

Animatable Gaussians: Learning Pose-dependent Gaussian Maps for High-fidelity Human Avatar Modeling

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<https://animatable-gaussians.github.io/>



Figure 1. Lifelike animatable avatars with *highly dynamic, realistic and generalized* details created by our method.

Abstract

Modeling animatable human avatars from RGB videos is a long-standing and challenging problem. Recent works usually adopt MLP-based neural radiance fields (NeRF) to represent 3D humans, but it remains difficult for pure MLPs to regress pose-dependent garment details. To this end, we introduce Animatable Gaussians, a new avatar representation that leverages powerful 2D CNNs and 3D Gaussian splatting to create high-fidelity avatars. To associate 3D Gaussians with the animatable avatar, we learn a parametric template from the input videos, and then parameterize the template on two front & back canonical Gaussian maps where each pixel represents a 3D Gaussian. The learned template is adaptive to the wearing garments for modeling looser clothes like dresses. Such template-guided 2D parameterization enables us to employ a powerful StyleGAN-based CNN to learn the pose-dependent Gaussian maps for modeling detailed dynamic appearances. Furthermore, we introduce a pose projection strategy for better generalization given novel poses. Overall, our method can create lifelike avatars with dynamic, realistic and generalized appearances. Experiments show that our method outperforms other state-of-the-art approaches. Code: <https://github.com/lizhe00/AnimatableGaussians>.

1. Introduction

Animatable human avatar modeling, due to its potential value in holoportation, Metaverse, game and movie industries, has been a popular topic in computer vision for decades. However, how to effectively represent the human avatar is still a challenging problem.

Explicit representations, including both meshes and point clouds, are the prevailing choices, not just in human avatars but also throughout the entire 3D vision and graphics. However, previous explicit avatar representations [5, 47, 81] necessitate dense reconstructed meshes to model human geometry, thus limiting their applications in sparse-view video-based avatar modeling. In the past few years, with the rise of implicit representations, particularly neural radiance fields (NeRF) [52], many researchers tend to represent the 3D human as a pose-conditioned NeRF [38, 42, 55, 93] to automatically learn a neural avatar from RGB videos. However, implicit representations require a coordinate-based MLP to regress a continuous field, suffering from the low-frequency spectral bias [70] of MLPs. Although many works aim to enhance the avatar representation by texture feature [42] or structured local Nerf [93], they fail to produce satisfactory results because they still rely on an MLP to output the continuous implicit fields.

Recently, 3D Gaussian splatting [32], an explicit and ef-

ficient point-based representation, has been proposed for both high-fidelity rendering quality and real-time rendering speed. In contrary to implicit representations, explicit point-based representations have the potential to be parameterized on 2D maps [47], thus enabling us to employ more powerful 2D networks for modeling higher-fidelity avatars. Based on this observation, we present *Animatable Gaussians*, a new avatar representation that leverages 3D Gaussian splatting and powerful 2D CNNs for realistic avatar modeling. The first challenge lies in modeling general garments including long dresses. Inspired by point-based geometric avatars [41, 48], we first reconstruct a parametric template from the input videos and inherit the parameters of SMPL [43] by diffusing the skinning weights [41]. The character-specific template models the basic shapes of the wearing garments, even for long dresses. This allows us to animate 3D Gaussians in accordance with the template motion while avoiding density control in standard Gaussians [32], thereby ensuring the maintenance of a temporally consistent structure for 3D Gaussians in the following 2D parameterization.

For compatibility with 2D networks, it is necessary to parameterize the 3D template onto 2D maps. However, it remains challenging to unwrap the template with arbitrary topologies onto a unified and continuous UV space. Regarding that the front & back views almost cover the entire canonical human, we achieve the parameterization by orthogonally projecting the canonical template to both views. In each view, we define every pixel within the template mask as a 3D Gaussian, represented by its position, covariance, opacity, and color attributes, resulting in two front & back Gaussian maps. Similarly, given the driving pose, we obtain two posed position maps that serve as the pose conditions. Such a template-guided parameterization enables predicting pose-dependent Gaussian maps from the pose conditions through a powerful StyleGAN-based [29–31] conditional generator, StyleUNet [73].

Benefiting from the powerful 2D CNNs and explicit 3D Gaussian splatting, our method can faithfully reconstruct human details under training poses. On the other hand, given novel poses, the generalization of animatable avatars has not been extensively explored. Due to the data-driven nature of learning-based avatar modeling, direct extrapolation to poses out of distribution will certainly yield unsatisfactory results. Therefore, we propose to employ Principal Component Analysis (PCA) to project the driving pose signal, represented by the position maps, into the PCA space, facilitating reasonable interpolation within the distribution of training poses. Such a pose projection strategy realizes reasonable and high-quality synthesis for novel poses.

In summary, our technical contributions are:

- Animatable Gaussians, a new avatar representation that introduces explicit 3D Gaussian splatting into avatar modeling to employ powerful 2D CNNs for creating life-

like avatars with high-fidelity pose-dependent dynamics.

- Template-guided parameterization that learns a character-specific template for general clothes like dresses, and parameterizes 3D Gaussians onto front & back Gaussian maps for compatibility with 2D networks.
- A simple yet effective pose projection strategy that employs PCA on the driving signal, promoting better generalization to novel poses.

Overall, benefiting from these contributions, our method can create lifelike animatable avatars with *highly dynamic, realistic* and *generalized* appearances as shown in Fig. 1.

2. Related Work

2.1. Mesh-based Human Avatars

The polygon mesh is the most popular 3D representation for its compatibility with traditional rendering pipelines. To model animatable human avatars using meshes, early approaches propose to reconstruct a character-specific textured mesh and animate it by physical simulation [17, 65] or retrieval from a database [82]. Recently, researchers tend to utilize neural networks to model dynamic textures and motions. Bagautdinov *et al.* [5], Xiang *et al.* [80, 81] and Halimi *et al.* [22] reconstruct topology-consistent meshes from dense multi-view videos and learn the dynamic texture in a UV space. DDC [20] and HDHumans [21] learn the deformation parameterized by both skeletons and embedded graph [69] of a pre-scanned template. DELIFFAS [36] employs DCC as a deformable template and parameterizes the light field around the body onto double surfaces for fast synthesis. These mesh-based methods require dense reconstruction, non-rigid tracking, or pre-scanned templates for representing dynamic humans. Besides, some works optimize the non-rigid deformation upon SMPL [43] from a monocular RGB [3, 4, 91] or RGB-D [7, 33] video, but the avatar quality is limited by the SMPL+D representation.

2.2. Implicit Function-based Human Avatars

Implicit function is a coordinate-based function, usually represented by an MLP, that outputs a continuous field, e.g., signed distance function (SDF) [26, 84], occupancy [50], and radiance (NeRF) [55] fields. In geometric avatar modeling, many works represent the human avatar as pose-conditioned SDF [13, 24, 63, 72, 75] or occupancy [8, 9, 11, 39, 50, 51] fields learned from human scans or depth sequences. In contrast, NeRF containing a density and color field is widely used in textured avatar modeling [14, 19, 27, 28, 54, 56, 66, 71, 78] because of its good differentiable property. Animatable NeRF [55] introduces SMPL deformation into NeRF for animatable human modeling. Neural Actor [42] and UV volumes [10] parameterize 3D humans on SMPL or DensePose [18] UV space, thus limiting modeling loose clothes far from the human body.

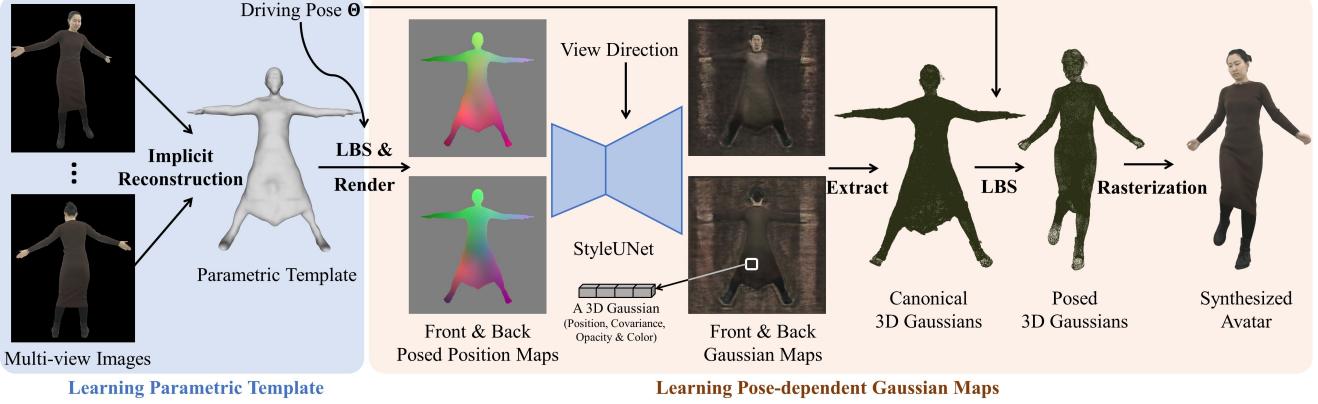


Figure 2. **Illustration of the pipeline.** It contains two main steps: 1) Reconstruct a character-specific template from multi-view images. 2) Predict pose-dependent Gaussian maps through the StyleUNet, and render the synthesized avatar by LBS and differentiable rasterization.

SLRF [93] defines local NeRF around sampled nodes upon SMPL and learns the pose-dependent dynamics in the local space. TAVA [38] models the human or animal deformation using only 3D skeletons without the requirement of a parametric model. ARAH [76] represents the avatar geometry as SDF and adopts SDF-based volume rendering [74, 87] for learning more plausible geometry from RGB videos. DANBO [67] employs GNNs to learn the part-based pose feature. Li *et al.* [40] introduce a learnable pose vocabulary to learn higher-frequency pose conditions for the conditional NeRF. Besides the body avatar, TotalSelfScan [12], X-Avatar [64] and AvatarReX [94] propose compositional full-body avatars for expressive control of the human body, hands and face. However, the implicit function-based methods usually adopt pure MLPs to represent the human avatar, yielding smooth or blurry quality due to the low-frequency bias of MLPs [70]. What’s worse, the rendering speed of these methods is usually slow because rendering from implicit fields requires dense sampling along a ray.

2.3. Point-based Human Avatars

Point cloud is also a powerful and popular representation in human avatar modeling. Given 3D scans of a character, SCALE [46] and POP [47] learn the non-rigid deformation of dense points on SMPL UV maps to represent the dynamic garment wrinkles. FITE [41] and CloSET [89] extract pose features from projective maps or PointNet [59, 60] to avoid discontinuity on the UV map. SKiRT [48] and FITE learn a coarse template from the input scans and utilize learned or diffused skinning weights to animate loose clothes. Prokudin *et al.* [58] propose dynamic point fields for general dynamic reconstruction. This work and NPC [68] show results on avatars created from RGB videos using Point-NeRF [83]. However, applying Point-NeRF to avatar modeling still relies on a low-frequency coordinate-based MLP, struggling with the same problems

in Sec. 2.2. On the other hand, point-based rendering via splatting [2, 35, 37, 57, 62, 88, 95–97] offers another probability for animatable avatar modeling. PointAvatar [92] learns a canonical point cloud and deformation field to model head avatars from a monocular video via PyTorch3D’s [61] differentiable point renderer. Recently, 3D Gaussian splatting [32], an efficient differentiable point-based rendering method, has been proposed for real-time photo-realistic scene rendering. We observe such an explicit point-based representation can be combined with 2D CNNs for high-quality avatar modeling. Although concurrent works [45, 79, 85, 86] have extended 3D Gaussian splatting for dynamic scene modeling, they cannot model long-term articulated human motions because of the absence of parametric templates, let alone animation. To the best of our knowledge, we are the first to introduce 3D Gaussian splatting into animatable human avatar modeling.

3. Method

3.1. Preliminary: 3D Gaussian Splatting

3D Gaussian splatting [32] is an explicit point-based 3D representation that consists of a set of 3D Gaussians. Each 3D Gaussian is parameterized by its position (mean) μ , covariance matrix Σ , opacity α and color c , and its probability density function is formulated as

$$f(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) = \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right), \quad (1)$$

where we omit the constant factor in Eq. 1. For rendering a 2D image, the 3D Gaussians are splatted onto 2D planes, resulting in 2D Gaussians. The pixel color C is computed by blending N ordered 2D Gaussians overlapping this pixel:

$$\mathbf{C} = \sum_{i=1}^N \alpha_i \prod_{j=1}^{i-1} (1 - \alpha_j) \mathbf{c}_i, \quad (2)$$

where c_i is the color of each 2D Gaussian, and α_i is the blending weight derived from the learned opacity and 2D Gaussian distribution [95].

3.2. Overview

Given multi-view RGB videos of a character and the corresponding SMPL-X [53] registrations about the per-frame pose and shared shape, our objective is to create a lifelike animatable avatar. As illustrated in Fig. 2, our method contains two main steps:

- 1. Learning Parametric Template.** We begin by selecting a frame with a near A-pose from the input videos, and then optimize a canonical SDF and color field to fit the multi-view images through SMPL skinning and SDF-based volume rendering [87]. The template mesh is subsequently extracted from the canonical SDF field using Marching Cubes [44]. We then diffuse the skinning weights from the SMPL vertices to the template surface, obtaining a deformable parametric template.
- 2. Learning Pose-dependent Gaussian Maps.** Given a training pose, we first deform the template to the posed space via linear blend skinning (LBS) and render the posed vertex coordinates to canonical front & back views to obtain two position maps. The position maps serve as the pose condition and are translated into front & back Gaussian maps through a StyleUNet [73]. We then extract valid 3D Gaussians inside the template mask, and deform the canonical 3D Gaussians to the posed space by LBS. Eventually, we render the posed 3D Gaussians to a given camera view through differentiable splatting-based rasterization [32].

3.3. Avatar Representation

Learning Parametric Template. Given the multi-view videos, we first select one frame in which the character is under a near A-pose. Our goal is to reconstruct a canonical geometric model as the template from the multi-view images. Specifically, we represent the canonical character as an SDF and color field instantiated by an MLP. To associate the canonical and posed spaces, we precompute a skinning weight volume \mathcal{W} in the canonical space by diffusing the weights from the SMPL surface throughout the whole 3D volume along the surface normal [41]. For each point in the posed space, we search its canonical correspondence by root finding [8]:

$$\min_{\mathbf{x}_c} \|\text{LBS}(\mathbf{x}_c; \Theta, \mathcal{W}) - \mathbf{x}_p\|_2^2, \quad (3)$$

where $\text{LBS}(\cdot)$ is a linear blend skinning function that transforms a canonical point \mathbf{x}_c to its posed position \mathbf{x}_p in accordance with the SMPL pose Θ . Then the canonical correspondence is fed into the MLP to query its SDF and color, which are used to render RGB images by SDF-based volume rendering [87]. The rendered images are compared

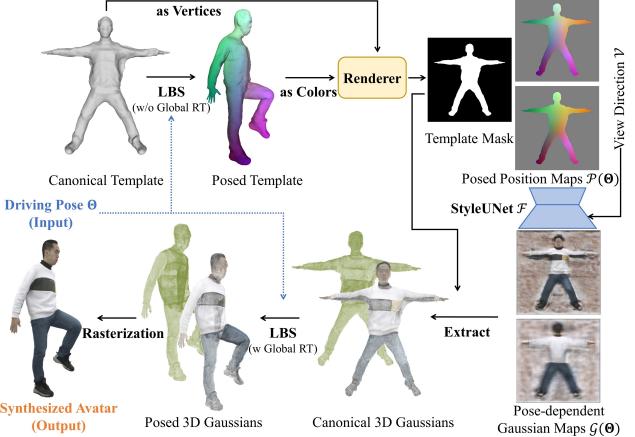


Figure 3. **Illustration of the avatar representation.** The driving pose is first used to generate posed position maps, which serve as the pose conditions. Then the StyleUNet takes the position maps as input and predicts pose-dependent Gaussian maps. We extract canonical 3D Gaussians from the Gaussian maps and deform them to the posed space by LBS. Finally, a high-fidelity synthesized avatar image is rendered through splatting-based rasterization.

with the ground truth for optimizing the canonical fields via differentiable volume rendering. Finally, we extract the geometric template from the SDF field and query the skinning weights for each vertex in the precomputed weight volume \mathcal{W} , obtaining a deformable parametric template.

Template-guided Parameterization. Previous human avatar representations in NeRF-based approaches [42, 55, 93] necessitate the coordinate-based MLPs for the formulation of the implicit NeRF function. However, MLPs have demonstrated a low-frequency bias [70], hindering their ability to model high-frequency human dynamics. In light of this observation, we replace MLPs with more powerful 2D CNNs for creating higher-quality human avatars. To ensure compatibility with 2D networks, the 3D representation of the human avatar needs to be parameterized in 2D space. Therefore, we propose to parameterize the 3D Gaussians anchored on the canonical template onto front & back views via orthogonal projection. As illustrated in Fig. 3, given a driving pose Θ , we first deform the template to the posed space via LBS. Note that we do not consider the global transformation in this skinning process, because the global orientation and translation would not change the human dynamic details. Then we take the posed coordinate as the vertex color on the canonical template, and render it to both front & back views by orthogonal projection, obtaining posed position maps $P_f(\Theta)$ and $P_b(\Theta)$ that serve as pose conditions for the network.

Pose-dependent Gaussian Maps. We employ a powerful StyleGAN-based CNN, StyleUNet [73] F , to predict

pose-dependent Gaussian maps from the pose conditions:

$$\mathcal{G}_f(\Theta), \mathcal{G}_b(\Theta) \leftarrow \mathcal{F}(\mathcal{P}_f(\Theta), \mathcal{P}_b(\Theta), \mathcal{V}), \quad (4)$$

where $\mathcal{G}_f(\Theta)$ and $\mathcal{G}_b(\Theta)$ are front and back pose-dependent Gaussian maps, respectively, and each pixel represents a 3D Gaussian [32] including a position, covariance, opacity and color. We also modulate the output color attributes on Gaussian maps with a view direction map \mathcal{V} to model view-dependent variance like NeRF-based approaches [55]. We extract canonical 3D Gaussians inside the template mask from the pose-dependent Gaussian maps. As illustrated in Fig. 3, the canonical 3D Gaussians involve pose-dependent non-rigid deformations and appearances, e.g., garment wrinkles.

LBS of 3D Gaussians. To render the synthesized avatar under the driving pose, we need to deform the canonical 3D Gaussians to the posed space. Specifically, given a canonical 3D Gaussian, we transform its position \mathbf{p}_c and covariance Σ_c attributes:

$$\begin{aligned} \mathbf{p}_p &= \mathbf{R}\mathbf{p}_c + \mathbf{t}, \\ \Sigma_p &= \mathbf{R}\Sigma_c\mathbf{R}^\top, \end{aligned} \quad (5)$$

where \mathbf{R} and \mathbf{t} are the rotation matrix and translation vector calculated with the skinning weights of each 3D Gaussian. It is worth mentioning that despite utilizing only front and back views for parameterizing the 3D Gaussians, the resulting point clouds still cover the side regions of the human body as demonstrated in the posed 3D Gaussians in Fig. 3. This is achievable because the positions of the pose-dependent 3D Gaussians are learnable and will be optimized to encompass the side regions. Finally, we render the posed 3D Gaussians to a desired camera view through splatting-based rasterization (Eq. 2).

Training. To ensure that the position attribute of predicted Gaussian maps approximates the canonical human body, we opt to predict an offset map $\Delta\mathcal{O}(\Theta)$ on the parametric template instead of a position map. Our training losses include L1 and perceptual losses [90] between the rendered images and ground truth, and a regularization loss:

$$\mathcal{L} = \mathcal{L}_1 + \lambda_{\text{perceptual}}\mathcal{L}_{\text{perceptual}} + \lambda_{\text{reg}}\mathcal{L}_{\text{reg}}, \quad (6)$$

where λ s are loss weights, and the regularization loss $\mathcal{L}_{\text{reg}} = \|\Delta\mathcal{O}(\Theta)\|_2^2$ restrains the predicted offsets from being extremely large.

3.4. Pose Projection Strategy

Benefiting from the effective avatar representation, our method can reconstruct detailed human appearances under the training poses. However, given the inherently data-driven nature of learning-based avatars, addressing generalization to novel poses is also necessary and important.

Hence, we propose to utilize Principal Component Analysis (PCA) to project a novel driving pose signal into the distribution of seen training poses for better generalization. Specifically, given a pose condition represented by posed position maps, we extract valid points and concatenate them as a vector $\mathbf{x}_t \in \mathbb{R}^{3M}$ (M is the point number). The feature of each training frame composes a matrix $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_T]$, where T is the number of training frames. We perform PCA on \mathbf{X} , producing N principal components $\mathbf{S} = [\mathbf{s}_1, \dots, \mathbf{s}_N] \in \mathbb{R}^{3M \times N}$ and standard deviation of each component σ_i . Given position maps derived by a novel driving pose, we project the corresponding feature \mathbf{x} into the PCA space by

$$\beta = \mathbf{S}^\top \cdot (\mathbf{x} - \bar{\mathbf{x}}), \quad (7)$$

where $\bar{\mathbf{x}}$ is the mean of \mathbf{X} . Then we reconstruct the positions from the low-dimensional coefficient β by

$$\mathbf{x}_{\text{recon}} = \mathbf{S} \cdot \beta + \bar{\mathbf{x}}, \quad (8)$$

then we reshape $\mathbf{x}_{\text{recon}}$ into a $M \times 3$ tensor, and scatter it onto the position maps. To constrain the reconstructed position maps to lie in the distribution of training poses, we clip each component of β within the bound of $[-2\sigma_i, 2\sigma_i]$. Overall, the pose projection strategy ensures reasonable interpolation within the distribution of training poses, enabling better generalization to novel poses as shown in Fig. 9.

4. Experiments

Results. As shown in Fig. 1 and Fig. 4, our method can create realistic avatars with high-fidelity dynamic details from multi-view videos. More sequential results animated by challenging out-of-distribution poses [49] like sports and dancing can be found in the Supp. document and video.

Dataset. We mainly utilize two public datasets for the experiments, including 3 sequences with 24 views from THuman4.0 dataset [93] and 5 sequences with 160 views from ActorsHQ dataset [25] (but we only use 47 full-body views for avatar modeling). For the comparison with AvatarReX [94], we also request their dataset including 2 sequences with 16 views. THuman4.0 and AvatarReX datasets also provide the SMPL-X [53] registrations. We fit SMPL-X for ActorsHQ dataset using an open-source tool [1]. We split each sequence as training and testing chunks, and the training chunk contains $2000 \sim 3000$ frames.

Metric. We adopt Peak Signal-to-Noise Ratio (PSNR), Structure Similarity Index Measure (SSIM) [77], Learned Perceptual Image Patch Similarity (LPIPS) [90] and Frechet Inception Distance (FID) [23] for quantitative experiments.

4.1. Comparison

We compare our method with recent state-of-the-art works on avatar quality and generalization. These works include



Figure 4. Example animatable avatars with high-fidelity dynamic appearances created by our method.

both body-only (TAVA [38], ARAH [76], SLRF [93], PoseVocab [40]) and full-body (AvatarReX [94]) avatars.

Body-only Avatars. We compare our method with TAVA, ARAH, SLRF, and PoseVocab on “subject00” and “subject02” sequences of THuman4.0 dataset [93]. We run the released codes of TAVA, ARAH and PoseVocab on the dataset, and request the results of SLRF from the authors. We present qualitative comparisons on novel pose synthesis in Fig. 5. In contrast to other methods, our approach excels in animating highly realistic avatars with significant improvement on high-fidelity dynamic details, including garment wrinkles, logos and other textural patterns. The quantitative comparison is also performed on the testing chunk of the “subject00” sequence as shown in Tab. 1, and these numerical results prove that our method achieves more accurate animation. Although PoseVocab and SLRF introduce a learnable pose dictionary or local NeRFs to improve the representation ability of the NeRF MLP, they still suffer from the low-frequency bias [70] of MLPs and fail to create highly realistic avatars. Contrarily, our method leverages powerful 2D CNNs and explicit 3D Gaussian splatting, thus achieving modeling finer-grained dynamic appearances.

Full-body Avatars. Full-body avatars including TotalSelf-Scan [12], X-Avatar [64] and AvatarReX [94] can realize expressive control of the body, hands and face. TotalSelf-Scan reconstructs full-body avatars from monocular self-rotation videos, and only displays animations that appear

Table 1. Quantitative comparison with state-of-the-art body-only avatars.

Method	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	FID \downarrow
Ours	28.0714	0.9739	0.0515	29.4831
PoseVocab [40]	26.3784	0.9707	0.0592	49.4541
SLRF [93]	26.9015	0.9724	0.0600	52.0613
ARAH [76]	22.3004	0.9616	0.1075	90.6077
TAVA [38]	26.8019	0.9705	0.0915	96.3474

Table 2. Quantitative comparison with AvatarReX.

Method	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	FID \downarrow
Ours	30.6143	0.9803	0.0290	13.2417
AvatarReX [94]	23.2475	0.9567	0.0646	31.1387

very rigid. X-Avatar requires 3D human scans under different poses as input for creating avatars. AvatarReX is the most relevant work with our method, i.e., creating avatars from multi-view videos. Since AvatarReX does not release the data and code, we request the dataset and results from the authors for comparison. Fig. 6 shows the comparison with AvatarReX on both training and novel poses. Fig. 6 (a) demonstrates that our method can reconstruct more faithful and vivid details compared with AvatarReX. Although AvatarReX introduces local feature patches to encode more details, it remains constrained by the representation ability of the conditional NeRF MLPs. Fig. 6 (b) shows that given

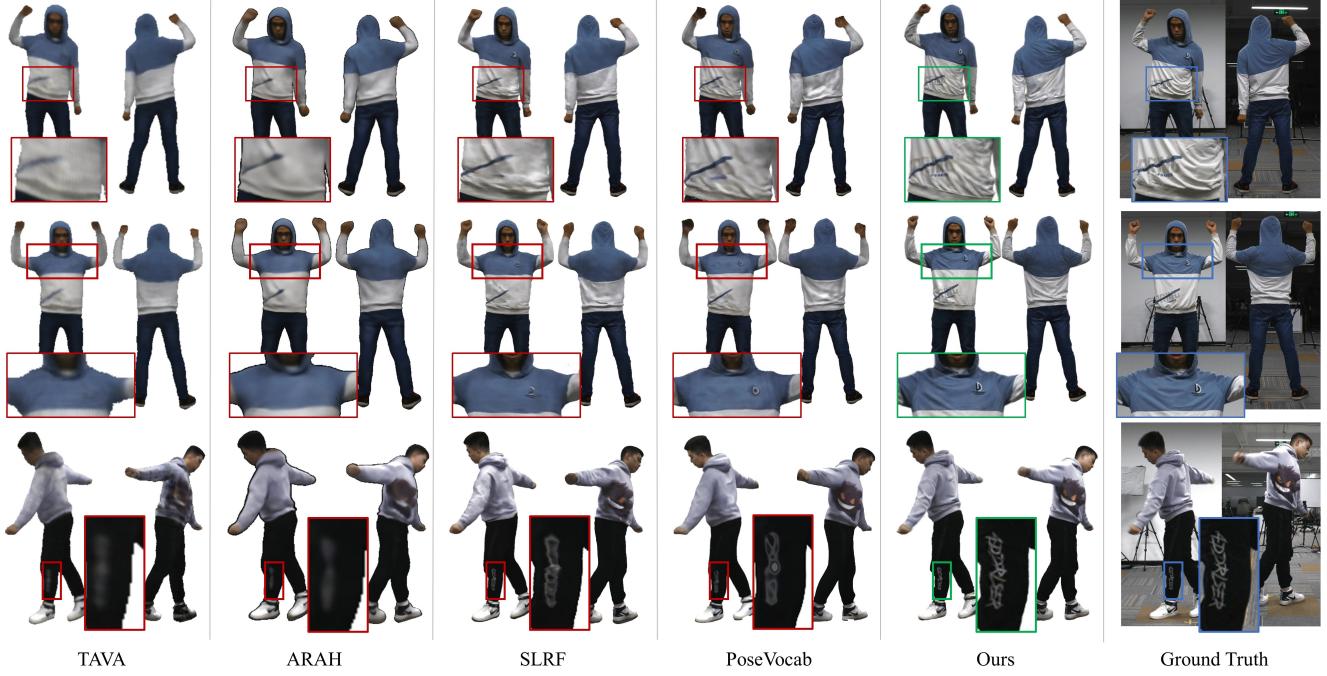


Figure 5. Qualitative comparison with state-of-the-art body-only avatars on novel pose synthesis.

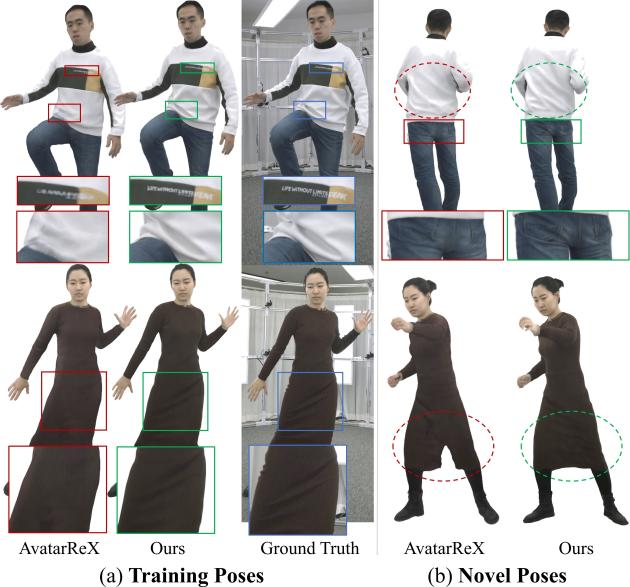


Figure 6. Qualitative comparison with AvatarReX on both training pose reconstruction (a) and novel view synthesis (b).

a novel pose, our method not only generates more realistic details but also produces more reasonable non-rigid deformation, particularly for long dresses, in comparison with AvatarReX. This is attributed to the ability of our method to learn pose-dependent deformations on a character-specific template that has already modeled the basic shape of the

wearing garments. In contrast, AvatarReX learns sparse node translations on the naked SMPL model, resulting in artifacts for long dresses. Tab. 2 reports the quantitative comparison on training pose reconstruction as ground-truth images are only available for training poses. Our method also outperforms AvatarReX on the reconstruction accuracy.

Animation Speed. We additionally compare our method with other works on the animation speed in Tab. 3. Benefiting from the efficient 3D Gaussian splatting [32], our method can realize fast inference for animation.

Conclusion. Overall, benefiting from the powerful 2D CNNs and explicit 3D Gaussian splatting, our method, Animatable Gaussians, achieves lifelike avatar modeling with more *dynamic*, *realistic* and *generalized* appearances in comparison to state-of-the-art approaches.

4.2. Ablation Study

We qualitatively evaluate the core contributions of our method in this subsection. Quantitative results and additional experiments can be found in the Supp. document.

Parametric Template. We evaluate the learned parametric template by replacing it with a naked parametric model, SMPL-X [53]. Fig. 7 shows that SMPL-X fails to represent the long dress whose topology is not consistent with the SMPL-X model, yielding poor generalization to novel poses. Conversely, our character-specific template is adaptively reconstructed from the input video to model the basic shape of the wearing garments.

2D CNNs vs. MLPs. To demonstrate the superior repre-

Table 3. **Comparison on animation speed.** These framerates are evaluated on a PC with one RTX 3090 when rendering images at a resolution of 1024×1024 . We highlight the highest and second-highest framerates.

Method	TAVA [38]	ARAH [76]	SLRF [93]	PoseVocab [40]	AvatarReX [94] (PyTorch)	AvatarReX (TensorRT)	Ours (PyTorch)
Framerate (FPS) \uparrow	0.003	0.07	0.16	0.20	0.03	25	10

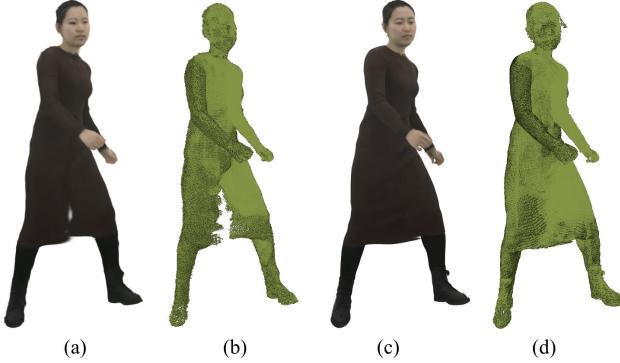


Figure 7. **Ablation study of the parametric template.** (a,b) Rendered results and 3D Gaussians using SMPL-X. (c,d) Rendered results and 3D Gaussians using the character-specific template.

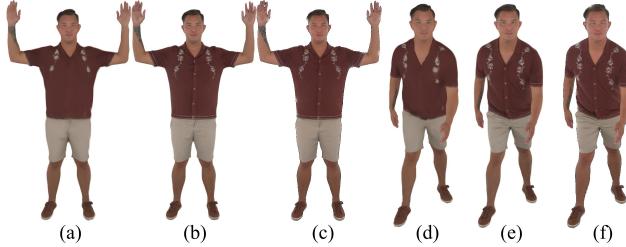


Figure 8. **Comparison between representations with 2D CNNs and MLPs on training pose reconstruction.** (a,d) Results of the MLP baseline. (b,e) Our results. (c,f) Ground truth.

sentation ability of 2D CNNs (StyleUNet in our settings), we replace the 2D networks with a coordinate-based MLP. The MLP takes a canonical point and pose vector as input, and returns the 3D Gaussian attributes of this point. Fig. 8 shows the animation results of our method with 2D CNNs and the baseline with MLPs. It demonstrates that 2D CNNs are able to regress more detailed and realistic appearances, while MLPs suffer from limited representation ability, yielding blurry animation results.

Pose Projection. We evaluate the pose projection strategy by removing it, i.e., directly inputting the position map into the StyleUNet. Fig. 9 shows the animation results with and without the pose projection under novel poses, respectively. It demonstrates that direct extrapolation with the novel position map results in unreasonable 3D Gaussians, since no similar poses in the training dataset. In contrast, the pose projection guarantees that the reconstructed position maps

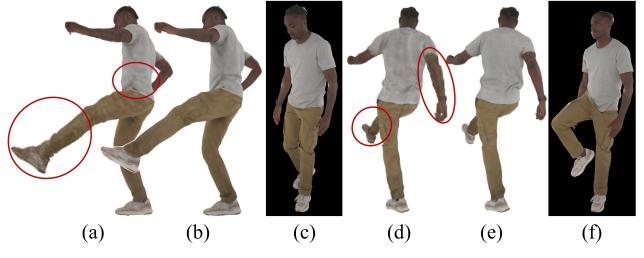


Figure 9. **Ablation study of the pose projection strategy.** (a,d) and (b,e) are the animation results without and with the pose projection strategy, respectively. (c,f) are the reference images with the closest pose in the training dataset.

(Eq. 8) lie within the distribution of training poses, leading to reasonable and vivid synthesized appearances.

5. Discussion

Conclusion. We present Animatable Gaussians, a new avatar representation for creating lifelike human avatars with highly dynamic, realistic and generalized appearances from multi-view RGB videos. Compared with implicit NeRF-based approaches, we introduce the explicit point-based representation, 3D Gaussian splatting, into the avatar modeling, and leverage powerful 2D CNNs for modeling higher-fidelity human appearances. Based on the proposed template-guided parameterization and pose projection strategy, our method can not only faithfully reconstruct detailed human appearances, but also generate realistic garment dynamics for novel pose synthesis. Overall, our method outperforms other state-of-the-art avatar approaches, and we believe that the proposed 3D Gaussian splatting-based avatar representation will make progress towards effective and efficient 3D human representations.

Limitation. Our method entangles the modeling of the human body and clothes, limiting to changing the clothes of the avatar for applications like virtual try-on. A possible solution is to separately represent the body and clothes with multi-layer 3D Gaussians as NeRF-based approaches [14, 15]. Moreover, our method relies on the multi-view input to reconstruct a parametric template, limiting the application for modeling loose clothes from a monocular video.

Potential Social Impact. Our method can synthesize virtual motions of the human avatar to generate fake videos, so we must carefully employ this technology.

References

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Supplemental Document

In this supplemental document, we will show implementation & experiment details, more results and additional experiments.

A. Implementation Details

Template Reconstruction. We optimize an SDF and color field represented by an MLP consisting of intermediate layers with (512, 256, 256, 256, 256, 256) neurons. Given a posed point, we find accurate correspondence in the canonical space by root finding. Following ARAH [76], we initialize the correspondence as the canonical position that is computed by inverse skinning based on blending weights of the closest SMPL vertex. Different from SNARF [8] and ARAH [76] that utilize the Broyden’s method [6] to solve Eq. 3, we employ the Gauss-Newton method by implementing a customized CUDA kernel. The training loss of template reconstruction involves an RGB loss, a mask loss and an Eikonal loss [16].

Network Architecture. The network module in our avatar representation is a StyleUNet [73], a conditional StyleGAN-based [29] generator. Differently, we adapt the original StylelUNet by incorporating two decoders to predict both front & back Gaussian maps. The resolution of the input position map is 512×512 , and the resolution of the output Gaussian maps is 1024×1024 .

Training. We adopt the Adam optimizer [34] for training the StyleUNet with a learning rate of 5×10^{-4} . The loss weights are set as: $\lambda_{\text{perceptual}} = 0.01$, $\lambda_{\text{reg}} = 0.005$. The batch size is 1, the total iteration number is 500k, and the training procedure takes about two days on one RTX 4090.

B. Experiment Details

Metric Evaluation. We utilize PSNR, SSIM [77], LPIPS [90] and FID [23] as the metrics for quantitative evaluations. PSNR and SSIM are computed on the entire image at the original resolution, while LPIPS and FID are computed on the largest square that covers the human body.

Comparison with Body-only Avatars. The quantitative comparison (Tab. 1 in the main paper) is conducted on the “subject00” sequence of THuman4.0 dataset [93]. The first 2000 frames are utilized as the training dataset, and the numerical results of Tab. 1 are evaluated on the rest 500 frames and the 18th camera view.

Comparison with Full-body Avatars. The quantitative comparison (Tab. 2 in the main paper) is conducted on the “white long sleeves” sequence of AvatarReX dataset [94]. Since the provided results of AvatarReX are trained on the whole sequence, we have to conduct a quantitative comparison on the reconstruction accuracy. The numerical results of Tab. 2 are evaluated on the first 500 frames and the 1st

Table A. Quantitative ablation study on the parametric template.

	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	FID \downarrow
Parametric Template	31.2183	0.9858	0.0344	36.9905
SMPL-X	30.5241	0.9842	0.0401	47.5066

Table B. Quantitative comparison between representations with 2D CNNs and MLPs.

	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	FID \downarrow
2D CNNs	29.3127	0.9664	0.0378	27.3143
MLPs	26.8961	0.9497	0.0650	87.0793

camera view.

C. Additional Sequential Results

Fig. A shows additional sequential results animated by challenging out-of-distribution pose sequences from the AMASS dataset [49], including basketball, football and dancing. It demonstrates that our method can also generate realistic and reasonable dynamic details under out-of-distribution poses thanks to the effective avatar representation and pose projection strategy.

D. Additional Experiments

Quantitative Ablation Study on Parametric Template. We conduct a qualitative ablation study on the parametric template in Fig. 7 of the main paper. We also quantitatively compare the reconstructed parametric template with the naked SMPL-X model [53] on the animation accuracy in Tab. A. The numerical results are computed on the first 500 frames and the first camera view in the “long dress” sequence from AvatarReX dataset [94].

Quantitative Ablation Study on 2D CNNs. We additionally report quantitative results of 2D CNNs and MLPs in Tab. B to further prove the effectiveness of the introduction of 2D CNNs and 2D parameterization. The numerical results are computed on the first 500 frames and the 126th camera view in the “actor02_sequence1” from ActorsHQ dataset [25].

Number of Principal Components in Pose Projection. Fig. B shows the animation results with different numbers of principal components in the pose projection strategy. It demonstrates that although PCA can project a novel pose into the distribution of the training poses for better pose generalization as shown in Fig. 9 of the main paper, too few principal components may lose some fine-grained garment details. We empirically found that setting the number of principal components to 20 could produce both detailed and generalized animation.



Figure A. **Example sequential animation results by our method.** Each row is an animation sequence involving 3 subjects. Our method can generate realistic and reasonable dynamic details even under novel poses from the AMASS dataset [49].

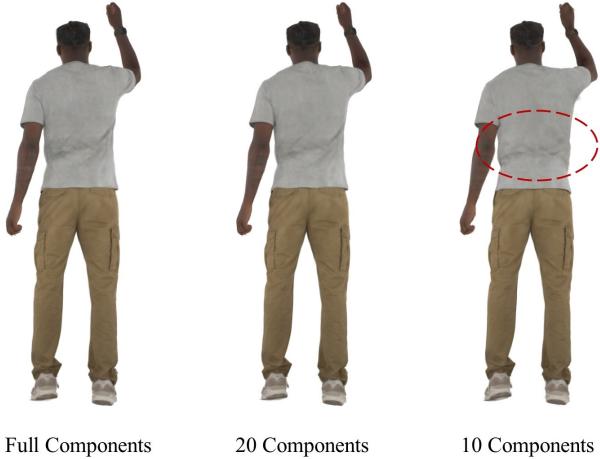


Figure B. **Ablation study on the component number in the pose projection.**

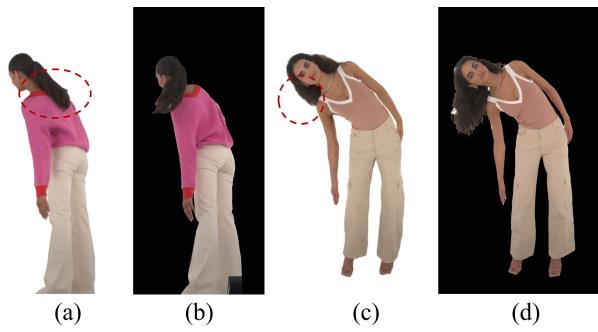


Figure C. **Failure cases.** (a,c) Animation results by our method, (b,d) ground-truth images. Our method fails to model the motion of hairs.

E. Failure Cases

Our method cannot model the physical motion of components that are not driven by the body joints, e.g., the hairs, as illustrated in Fig. C since we model the whole body including clothes, hands and hairs as an entangled Gaussian representation. We leave for future work a disentangled and compositional representation for representing the dynamics of different components of the character.