3D human avatars in seconds from single images. We represent the human avatar as Gaussian splatting considering its real-time photo-realistic rendering. Our method takes a single image as input and directly predicts the canonical human as a set of 3D Gaussians in canonical space. To enable animation, our method starts from a set of surface points sampled from the SMPL-X [44] template mesh to serve as geometric anchors for predicting

3D Gaussian properties.

The network architecture of our method is inspired by the multimodal transformer (MM-transformer) block introduced by the state-of-the-art image generation model SD3 [11], which is designed to model the interaction between the text and image tokens. We adapt the MM-transformer to our task to effectively encode the body 3D point features and 2D image features with attention operation, enabling detailed preservation of clothing geometry and texture. To address the problem of facial identity preservation, we further introduce a *head feature pyramid encoding* (HFPE) scheme that aggregates multi-scale visual features from head regions, significantly improving detail recovery in these perceptually sensitive areas.

During training, to boost the performance of this transformer from large-scale data, we transform the predicted canonical Gaussians to various poses using SMPL-X skeleton parameters and optimize through a combination of rendering losses and regularizations. This self-supervised strategy allows learning generalizable human priors from readily available video data rather than scarce 3D scans.

In summary, our contributions are:

- We introduce a generalizable large human reconstruction model that produces animatable 3D avatars from single images in seconds.
- We propose a multimodal human transformer to fuse 3D surface point features and image features via an attention mechanism, enabling joint reasoning across geometric and visual domains.
- Our method, trained on a large-scale video dataset without rigged 3D data, achieves state-of-the-art performance on real-world imagery, surpassing existing approaches in generalization and animation consistency.

2. Related Work

2.1. Single-Image Human Reconstruction

Early approaches to single-image 3D human reconstruction primarily relied on parametric body models like SMPL [34, 44] to predict geometric offsets for naked or clothed subjects [1, 3, 9, 24]. These methods often struggle to capture diverse clothing styles due to their rigid mesh-based representations. Subsequent advancements leveraged implicit functions [5, 50, 51, 58, 59, 63, 67, 68] to model complex geometries, providing greater flexibility in handling fine surface details without resolution constraints. Generative frameworks, such as diffusion models [7, 15, 43] and GANs [28, 36], have been adopted to synthesize detailed 3D humans conditioned on the input images. Some researchers [19, 21, 60, 61] have explored generating avatars distilled from diffusion models using SDS loss. However, these methods tend to be time-consuming.

Recently, large reconstruction models (LRMs) have been

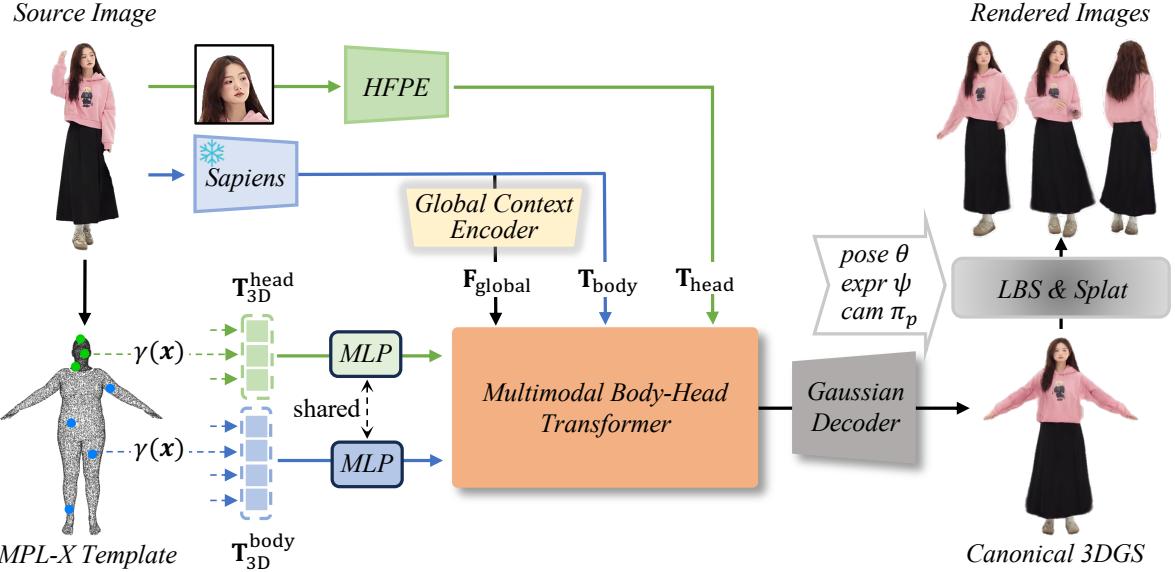


Figure 2. **Overview of the proposed LHM.** Our method extracts body and head image tokens from the input image, and utilizes the proposed Multimodal Body-Head Transformer (MBHT) to fuse the 3D geometric body tokens with the image tokens. After the attention-based fusion process, the geometric body tokens are decoded into Gaussian parameters.

introduced to enable generalizable feed-forward object reconstruction [16, 55], significantly accelerating inference time. Human-LRM [57] employs a feed-forward transformer to decode triplane-NeRF representations to enable multi-view rendering, followed by diffusion-based 3D reconstruction. Human-Splat [42] first generates multi-view images using video diffusion, and then applies a latent reconstruction transformer to predict human avatars in 3D Gaussian Splatting (3DGS). PSHuman [29] utilizes multi-view diffusion with the ID diffusion to improve the face quality. In contrast to these methods, which focus on static human reconstruction, our approach generates photorealistic, animatable human avatars, enabling high-quality dynamic rendering and interaction.

2.2. Animatable Human Generation

Creating animatable avatars has evolved from parametric-model-driven methods [2] to hybrid approaches combining implicit surfaces and human priors for clothed body modeling [14]. Video-based techniques further improved reconstruction consistency by leveraging temporal cues from monocular [18, 23, 48, 53, 56, 64] or multi-view sequences [8, 30, 31, 39, 46]. The rise of text-to-3D methods [47] has enabled avatar generation from text prompts through a long optimization process [6, 20, 28].

In 3D animatable human reconstruction, CharacterGen [45] has explored cartoon-style avatar generation using diffusion models for canonical view synthesis and transformer-based shape reconstruction. AniGS [49] em-

ploys a video diffusion model to generate multi-view canonical images, followed by a 4D Gaussian splatting (4DGS) optimization to achieve consistent 3D generation. GAS [35] adopts a generalizable human NeRF to reconstruct the subject in a canonical space, followed by video diffusion for refinement. More recently, IDOL [70] introduces a feed-forward transformer model to decode Gaussian attribute maps in UV spaces, and requires post-processing to refine the face and hands. Unlike these methods, we propose an efficient and expressive multimodal human transformer that directly regresses 3D human Gaussians without relying on UV representations or requiring post-processing for hands and face refinement.

3. Preliminary

Human Parametric Model The SMPL [34] and SMPL-X [44] parametric models are commonly employed for representing human body structures in computer vision applications. These frameworks employ advanced deformation techniques, including skinning mechanisms and blend shapes, which are derived from extensive datasets comprising thousands of 3D body scans.

In particular, the SMPL-X model utilizes two primary types of parameters to capture human body configurations. These include shape parameters $\beta \in \mathbb{R}^{20}$, and pose parameters $\theta \in \mathbb{R}^{55 \times 3}$, which determine the articulation and deformation of the body mesh based on skeletal poses.

3D Gaussian Splatting The 3D Gaussian Splatting framework [25] models three-dimensional information through a

set of anisotropic Gaussian distributions. Each primitive is parameterized by a centroid $\mathbf{p} \in \mathbb{R}^3$, scale parameters $\sigma \in \mathbb{R}^3$, and a quaternion $\mathbf{r} \in \mathbb{R}^4$ representing rotation. The model also incorporates an opacity parameter $\rho \in [0, 1]$ and appearance features $\mathbf{f} \in \mathbb{R}^C$ encoded with spherical harmonics to account for view-dependent lighting effects. During differentiable rendering, these volumetric primitives are projected into 2D screen space as oriented Gaussian distributions, followed by view-ordered alpha blending to composite the final pixel colors.

4. Method

4.1. Overview

Given an input RGB human image $I \in \mathbb{R}^{H \times W \times 3}$, our goal is to reconstruct an animatable 3D human avatar in seconds. The avatar is represented via 3D Gaussian Splatting (3DGS), which supports real-time, photorealistic rendering and pose-controlled animation. To achieve this, we propose *Large Animatable Human Reconstruction Model (LHM)*, a feed-forward, transformer-based architecture that directly predicts the canonical 3D avatar from a single image.

Inspired by recent multimodal transformers [11], we design a *Multimodal Body-Head Transformer* (MBHT) to effectively integrate geometric and image features. As illustrated in Fig. 2, our framework processes training pairs that consist of a source image, a target view image, a foreground mask, SMPL-X pose parameters, and a camera matrix.

The proposed MBHT employs attention operations to integrate three types of tokens: geometric tokens, body image tokens, and head image tokens, where geometric tokens can effectively attend to other tokens, allowing local and global refinement. In addition, Body and head tokens interact through a part-aware transformer, ensuring balanced attention across different body regions.

After the attention-based token fusion process, the geometric body tokens are decoded into per-Gaussian parameters, including deformation, scaling, rotation, and spherical harmonic (SH) coefficients. During training, we employ Linear Blend Skinning (LBS) to warp the canonical avatar to the target view, where photometric and regularization losses guide the learning process.

4.2. Geometric and Image Feature Encoding

Geometric tokens are derived from SMPL-X surface points, encoding structural priors of the human body. Body image tokens are extracted from a pretrained vision transformer [26], encoding texture and appearance. Head tokens specialize in capturing high-frequency facial details through a multi-scale feature extraction process.

Human Geometric Feature Encoding Leveraging SMPL-X’s human body prior, we initialize 3D query points $\{\mathbf{x}_i\}_{i=1}^{N_{\text{points}}} \subset \mathbb{R}^3$ by strategically sampling the canonical

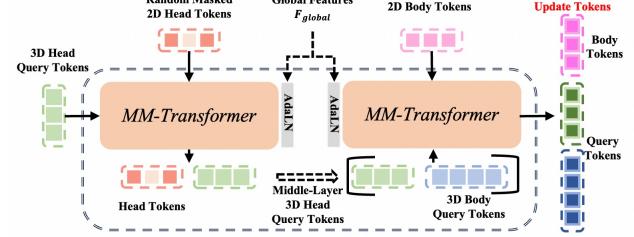


Figure 3. Architecture of the proposed Multimodal Body-Head Transformer Block (MBHT-block).

pose mesh. Each point undergoes positional encoding [38], followed by a multi-layer perceptron (MLP) projection to match the token channel dimension of the transformer:

$$\mathbf{T}_{3D} = \text{MLP}_{\text{proj}}(\gamma(\mathbf{X})) \in \mathbb{R}^{N_{\text{points}} \times C}, \quad (1)$$

where $\gamma : \mathbb{R}^3 \rightarrow \mathbb{R}^{3L}$ applies L -frequency sinusoidal encoding to spatial coordinates, and C is the token dimension.

Body Image Tokenization Building on large-scale vision transformers pretrained on human-centric datasets [26], we convert image pixels into transformer-compatible tokens. Specifically, we employ the frozen Sapiens-1B encoder $\mathcal{E}_{\text{Sapiens}}$, pretrained on 10 million human images, to extract semantic body features:

$$\mathbf{T}_{\text{body}} = \text{MLP}_{\text{proj}}(\mathcal{E}_{\text{Sapiens}}(I)) \in \mathbb{R}^{N_{\text{body}} \times C}, \quad (2)$$

where N_{body} denotes the body token numbers.

Head Feature Pyramid Tokenization However, since the human head occupies only a small region in the input image and undergoes spatial downsampling in the encoder, critical facial details are often lost. To mitigate this issue, we propose a head feature pyramid encoding (HFPE) that aggregates multi-scale features $\{\mathcal{E}_{\text{dino}}^i\}$ from DINOv2 [40]:

$$\mathbf{T}_{\text{head}} = \mathcal{F}_{\text{fusion}}(\mathcal{E}_{\text{dino}}^4, \mathcal{E}_{\text{dino}}^{11}, \mathcal{E}_{\text{dino}}^{17}, \mathcal{E}_{\text{dino}}^{23}) \in \mathbb{R}^{N_{\text{head}} \times C}, \quad (3)$$

where $\mathcal{F}_{\text{fusion}}$ fuses features from the 4th, 11th, 17th, and 23rd transformer blocks using depthwise concatenation and 1×1 convolutions, followed by feature projection. This design captures a hierarchy of semantic abstractions: early blocks retain high-frequency texture details, while deeper layers encode robust head geometry priors.

4.3. Multimodal Body-Head Transformer

Global Context Feature The global context token is used for the modulation of the attention block. To capture global context information for attention modulation, we take body tokens as the input, followed by max pooling and two MLP layers to extract the global context embeddings:

$$\mathbf{F}_{\text{global}} = \text{MLP}_{\text{global}}(\text{MaxPool}(\mathbf{T}_{\text{body}})). \quad (4)$$

Multimodal Body-Head Transformer Block The core design of the proposed model architecture is the multimodal body-head transformer block (MBHT-block) that efficiently fuse 3D geometric tokens with the body and head image features, as shown in Fig. 3.

Specifically, the global context features, image tokens, and query point tokens are fed simultaneously into the MBHT-block. To enhance the learning of features specific to the head and body, the 3D head point tokens will first fuse with the head image features, and then concatenate with the 3D body point token to interact with the body image tokens.

$$\begin{aligned} \mathbf{T}_{3D}^{\text{head}}, \mathbf{T}_{\text{head}} &:= \text{MM-T}(\mathbf{T}_{3D}^{\text{head}}, \mathbf{T}_{\text{head}}; \mathbf{F}_{\text{global}}) \\ \mathbf{T}_{3D} &:= \text{Norm}(\mathbf{T}_{3D}^{\text{head}}) \parallel \text{Norm}(\mathbf{T}_{3D}^{\text{body}}) \quad (5) \\ \mathbf{T}_{3D}, \mathbf{T}_{\text{body}} &:= \text{MM-T}(\mathbf{T}_{3D}, \mathbf{T}_{\text{body}}; \mathbf{F}_{\text{global}}) \end{aligned}$$

where $\mathbf{T}_{3D}^{\text{body}}$ and $\mathbf{T}_{3D}^{\text{head}}$ are 3D body and head points in \mathbf{T}_{3D} , respectively. MM-T indicates the Multimodal Transformer Block [11], and \parallel denotes token-wise concatenation (see supplementary materials for details).

Head Token Shrinkage Regularization Our experiments show that the attention mechanism in MBHT-block relies heavily on head-region features, which limits its ability to learn body-part features effectively. To address this imbalance, we take inspiration from MAE [13] and randomly mask the head region of the input crop during training.

Specifically, we apply spatial masking to head tokens with a ratio ranging from 0% to 50%, encouraging the model to compensate through enhanced body-context utilization. This regularization strategy improves body-part self-attention capacity while maintaining head reconstruction fidelity.

3DGS Parameter Prediction After N_{layer} MBHT-block blocks, an MLP heads predict 3DGS parameters:

$$\begin{aligned} \{\Delta \mathbf{p}_i, \mathbf{r}_i, \mathbf{f}_i, \rho_i, \sigma_i\} &= \text{MLP}_{\text{regress}}(\mathbf{T}_{\text{points}}^{(i)}) \quad (6) \\ \mathbf{p}_i &= \mathbf{x}_i + \Delta \mathbf{p}_i, \quad \forall i \in \{1, \dots, N_{\text{points}}\} \end{aligned}$$

where $\Delta \mathbf{p}_i \in \mathbb{R}^3$ represents residual position offsets from the canonical SMPL-X.

4.4. Loss Function

Our training objective combines photometric supervision from in-the-wild video sequences with regularization constraints in canonical space. The complete optimization framework enables the learning of animatable avatars without requiring ground truth 3D supervision.

4.4.1. View Space Supervision

Given the predicted 3DGS parameters $\chi = (\mathbf{p}, \mathbf{r}, \mathbf{f}, \rho, \sigma)$, we first transform the canonical avatar to target view space using Linear Blend Skinning (LBS). The transformed Gaussian primitives are then rendered through differentiable

splatting to produce the RGB image \hat{I} and alpha mask \hat{M} under target camera parameters π_t . To better model clothing deformations, we use a diffused voxel skinning [48].

The view-consistent supervision comprises three components in view space:

$$\mathcal{L}_{\text{photometric}} = \underbrace{\lambda_{\text{rgb}} \mathcal{L}_{\text{color}}}_{\text{Appearance}} + \underbrace{\lambda_{\text{mask}} \mathcal{L}_{\text{mask}}}_{\text{Silhouette}} + \underbrace{\lambda_{\text{per}} \mathcal{L}_{\text{lips}}} \quad . \quad (7)$$

In our implementation, the loss weights balance reconstruction aspects: $\lambda_{\text{rgb}} = 1.0$ for direct color supervision, $\lambda_{\text{mask}} = 0.5$ for geometric alignment, and $\lambda_{\text{per}} = 1.0$ to preserve high-frequency details.

4.4.2. Canonical Space Regularization

While photometric loss provides effective supervision in target view space, the canonical representation remains under-constrained due to the ill-posed nature of monocular reconstruction. This limitation manifests as deformation artifacts when warping the avatar to novel poses. To address this fundamental challenge, we introduce two complementary regularization terms that enforce geometric coherence in canonical space.

Gaussian Shape Regularization We apply the *as spherical as possible* loss to penalize excessive anisotropy in Gaussian primitives:

$$\mathcal{L}_{\text{ASAP}} = \frac{1}{N} \sum_{i=1}^N \|\mathbf{S}_i - \text{diag}(1)\|_F^2, \quad (8)$$

where \mathbf{S}_i represents the covariance matrix, effectively discouraging needle-like ellipsoids while preserving necessary shape variation.

Positional Anchoring To maintain body surface plausibility, we include the *as close as possible* loss to encourage Gaussian positions to be close to their SMPL-X initialized locations by a hinged distance constraint:

$$\mathcal{L}_{\text{ACAP}} = \frac{1}{N_{\text{points}}} \sum_{i=1}^{N_{\text{points}}} \max(\|\Delta \mathbf{p}_i\|_2 - d, 0), \quad (9)$$

where d represents an empirically determined threshold (5.25cm) in practice) that permits local adjustments while preventing catastrophic drift.

The combined canonical regularization operates as:

$$\mathcal{L}_{\text{reg}} = 50\mathcal{L}_{\text{ASAP}} + 10\mathcal{L}_{\text{ACAP}}. \quad (10)$$

In summary, our composite training objective combines photometric fidelity preservation with geometric regularization, formulated as:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{photometric}} + \mathcal{L}_{\text{reg}}. \quad (11)$$



Figure 4. Single-view reconstruction comparisons on DeepFashion [33] and in-the-wild images. LHM achieves superior appearance fidelity and texture sharpness, particularly evident in facial details and garment wrinkles.

5. Experiments

5.1. Implementation Details

In-the-Wild Training Data We curate a large-scale dataset of 301,733 single-person video sequences from 500K initial human motion footage samples collected from public video repositories. Our multi-stage filtering pipeline removes sequences containing multi-person interactions, occluded faces, or low-quality frames through manual inspection and automated metric thresholds.

Synthetic Data Augmentation To address viewpoint bias in natural videos, we supplement the training with synthetic human scans from three sources: 2K2K [12], Human4DiT [52] and RenderPeople (see supplementary materials for details).

Preprocessing Pipeline We employ SAMURAI [62] to extract foreground masks across video sequences. For SMPL-X parametric estimation, we leverage Multi-HMR [4] to estimate pose and shape parameters.

Training Configuration Our implementation utilizes

AdamW [27] optimization with an initial learning rate of 4×10^{-4} . We employ mixed-precision training with dynamic loss scaling, gradient clipping at $\|\nabla\|_2 = 0.1$, and weight decay regularization ($\lambda = 5 \times 10^{-4}$). Distributed training executes on NVIDIA A100 clusters for 40K iterations - 32 GPUs for 500M/700M models (16 samples/GPU), 64 GPUs for the 1B parameter variant (8 samples/GPU). The total training times reach 78, 112, and 189 hours, respectively. During training, we randomly sample a source view image and four target view images from a video sequence.

5.2. Comparison with Existing Methods

Single-Image Human Reconstruction We evaluate LHM against four baseline methods for single-view image human reconstruction. GTA [65] and SIFU [66] employ recursive optimization loops and pixel-aligned feature extraction, respectively, focusing on geometric refinement through successive approximation steps. PSHuman [29] employs multi-view diffusion in conjunction with local ID



Figure 5. Single-view animatable human reconstruction comparisons on in-the-wild sequences. LHM produces more accurate and photo-realistic animation results than the baseline methods. Note that the results of AniGS are not faithful to the input images.

diffusion to boost the quality of facial features in multi-view human RGB and normal images, which is subsequently followed by multi-view mesh reconstruction. DreamGaussian [54] leverages score distillation sampling (SDS) [47] from 2D diffusion models to distill 3D representations. While their progressive Gaussian densification strategy reduces convergence time to approximately 2 minutes per asset, this remains orders of magnitude slower than real-time requirements.

Table 1 compares the quantitative results on 200 synthetic datasets among baseline methods on four metrics: PSNR, SSIM, LPIPS, and Face Consistency (FC) measured via L2 distance in the ArcFace [10] embedding space. Notably, for a fair comparison, we report metrics of the model trained on the same synthetic dataset as baseline methods.

With respect to qualitative results, as illustrated in Fig. 4, the visual comparisons highlight our method’s ability to maintain input-aligned features while suppressing common artifacts such as over-smoothing.

Table 1. Evaluation of static 3D reconstruction on synthetic data. * indicates this model only trains on synthetic data.

Methods	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	FC \downarrow
GTA [65]	17.025	0.919	0.087	0.051
SIFu [66]	16.681	0.917	0.093	0.060
PSHuman [29]	17.556	0.921	0.076	0.037
DreamGaussian [41]	18.544	0.917	0.075	0.056
LHM-0.5B*	25.183	0.951	0.029	0.035

Single-Image Animatable Human Reconstruction We assess LHM against two baseline approaches for reconstructing animatable humans from a single-view image. The first baseline is En3D [36], which generates 3D human models in canonical space using physics-based 2D data alongside normal-constrained sculpting techniques. The second baseline, AniGS [49], utilizes multi-view diffusion models to create canonical human images and employs 4D Gaussian splatting (4DGS) optimization to address inconsistencies in different views.

Table 2. Human animation results on in-the-wild video dataset.

Methods	PSNR ↑	SSIM ↑	LPIPS ↓	FC ↓	Time ↓	Memory ↓
En3D [36]	15.231	0.734	0.172	0.058	5 minutes	32 GB
AniGS [49]	18.681	0.871	0.103	0.053	15 minutes	24 GB
LHM-0.5B	21.648	0.924	0.044	0.042	2.01 seconds	18 GB
LHM-0.7B	21.879	0.930	0.039	0.039	4.13 seconds	21 GB
LHM-1B	22.003	0.930	0.040	0.035	6.57 seconds	24 GB

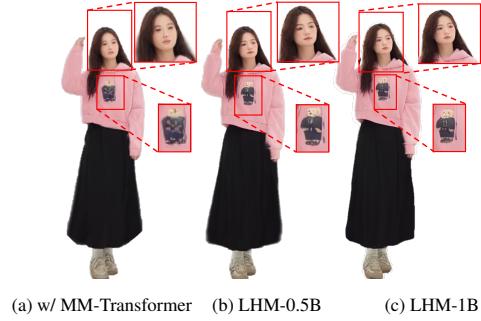


Figure 6. Ablation study on model design and parameters.

For our evaluation, we utilize 200 in-the-wild video sequences drawn from the validation subset of our dataset. Specifically, we take the first front view image of each video as input and compare the synthesized animations against the corresponding ground-truth sequences using foreground segmentation masks. As shown in Table 2, our method surpasses the baseline approaches, demonstrating superior rendering quality in the animation sequences. In comparison to the best baseline method, AniGS, our approach achieves performance gains of 3.322, 0.059, 0.063, and 0.018 in PSNR, SSIM, LIPIS, and FC metrics, respectively. As illustrated in Fig. 5, our method yields more accurate and photorealistic animation results compared to the baseline techniques. Additional results can be found in the supplementary material.

5.3. Ablation Study

Model Parameter Scalability To verify the scalability of our LHM, we train variant models with increasing parameter numbers by scaling the layer numbers. Table 2 compares performance across various model capacities. Our experiments indicate that increasing the number of model parameters correlates with improved performance. Figure 6 presents the comparison between LHM-0.5B and LHM-1B, where the larger model achieves more accurate reconstruction, especially in the face regions.

Dataset Scalability To evaluate data scalability, we conduct controlled experiments using stratified random subsets (10K, 50K, 100K) from the original video training dataset of 300K. Table 3 illustrates that using only the synthetic dataset results in poor model generalization. Incorporating an in-the-wild dataset significantly enhances the model’s generality and performance on in-the-wild tests. Moreover, larger dataset sizes yield improved model results, al-

Table 3. Quantitative results on in-the-wild video dataset.

Methods	PSNR ↑	SSIM ↑	LPIPS ↓	FC ↓
LHM-0.5B + Synthetic Data	19.753	0.904	0.060	0.057
LHM-0.5B + 10K Videos	20.692	0.911	0.052	0.048
LHM-0.5B + 50K Videos	21.108	0.915	0.050	0.043
LHM-0.5B + 100K Videos	21.429	0.920	0.049	0.045
LHM-0.5B + All	21.648	0.924	0.044	0.042

Table 4. Ablation study for the transformer architecture.

Methods	PSNR ↑	SSIM ↑	LPIPS ↓	FC ↓
LHM-0.5B w/ MM-Transformer	20.072	0.907	0.100	0.053
LHM-0.5B w/o Shrinkage Regularization	21.037	0.915	0.049	0.041
LHM-0.5B	21.648	0.924	0.044	0.042

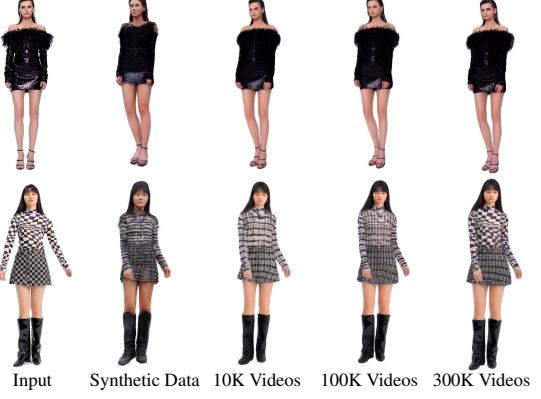


Table 5. Ablation study on dataset scalability.

though the rate of performance improvement diminishes as the dataset size increases. Figure 5 showcases the ablation study on dataset scalability.

Transformer Block Design Table 4 presents the quantitative results of our transformer block design. Compared to the vanilla MM-transformer block, our proposed transformer block demonstrates performance improvements of 1.576, 0.017, 0.056, and 0.011 in PSNR, SSIM, LIPIS, and FC metrics, respectively. Additionally, shrinkage regularization enhances the overall performance of our model, albeit with a slight reduction in face consistency. Figure 6 illustrates the qualitative results comparing the vanilla MM-transformer with our proposed BH-Transformer block.

6. Conclusion

In this work, we introduce LHM, a feed-forward model for animatable 3D human reconstruction from a single image in seconds. Our approach leverages a multimodal transformer and a head feature pyramid encoding scheme to effectively fuse 3D positional features and 2D image features via an attention mechanism, enabling joint reasoning across geometric and visual domains. Trained on a large-scale video dataset with an image reconstruction loss, our model exhibits strong generalization ability to diverse real-world scenarios. Extensive experiments on both synthetic and in-the-wild datasets demonstrate that LHM achieves state-of-the-

art reconstruction accuracy, generalization, and animation consistency.

Limitations and Future Work One limitation of our approach is that real-world video datasets often contain biased view distributions, with limited coverage of uncommon poses and extreme angles. This imbalance can affect the model’s ability to generalize to novel viewpoints. In future work, we aim to develop improved training strategies and curate a more diverse and comprehensive dataset to enhance robustness.

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A. Demo Video

Please kindly check the [Demo Video](#) for animation results of the reconstructed 3D avatar.

B. Details of the Multimodal Transformer

Our Multimodal Body-Head Transformer (MBHT) is built on top of the recent Multimodal Transformers (MM-Transformer) [11].

The detailed architecture of MM-Transformer is summarized in Fig. 7. The 3D geometric body and head query tokens are fed as q and semantic image feature tokens are fed as h . MM-Transformer aggregates both features by attention mechanism with Adaptive Layer Normalization modulation guided by the extracted global context features.

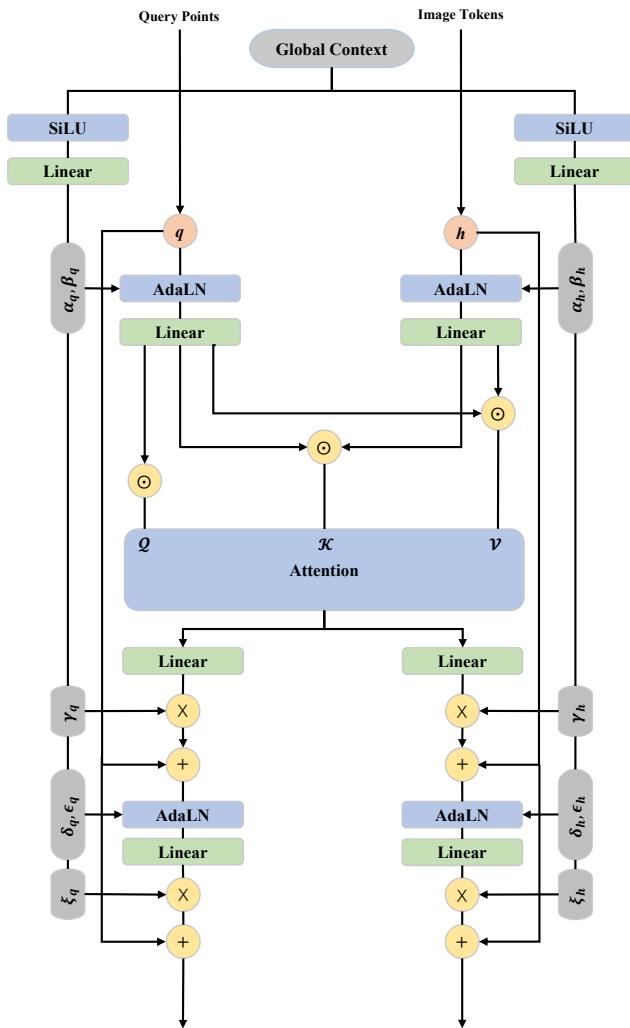


Figure 7. Detailed architecture of Multi-Modal Transformer [11].

C. Details of Head Feature Pyramid Encoding

Given that the human head occupies a relatively small area within the input image and is subject to spatial down-sampling during the encoding process, essential facial details are frequently lost. To address this challenge, we introduce a head feature pyramid encoding (HFPE) designed to aggregate multi-scale features of DINOv2 [40]. Figure 8 illustrates the architecture of HFPE.

D. Details of the Synthetic Training Dataset

To address viewpoint bias in natural videos, we supplement training with synthetic human scans from three sources: (1) 2K2K dataset [12] sampling 1,000 textured models, (2) Human4DiT [52] sampling 4,324 textured characters, and (3) 400 commercial assets from RenderPeople, culminating in 5,724 high-fidelity 3D human scans. Following AniGS [49]’s multi-view rendering protocol, we generate 30 azimuthal views per model with uniform angular spacing (12° intervals) under HDRI lighting conditions.

E. Effects of Canonical Space Regularization

We conduct an ablation study to assess the impact of the canonical space regularization design. Figure 9 shows that the *as spherical as possible* loss \mathcal{L}_{ASAP} is effective in reducing semi-transparent boundary artifacts caused by Gaussians with distorted shapes.

Without the *as close as possible* loss \mathcal{L}_{ACAP} , the reconstruction results exhibit noticeable floating points around the human. These results clearly demonstrate the effectiveness of the proposed canonical space regularization losses.

F. More Results

Figure 10–Figure 11 showcase the reconstruction and animation results for input images featuring diverse appearances, clothing, and poses. Our method enables high-fidelity, animatable human avatar reconstruction in a single forward pass with photorealistic rendering, demonstrating its strong generalization and effectiveness.

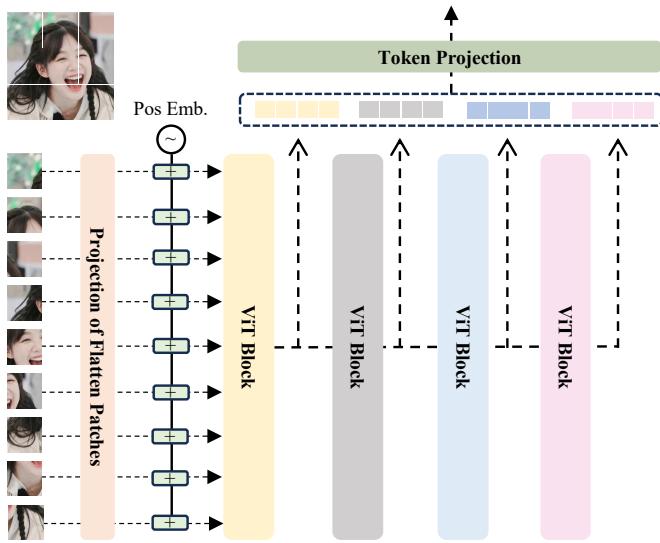


Figure 8. Architecture of our HFPE for multi-scale facial feature extraction



Figure 9. Ablation for canonical space shape regularization.



Figure 10. Visual results of 3D human reconstruction results from a single image (Part I). Best viewed with zoom-in.



Figure 11. Visual results of 3D human animation from a single image (Part II). Best viewed with zoom-in.