

ASH: Animatable Gaussian Splats for Efficient and Photoreal Human Rendering

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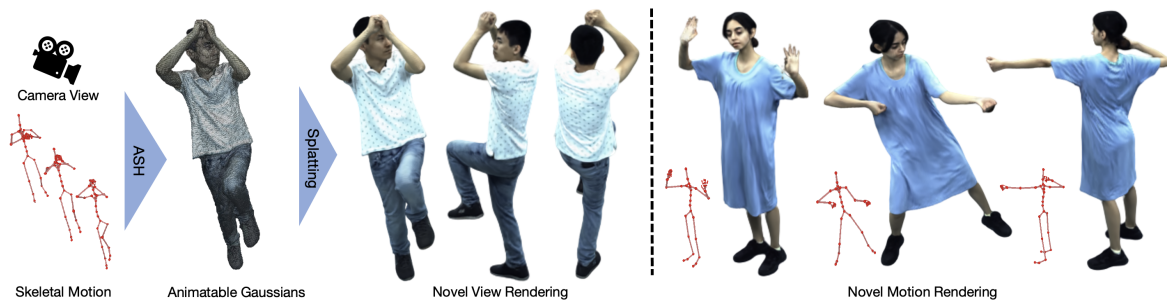


Figure 1. ASH takes an arbitrary 3D skeletal pose and virtual camera view, which can be controlled by the user, as input, and generates a photorealistic rendering of the human in real time. To achieve this, we propose an efficient and animatable Gaussian representation, which is parameterized on the surface of a deformable template mesh.

Abstract

Real-time rendering of photorealistic and controllable human avatars stands as a cornerstone in Computer Vision and Graphics. While recent advances in neural implicit rendering have unlocked unprecedented photorealism for digital avatars, real-time performance has mostly been demonstrated for static scenes only. To address this, we propose ASH, an animatable Gaussian splatting approach for photorealistic rendering of dynamic humans in real time. We parameterize the clothed human as animatable 3D Gaussians, which can be efficiently splatted into image space to generate the final rendering. However, naively learning the Gaussian parameters in 3D space poses a severe challenge in terms of compute. Instead, we attach the Gaussians onto a deformable character model, and learn their parameters in 2D texture space, which allows leveraging efficient 2D convolutional architectures that easily scale with the required number of Gaussians. We benchmark ASH with competing methods on pose-controllable avatars, demonstrating that our method outperforms existing real-time methods by a large margin and shows comparable or even better results than offline methods.

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1. Introduction

Generating high-fidelity human renderings is a long-standing problem in the field of Computer Graphics and Vision, with a multitude of real-world applications, such as gaming, film production, and AR/VR. Typically, this process is a laborious task, requiring complicated hardware setups and tremendous efforts from skilled artists. To ease the extensive manual efforts, recent advances, including this work, focus on generating photorealistic and controllable human avatars solely from multi-view videos.

Recent works on photorealistic human rendering can be categorized into explicit-based and hybrid methods. Explicit methods represent the human avatar as a deformable template mesh with learned dynamic textures [13, 53]. Although these methods are runtime-efficient and can be seamlessly integrated with the well-established rasterization-based rendering pipeline, the generated rendering often falls short in terms of photorealism and level of detail. Hybrid approaches usually attach a neural radiance field (NeRF) [38] onto a (deformable) human model [15, 32, 45]. Typically, they evaluate the NeRF in an unposed space to model the detailed appearance of clothed humans, and generate color and density values by querying a coordinate-based MLP per ray sample. Although hybrid methods can deliver superior rendering quality through NeRF’s capability to capture delicate appearance details, they are unsuitable for real-time applications due to the intensive sampling

and MLP evaluations required for volume rendering.

Recently, 3D Gaussian splatting [24] with its impressive rendering quality and real-time capability, has become a promising alternative to NeRFs, which are parameterized with a coordinate-based MLP. However, it originally is only designed for modeling static scenes, which is in stark contrast to our problem setting, i.e., modeling dynamic and animatable human avatars. Thus, one may ask: Can the rendering quality and speed of Gaussian splatting be leveraged to model the skeletal motion-dependent characteristics of clothed humans, and how can pose control be achieved?

To answer this, we propose ASH, a real-time approach for generating photorealistic renderings of animatable human avatars. Given a skeletal motion and a virtual camera view, ASH produces photorealistic renderings of clothed humans with motion-dependent details in real time (see Fig. 1). Importantly, during training, ASH only requires multi-view videos for supervision.

In more detail, our animatable human avatar is parameterized using Gaussian splats. However, naively learning a mapping from skeletal pose to Gaussian parameters in 3D leads to inferior quality when constraining ourselves to real-time performance. Thus, we propose to attach the Gaussians onto a deformable mesh template of the human. Given the mesh’s uv parameterization, it allows learning the Gaussian parameters efficiently in 2D texture space. Here, each texel covered by a triangle represents a Gaussian. Thus, the number of Gaussians remains *constant*, which is in stark contrast to the original formulation. Similarly, we encode the skeletal motion as pose-dependent normal maps. As a result, learning the mapping from skeletal motion to dynamic and controllable Gaussian parameters simplifies to a 2D-to-2D image translation task, which can be efficiently implemented using 2D convolutional architectures. For supervision, we transform the Gaussians into global 3D space using the deformable template and learned Gaussian displacements, splat the Gaussians following the original formulation, and supervise solely on multi-view videos. Our contributions are:

- We propose a novel method, ASH, that enables real-time and high-quality rendering of animatable clothed human avatars solely learned from multi-view video.
- To this end, we represent the human avatar as animatable and dynamic Gaussian splats, which we attach to a deformable template.
- To efficiently learn such a representation, we phrase the problem as a 2D-to-2D texture translation task effectively circumventing 3D architectures, which do not easily scale to the typically required large number of Gaussians.

Our evaluations and comparisons against state-of-the-art methods on animatable human rendering demonstrate that ASH is a significant step towards real-time, high-fidelity, and controllable human avatars.

2. Related Work

Neural Rendering and Scene Representation. In the last few years, volumetric representations [16, 54, 55] and neural radiance fields (NeRF) [38, 78] have received significant attention due to their ability to generate high-quality geometry and appearance [60, 74]. However, rendering a NeRF is typically slow as it requires querying an MLP for each ray sample during volume rendering. To address this, subsequent research focused on accelerating the inference process of NeRF: Neural Sparse Voxel Fields [32] adopts an octree to prune the ray samples. DVGO [59] models the scene with an explicit density and feature grid. Plenoxels [9] and PlenOctree [77] replace the MLP with a hierarchical 3D grid storing spherical harmonics, achieving an interactive test-time framerate. TensorRF [6] and Instant-NGP [39] achieved faster inference with compact scene representations, i.e., decomposed tensors and neural hash grids. 3D Gaussian Splatting [24] encodes the scene with Gaussian splats storing the density and spherical harmonics, which achieves state-of-the-art rendering quality and shows real-time capability. However, all the above methods are tailored for static scenes, and it is non-trivial to extend them for modeling the dynamic appearances of clothed humans.

There are also notable advancements for extending the concept of NeRFs [30, 42, 43, 47, 63, 71] to dynamic scenes. However, most of these works only support playback of the same dynamic sequence under novel views and, therefore, cannot be adopted for user-controlled pose-dependent dynamic appearance of clothed humans.

Animatable Neural Human Rendering. Since this work focuses on animatable human rendering, i.e., at test time, the approach solely takes the skeletal motion as input, we do not discuss works on replay [18, 26, 34, 46, 68, 70], reconstruction [1, 2, 11, 12, 14, 21, 28, 31, 36, 37, 50, 62, 72], and image-based free-viewpoint rendering [48, 52, 65]. Here, according to the underlying shape representation and rendering scheme, we can categorize the literature into two streams, i.e., mesh-based methods and hybrid methods.

Mesh-based methods [3, 5, 13, 53, 64, 73, 75] adopt an explicit, motion-controllable template mesh to model the geometry of clothed humans, with texture space for encoding appearance features. Xu et al. [75] first achieved novel motion and pose synthesis by querying and wrapping texture patches from the captured dataset. Casas et al. [5] and Volino et al. [64] proposed an interactive system that models the appearance as a temporally consistent layered representation in textures space. However, the rendering quality is limited due to the coarse geometry proxy. TNA [53] adopts a texture stack for modeling the dynamic humans’ appearances, though it cannot generate motion-dependent appearance. To address this issue, DDC [13] employs differen-

tiable rendering to learn the non-rigid deformations and dynamic texture maps of clothed humans. At test time, DDC can generalize to novel poses and views and produce real-time photorealistic renderings. Our method outperforms DDC in terms of rendering quality by a large margin while maintaining real-time capability.

Although mesh-based methods provide intuitive control through skeletal poses and integrate seamlessly with established rasterization pipelines, their rendering quality is restrained by the resolution of the template mesh. To this end, hybrid methods are introduced, which articulate the implicit fields with the explicit shape proxy, i.e., parametric human body models [22, 35, 41, 44], or person-specific template meshes. A popular line of research [4, 7, 8, 17, 20, 29, 40, 56, 57, 66, 69] introduced deformable human NeRFs that unwrap the posed space to a shared canonicalized space with inverse kinematics. To better model the pose-dependent appearance of humans, recent studies [10, 15, 27, 33, 45, 76, 80, 81] further introduce motion-aware residual deformations in the canonicalized space. Neural Actor [33] and HDHumans [15] are most closely related to our work within this category. Neural Actor utilizes the texture map of the parametric human body mesh as local pose features to infer dynamic appearances. However, it fails to generalize to characters with loose outfits. HDHumans jointly optimizes the neural implicit fields and the explicit template mesh and, thus, is able to handle loose clothing. However, both methods are slow and take roughly 5 seconds to render a single frame. In stark contrast, our proposed method is capable of real-time rendering with a quality on par with or even superior to HDHumans.

3. Method

Our goal is to generate motion-controllable, photorealistic renderings of humans learned solely from multi-view RGB videos (Fig. 2). Specifically, ASH takes the skeletal motions and a virtual camera view as input at inference and produces high-fidelity renderings in real-time ($\sim 30\text{fps}$). To this end, we propose to model the dynamic character with 3D Gaussian splats, parametrized as texels in the texture space of a deformable template mesh. This texel-based parameterization of 3D Gaussian splats enables us to model the mapping from skeletal motions to the Gaussian splat parameters as a 2D image-2-image translation task. Next, we will explain ASH from the following aspects: The background and problem setting (Sec. 3.1), modeling animatable Gaussian splats (Sec. 3.2), and our dedicated training strategy tailored towards our animatable Gaussians (Sec. 3.3).

3.1. Problem Setting and Background

We assume a segmented multi-view video $\mathbf{I}_{f,c}$ of an actor, recorded in a studio with C synchronized and calibrated cameras, where f and c denote the frame and camera IDs,

respectively. \mathbf{C}_c denotes the camera projection matrix. Additionally, each frame $\mathbf{I}_{f,c}$ is annotated with the 3D skeletal pose $\boldsymbol{\theta}_f \in \mathbb{R}^D$ using a markerless motion capture system [61]. Here, D indicates the number of degrees of freedom (DoFs) for the character’s skeleton. The skeletal motion of the subject $\bar{\boldsymbol{\theta}}_f \in \mathbb{R}^{k \times D}$ is depicted by a sliding window of skeletal poses from frame $f - k + 1$ to frame f where the root translation is normalized w.r.t. the f th frame.

For training, our model takes the skeletal poses $\boldsymbol{\theta}_f$ and camera parameters \mathbf{C}_c as input, renders the animatable Gaussians into image space, and is supervised solely on the multi-view video $\mathbf{I}_{f,c}$. During inference, ASH takes arbitrary skeletal poses $\boldsymbol{\theta}'$ and virtual cameras \mathbf{C}' as input and generates photorealistic rendering of the subjects at real-time frame rates (**29.64fps**). The detailed runtime breakdown is reported in the appendix.

Gaussian Splatting. We parameterize the actor representation as 3D Gaussians, which has been proven to be an efficient representation for modeling and rendering static 3D scenes [24]. Here, the static scene is depicted as a collection of 3D Gaussians

$$G(\mathbf{x}) = e^{-\frac{1}{2}(\mathbf{x})^T \Sigma^{-1}(\mathbf{x})} \quad (1)$$

where Σ denotes the covariance matrix and the Gaussian is centered at $\boldsymbol{\mu}$. In Kerbl et al. [24], the Gaussians are parameterized with the set $\mathcal{G}_i = (\boldsymbol{\mu}_i, \mathbf{q}_i, \mathbf{s}_i, \alpha_i, \boldsymbol{\eta}_i)$, each defined by its position $\boldsymbol{\mu}_i \in \mathbb{R}^3$, rotation quaternion $\mathbf{q}_i \in \mathbb{R}^4$, scaling $\mathbf{s}_i \in \mathbb{R}^3$, opacity $\alpha_i \in \mathbb{R}$, and spherical harmonics coefficients $\boldsymbol{\eta}_i \in \mathbb{R}^{48}$. To render the Gaussians into a particular camera view c , the Gaussian i has to be projected into image-space by updating the covariance as

$$\Sigma_{i,c} = \mathbf{J}_c \mathbf{C}_c \mathbf{R}_i \mathbf{S}_i \mathbf{S}_i^T \mathbf{R}_i^T \mathbf{C}_c^T \mathbf{J}_c^T \quad (2)$$

where \mathbf{R}_i and \mathbf{S}_i are rotation and scaling matrices obtained from the quaternion conversion \mathbf{q}_i and the scaling coefficients \mathbf{s}_i . \mathbf{J}_c is the Jacobian of the affine approximation of the projective transformation \mathbf{C}_c .

To render the color \mathbf{c}_p of a pixel \mathbf{p} in camera c , 3D Gaussian splatting [24] adopts a point-based splatting formulation, which blends the spherical harmonics $\boldsymbol{\eta}_i$ of the depth-ordered Gaussian splats overlapping with the pixel as

$$\mathbf{c}_p = \sum_{j \in \mathcal{N}_p} H(\boldsymbol{\eta}_i, \mathbf{d}_p) \alpha'_j \prod_{k=1}^{j-1} (1 - \alpha'_k), \quad (3)$$

where \mathcal{N}_p denotes the set of Gaussian splats covering pixel \mathbf{p} . α'_j refers to the opacity for the j th ordered Gaussian splat with respect to the current pixel, i.e. $\alpha'_j = \alpha_j G_j(\mathbf{p})$. $H(\cdot)$ indicates the function that converts the spherical harmonics coefficients $\boldsymbol{\eta}_i$ and the view direction \mathbf{d}_p to an RGB color.

While 3D Gaussian splatting can produce high-quality renderings at very high frame rates (more than 100 fps), its

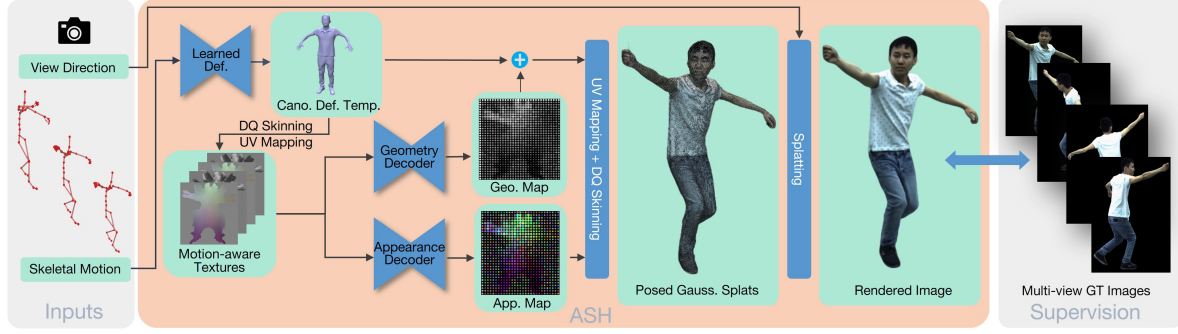


Figure 2. ASH generates high-fidelity rendering given a skeletal motion and a virtual camera view. A motion-dependent, canonicalized template mesh is generated with a learned deformation network. From the canonical template mesh, we can render the motion-aware textures, which are further adopted for predicting the Gaussian splat parameters with two 2D convolutional networks, i.e., the Geometry and Appearance Decoder, as the texels in the 2D texture space. Through UV mapping and DQ skinning, we warp the Gaussian splats from the canonical space to the posed space. Then, splating is adopted to render the posed Gaussian splats.

usage is primarily demonstrated for static scenes, and it is non-trivial to adopt this concept for controllable, detailed, and dynamic 3D human avatars. What is required here is *animatable* 3D Gaussians, i.e. we want to model the set of Gaussian parameters $\{\mathcal{G}_i\}_{N_g}$ as a function of skeletal motion $\bar{\theta}_f$ where N_g denotes the total number of Gaussians. Note that we consider motion rather than pose to account for potential surface dynamics.

3.2. Animatable Gaussian Splats

Intuitively, we want to learn a function $\mathcal{F}(\bar{\theta}_f) = \{\mathcal{G}_i\}_{N_g}$ that maps the skeletal motion to animatable 3D Gaussian parameters. However, more than 20,000 Gaussian splats are typically required to achieve high-fidelity renderings of clothed humans. Thus, modeling and learning such a function can be challenging, especially when modeling it in 3D. Instead, our idea is to attach the Gaussian splats onto an animatable template mesh of the human, and parameterize the Gaussian splats in 2D texture space, i.e., each texel of the template mesh (covered by a face) stores the parameters of a 3D Gaussian. This enables ASH to efficiently learn the Gaussian parameters in 2D texture space, which we will now describe in more detail.

Animatable Template. To achieve this, we require an animatable human template denoted as $M(\theta_f) = \mathbf{V}_f$, which takes the skeletal motion and computes posed and deformed 3D vertices \mathbf{V}_f of a person-specific template mesh \mathbf{V}_m . In practice, we leverage the character model of Habermann et al. [13] and refer to the appendix for further details. To generate the animatable template mesh \mathbf{V}_f , we first non-rigidly deform the original template mesh vertices \mathbf{V}_m in the unposed-canonical space, denoted as $\bar{\mathbf{V}}_f$, with skeletal motion-dependent, i.e. $\bar{\theta}_f$, and learned embedded deformations [58] and per-vertex displacements. Given the skeletal pose θ_f , the canonically deformed template mesh vertices $\bar{\mathbf{V}}_f$ can then be posed using Dual Quaternion skin-

ning [23], denoted as \mathbf{V}_f .

Animatable Gaussian Textures. ASH depicts the character’s appearance with a *fixed* number of animatable Gaussian splats $\{\mathcal{G}_i\}_N = (\bar{\boldsymbol{\mu}}_{uv,i}, \bar{\mathbf{d}}_{uv,i}, \mathbf{q}_{uv,i}, \mathbf{s}_{uv,i}, \alpha_{uv,i}, \boldsymbol{\eta}_{uv,i}) \in \mathbb{R}^{N \times 62}$ as the texels on the texture space of the animatable template mesh $M(\theta_f)$. Here, N denotes the number of texels that are covered by triangles in the UV map. Specifically, $\bar{\boldsymbol{\mu}}_{uv,i}$ denotes the base position for Gaussian splats in the canonical space, which can be derived from the canonical animatable template mesh vertices $\bar{\mathbf{V}}_f$ through texture mapping:

$$\bar{\boldsymbol{\mu}}_{uv,i} = w_{a,i} \bar{\mathbf{V}}_{f,j} + w_{b,i} \bar{\mathbf{V}}_{f,k} + w_{c,i} \bar{\mathbf{V}}_{f,l}, \quad (4)$$

where $w_{(\cdot),i}$ denotes the barycentric weights for the texels and $\bar{\mathbf{V}}_{f,(\cdot)}$ stands for the canonical vertex position for the triangle that covers the texel. Similar to the animatable template, we can pose the Gaussian splats $\{\mathcal{G}_i\}$ stored in texels, from the canonical position $\bar{\boldsymbol{\mu}}_i$ to the posed space, through Dual Quaternion skinning [23]:

$$\boldsymbol{\mu}_{uv,i} = \mathbf{T}_{uv,i}(\bar{\boldsymbol{\mu}}_{uv,i} + \bar{\mathbf{d}}_{uv,i}), \quad (5)$$

where $\mathbf{T}_{uv,i}$ denotes the Dual Quaternion skinning transformation matrix for the i th texel. $\bar{\mathbf{d}}_{uv,i}$ refers to a learned per-texel offset in the canonical space, which captures fine motion-dependent deformations of the Gaussian splats.

Parameterizing Gaussian splats as 2D texels enables us to predict them using efficient 2D convolutional architectures. Moreover, the shared canonical 2D space facilitates the learning of the motion-dependent Gaussian parameters. **Gaussian Texture Decoder.** Due to the texel-based 2D parameterization of the 3D Gaussian splats, we can leverage the well-established, efficient 2D convolutional architectures. To formulate the mapping between the 3D skeletal motion $\bar{\theta}_f$ and the dynamic Gaussian splats $\{\mathcal{G}_i\}_N$ on 2D

texture space as a image-2-image translation problem [19], we adopt the motion-aware textures $(\mathbf{T}_{n,f}, \mathbf{T}_{p,f})$ to depict the 3D skeletal motions $\bar{\theta}_f$ in the 2D texture space. The normal textures $\mathbf{T}_{n,f}$ and position textures $\mathbf{T}_{p,f}$ can be computed from the posed and deformed template mesh \mathbf{V}_f vertices through inverse texture mapping. Consequently, we propose motion-aware 2D convolutional neural networks, i.e., the geometry network \mathcal{E}_{geo} , and the appearance network \mathcal{E}_{app} , predicting the geometry and appearance parameters of the Gaussian splats from the motion-aware textures $(\mathbf{T}_{n,f}, \mathbf{T}_{p,f})$. The geometry network \mathcal{E}_{geo} predicts the shape-related parameters, namely, the canonical offset $\bar{\mathbf{d}}_{uv,i}$, scale $s_{uv,i}$, rotation quaternions $\mathbf{q}_{uv,i}$, and opacity $\alpha_{uv,i}$:

$$\mathcal{E}_{\text{geo}}(\mathbf{T}_{n,f}, \mathbf{T}_{p,f}) = (\bar{\mathbf{d}}_{uv,i}, s_{uv,i}, \mathbf{q}_{uv,i}, \alpha_{uv,i}). \quad (6)$$

A separated motion-aware convolution decoder \mathcal{E}_{app} is adopted for learning the appearances characterized by the Spherical Harmonics $\boldsymbol{\eta}_{uv,i}$:

$$\mathcal{E}_{\text{app}}(\mathbf{T}_{n,f}, \mathbf{T}_{p,f}, \Phi_f) = \boldsymbol{\eta}_{uv,i}, \quad (7)$$

where Φ_f indicates the global appearance features, which encodes the global root transition of the character with a shallow MLP, to account for the spatially varying lighting conditions within the capture space.

3.3. Training Strategy

Unlike static scenes, dynamic clothed humans exhibit motion-dependent appearances and varying geometry throughout the frames, posing a significant challenge in training. To make it tractable, we propose a carefully designed training paradigm, which decomposes the learning of the motion-aware convolutions into two stages, namely, the warmup stage, and the final training.

Warmup Stage. As mentioned in Sec. 4, the DynaCap dataset [13] and our proposed dataset feature long training sequences with various motion-dependent detailed appearances. Therefore, naively training the proposed motion-aware decoders \mathcal{E}_{geo} and \mathcal{E}_{app} , from scratch without proper initialization will not converge during training. To tackle this problem, we propose a warmup stage, providing a better weight initialization for the motion-aware decoders.

We first sample t frames evenly across the training sequence and learn 3D Gaussian splat parameters $\{\mathcal{G}_i''\}_{N_g}$ separately, which serves as a pseudo ground truth for the Gaussian splat parameters. In contrast to the original implementation for static 3D Gaussian splatting [24], we fix the position of the Gaussian splats $\boldsymbol{\mu}_{uv,i}''$ throughout the training while only optimizing the remaining parameters. Specifically, the initial value for the Gaussian splat positions $\boldsymbol{\mu}_{uv,i}''$ can be read out from the texture texels of the pose-deformed

template mesh $\boldsymbol{\mu}_{uv,i}$. Additionally, to preserve the correspondences across pseudo ground truth frames, we remove the splitting/merging of the Gaussian splats and keep the number of Gaussian splats fixed. The pretraining optimizes the L2 loss between the pseudo ground truth $\{\mathcal{G}_i''\}$ and the Gaussian splat parameters produced by the motion-aware decoders $\{\mathcal{G}_i'\}$:

$$\mathcal{L}_{\text{pre}} = \mathcal{L}_2(\{\mathcal{G}_i'\}, \{\mathcal{G}_i''\}). \quad (8)$$

Final Training. After the warmup stage, we can further train the motion-aware decoder on the whole training sequence by minimizing the pixel-wise L1 and structural-similarity-index loss between the generated images $\mathbf{I}'_{f,c}$ and the multi-view ground truth images $\mathbf{I}_{f,c}$:

$$\mathcal{L}_{\text{main}} = \lambda_{\text{pix}} \mathcal{L}_1(\mathbf{I}_{f,c}, \mathbf{I}'_{f,c}) + \lambda_{\text{str}} \mathcal{L}_{\text{ssim}}(\mathbf{I}_{f,c}, \mathbf{I}'_{f,c}), \quad (9)$$

where $\mathcal{L}_{\text{ssim}}$ denotes the structural similarity index loss [67] measuring the structural difference between two images. λ_{pix} and λ_{ssim} are set to 0.1 and 0.9, respectively.

4. Results

Dataset We adopted the DynaCap dataset [13] to quantitatively and qualitatively assess the effectiveness of our approach. We selected two representative subjects from the DynaCap dataset wearing loose and tight types of apparel for evaluating the accuracy of novel-view rendering and generalization ability to novel poses. Following the protocol proposed in DDC [13], we train our model using the training splits from the DynaCap dataset. Here, we hold out 4 camera views to assess the novel-view rendering accuracy. Moreover, we evaluate the model’s generalization ability to novel poses with motion sequences from the testing splits.

In addition to the DynaCap dataset, we recorded two novel sequences featuring distinct subjects to showcase the performance of our model qualitatively. The recorded subjects perform everyday motions such as dancing, jogging, and jumping. The sequences are recorded using a calibrated multi-camera system with 120 cameras at a frame rate of 25 fps. Separate training and testing sequences are recorded with a duration of 27,000 frames and 7,000 frames, respectively. All the captured frames are annotated with 3D skeletal poses [61] and foreground segmentations [25, 51].

4.1. Qualitative Results

We evaluate the performance of ASH on subjects from the DynaCap [13] dataset and our newly recorded sequences.

Novel View Synthesis. Fig. 3 presents the novel view synthesis results rendered from camera views unseen during training. ASH yields photorealistic rendering in real time, capturing sharp wrinkles details and view-dependent appearances. Remarkably, it can even generalize to loose

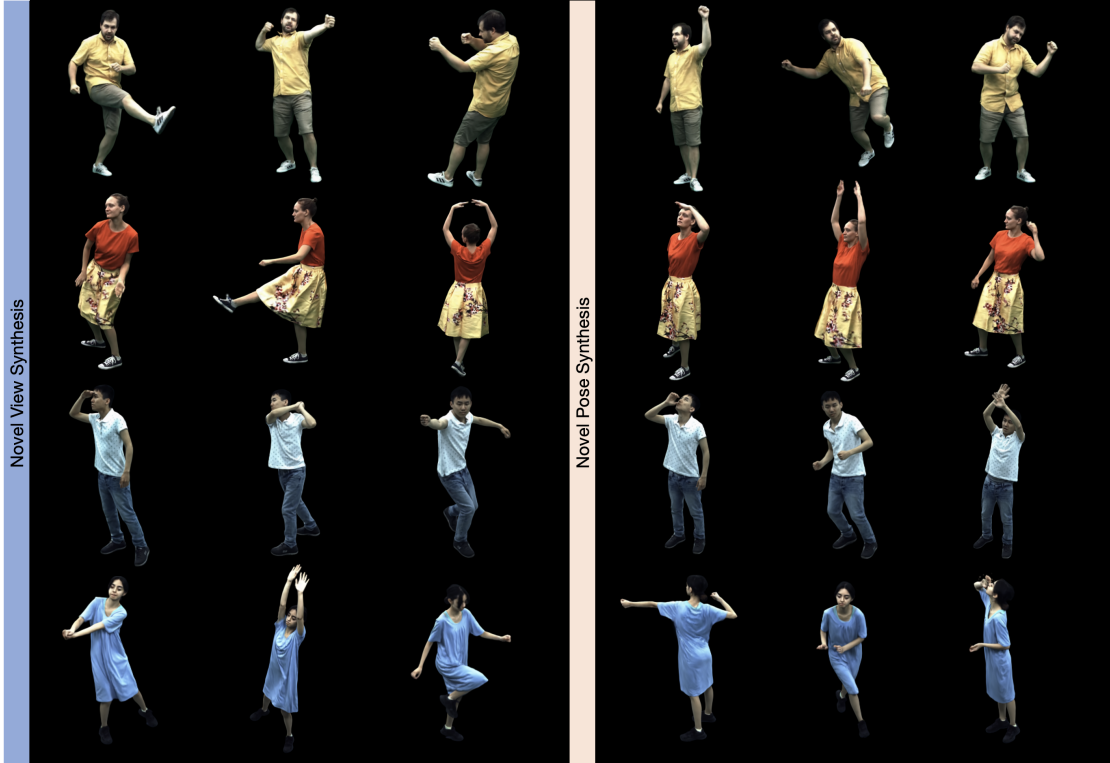


Figure 3. **Qualitative Results.** We present the results generated with ASH regarding novel view and pose synthesis. Note that our methods can produce high-quality rendering with delicate, motion-aware details for novel views and skeletal motions.

types of apparel and faithfully recovers the clothing dynamics, e.g., the swing of the skirts.

Novel Pose Synthesis. We further show the results generated on novel poses extracted from the testing sequences in Fig. 3. Given poses that significantly deviate from the training poses, our method still generates high-quality renderings with motion-aware appearances. For the dynamic results, we refer to the supplemental video.

4.2. Comparisons

Competing Methods. We compare our model with the state of the arts on animatable neural human rendering: 1) DDC [13] features a mesh-based approach where the geometry is represented with a learned embedded graph, and the appearance is encoded using learned dynamic textures. Specifically, DDC is the only real-time approach among competing methods, while other hybrid methods typically take seconds to volume-render an image. 2) TAVA [29] is a hybrid approach depicting the shape, appearance, and skinning weights as implicit fields in canonical space. The samples in the posed space are canonicalized w.r.t. the skeleton through iterative root finding. 3) NA [32] conditions the canonical color and density field of dynamic characters on the learned feature texture of the parametric human body models. The canonicalization of spatial samples is achieved

by inverse kinematics. 4) HDHumans [15] models the appearance of dynamic humans as the appearance and density fields conditioned on the feature texture map of the motion-aware deformable template mesh. Notably, the template mesh will deform w.r.t. the implicit density field, improving the alignment between the observation and canonical space.

Metrics. We adopt the Peak Signal-to-Noise Ratio (PSNR) metric to measure the quality of the rendered image. Moreover, we adopt the learned perceptual image patch similarity (LPIPS) [79] that better mirrors human perception. Note that the metrics are assessed at a 1K resolution, averaged across every 10th frame throughout the sequence. Here, we denote the subject with tight outfits as *Tight Outfits*, and the other wearing loose clothing as *Loose Outfits*.

Quantitative Comparison. Tab. 1 and Tab. 2 illustrate the quantitative comparison against the competing methods on novel view and pose synthesis. Compared with the real-time capable methods, our method significantly outperforms DDC [13] in PSNR and LPIPS regarding novel-view synthesis, highlighting our method’s superiority in capturing the motion-aware appearances from the training data. In novel pose synthesis, compared to DDC [13], our method demonstrates significantly improved performance. This underscores our method’s generalization ability to novel motions. As for the comparison against the non-real-time ap-

Methods	RT	Tight Outfits		Loose Outfits	
		PSNR	LPIPS	PSNR	LPIPS
TAVA	✗	24.61	62.26	27.31	37.55
NA	✗	30.33	23.71	25.30	50.01
HDHumans	✗	30.98	15.09	29.24	15.79
DDC	✓	31.21	22.56	28.10	31.68
Ours	✓	35.84	11.92	35.47	8.30

Table 1. **Quantitative Comparison on Novel View Synthesis.** We quantitatively compare ASH with other methods on seen skeletal motions but unseen views. We highlight the **best** and **second-best** scores. We outperform previous real-time and even non-real-time methods in all metrics by a large margin.

Methods	RT	Tight Outfits		Loose Outfits	
		PSNR	LPIPS	PSNR	LPIPS
TAVA	✗	28.30	37.47	26.31	50.11
NA	✗	28.78	25.78	25.03	44.20
HDHumans	✗	28.17	20.69	26.71	22.75
DDC	✓	27.77	30.16	26.43	32.22
Ours	✓	28.90	22.83	27.12	20.22

Table 2. **Quantitative Comparison on Novel Pose Synthesis.** We quantitatively compare ASH with other methods on unseen skeletal motions and unseen views. ASH achieves the highest PSNR and the second-best LPIPS on the subject with tight outfits, and outperforms other methods for the subject wearing loose clothing.

proaches, our method consistently surpasses previous works regarding PSNR and LPIPS. Notably, our method is capable of real-time rendering and achieves remarkably better quantitative accuracy than HDHumans in novel-view synthesis, and comparable performances in novel-pose synthesis.

Qualitative Comparison. Fig. 4 comprises the qualitative comparison on the novel-view and novel-pose rendering: TAVA [29] struggles to handle various motions in the DynaCap dataset [13], resulting in blurry renderings. While NA [33] effectively captures details for subjects wearing tight apparel, it struggles with significant artifacts for subjects in loose outfits. This issue arises from the inherent challenge of representing loose clothing as residual displacements on the parametric human body model. HDHumans [15] stands out among non-real-time competing methods, producing high-fidelity renderings with sharp details. However, due to the extensive sampling needed for volume rendering, it takes seconds for HDHumans to render a single frame. In contrast, ASH excels by delivering rendering quality that matches or exceeds HDHumans’ quality in real-time.

DDC [13] is the only competing method with real-time capability. Although it captures coarse motion-aware appearances, its output tends to be blurry and lacks detail. ASH matches the real-time capability as DDC, while generating renderings with much finer details.

Methods	Training Pose		Testing Pose	
	PSNR	LPIPS	PSNR	LPIPS
w/o mot.	27.19	33.16	26.86	32.35
w/o disp.	33.21	17.34	27.33	25.32
w/ 128.res.	35.15	11.26	27.13	22.00
w/ 512.res.	35.28	8.60	27.00	21.13
Ours	35.47	8.30	27.13	20.22

Table 3. **Ablation Study.** We assess our design choices on the image synthesis tasks on the subject with loose outfits. Our method achieves better performance against the design alternatives.

4.3. Ablations

To assess the effectiveness of the major components of our method, we conduct the following ablative experiments on the novel view and motion synthesis tasks.

Motion Conditions. Our method depicts the appearance of the clothed human through motion-aware, deformable Gaussian splats in the canonical space. To assess the efficacy of the motion conditions, we remove the motion-aware decoder and learn the appearance parameters of Gaussian splats from a truncated training sequence of 1,000 frames, termed as **w/o mot.**. As seen in Tab. 3 and Fig. 5, without motion conditioning, the synthesized results fail to recover the clothing dynamics and suffer from severe artifacts.

Motion-aware Offset. The motion-aware offset is adopted to account for the non-rigid motion-dependent deformation of the Gaussian splats. We remove the motion-aware offset applied to the canonical Gaussian splats, only allowing the appearance to be motion-dependent, termed as **w/o disp.**. As shown in Tab. 3, excluding the learned motion-aware offset leads to worse quantitative performance and noticeable blurry artifacts on the rendered images.

Texture Resolution. The animatable Gaussian splats are parameterized as texels in the texture space of the deformable template mesh, where the resolution is set to 256. To study the impact on the resolution of the texture space, we conducted ablative studies with different resolutions, i.e., halved resolution termed as **w/ 128.res.**, and doubled resolution termed as **w/ 512.res.**. As illustrated in Tab. 3 and Fig. 5, doubling the resolution results in comparable results, while it significantly increases computational complexity in both the U-Net [49] evaluation and tile-based rasterization, preventing the model from being real-time compatible. On the other hand, reducing the resolution to 128 leads to a significant decline in perceptual metrics and blurry rendering.

As seen in Tab. 3 and Fig. 5, our method outperforms the design alternatives quantitatively and qualitatively.

5. Conclusion

In this paper, we introduce ASH, a real-time method for high-quality rendering of animated humans, learned solely



Figure 4. **Qualitative Comparison.** We compared our methods with the state of the arts, i.e., TAVA [29], NA [33], HDHumans [15], DDC [13], in novel view and novel motion synthesis. Note that our results significantly outperform the real-time methods in quality while showing comparable or even better results than the offline methods.

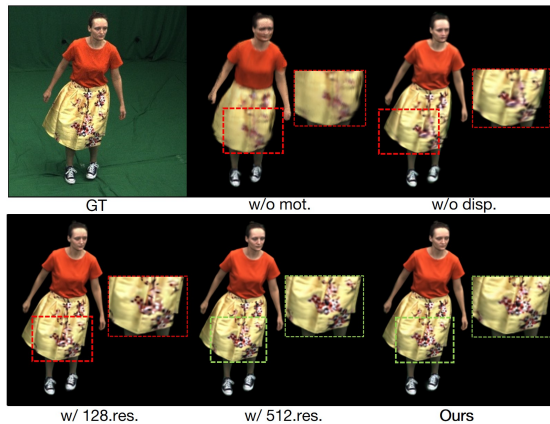


Figure 5. **Qualitative Ablation.** Our method excels in rendering quality and detail recovery than the design alternatives. Our method shows compatible rendering quality as **w/ 512.res.** with doubled texel resolution and much sharper rendering than **w/ 128.res.** with halved texel resolution.

from multi-view videos. ASH attaches the 3D Gaussians splats, initially designed for static scenes, onto a deformable mesh template. Bridged by the mesh’s UV parameterization, we can efficiently learn the 3D Gaussians in 2D texture space as an image-2-image translation task. ASH demonstrates significantly better performances quantitatively and qualitatively than state-of-the-art, real-time capable methods on animatable human rendering, and even better performance than the state-of-the-art offline methods. Currently, ASH does not update the underlying deformable template mesh. In the future, we will explore whether the Gaussian splatting can directly improve the 3D mesh geometry.

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