HDhuman: High-quality Human Performance Capture with Sparse Views

Tiansong Zhou, Tao Yu, Ruizhi Shao, Kun Li

Abstract—In this paper, we introduce HDhuman, a method that addresses the challenge of novel view rendering of human performers that wear clothes with complex texture patterns using a sparse set of camera views. Although some recent works have achieved remarkable rendering quality on humans with relatively uniform textures using sparse views, the rendering quality remains limited when dealing with complex texture patterns as they are unable to recover the high-frequency geometry details that observed in the input views. To this end, the proposed HDhuman uses a human reconstruction network with a pixel-aligned spatial transformer and a rendering network that uses geometry-guided pixel-wise feature integration to achieve high-quality human reconstruction and rendering. The designed pixel-aligned spatial transformer calculates the correlations between the input views, producing human reconstruction results with high-frequency details. Based on the surface reconstruction results, the geometry-guided pixel-wise visibility reasoning provides guidance for multi-view feature integration, enabling the rendering network to render high-quality images at 2k resolution on novel views. Unlike previous neural rendering works that always need to train or fine-tune an independent network for a different scene, our method is a general framework that is able to generalize to novel subjects. Experiments show that our approach outperforms all the prior generic or specific methods on both synthetic data and real-world data.

Index Terms—Image-based rendering, neural rendering, human reconstruction, transformer, visibility reasoning

1 INTRODUCTION

Realistic free-viewpoint rendering of human performers is in increasing demand with the development of AR/VR and Image-Based Rendering (IBR) is a promising way that can render realistic images on novel views. However, current IBR methods [1], [2], [3], [4] always need to warp the input views to the novel views, which means they will rely on dense views as input. If only a sparse set of camera views is available, the performances of these warping-based methods will degrade dramatically as the wide camera baselines will cause severe occlusion problems.

To render human performers from sparse views, neural body [5] presents an implicit neural representation of dynamic humans. They anchor a latent code on each vertex of SMPL model [6] to integrate the observations over video frames. However, when the human performers wear clothes with complex texture patterns or wear loose clothes such as long dresses, the rendering quality of [5] remains limited as the SMPL model does not contain any geometry details, which is not suitable for the rendering of loose clothes or clothes with complex texture patterns. Moreover, [5] needs to train an independent network for each human and the training procedure is extremely time-consuming (at least 10 hours for each subject), which further limits its applications. Some works [7], [8] also seek to use a general model to render novel views from sparse views. But the rendering quality of these works remains limited without any fine-tuning.

In this work, we propose HDhuman, a general method that is able to render high quality human images at 2k resolution using sparse views. The used camera views are no more than 8 views in a uniformly distributed circle arrangement. To our knowledge, it is the first work that can take into consideration of sparsity, generalization and high quality rendering at the same time. Besides, we do not use any human geometry prior such as SMPL, so we can handle the human cases that wear loose clothes, such as long dress. An illustration is shown in Fig. 1. Table 1 summarizes the key aspects of our approach relative to prior works.

Fig. 1. High quality reconstruction and rendering of a challenging human performer that wears long dress with complex texture patterns from only 6 input views, without any fine-tuning.
will suffer severe artifacts and blurring as many pixels or areas are invisible in the novel view. For this end, we propose geometry-guided pixel-wise feature integration to map the source views to the novel view. We will perform visibility reasoning and find the visible source views for each pixel of the novel view, which will provide a guidance for the following feature integration.

For efficient visibility reasoning, a high quality reconstruction is essential. If the reconstruction results lose the geometry details that observed in the source views, the visibility reasoning will be inaccurate, resulting in rendering artifacts and blurring. Therefore, we present a pixel-aligned spatial transformer for multi-view feature fusion in the reconstruction network. The proposed transformer is able to preserve geometry details such as clothing folds that observed in the input views, resulting in highly-detailed reconstruction.

Unlike most of the neural-network-based rendering works that always need to train or fine-tune an independent network for each scene or human [5], [9], [10], the proposed HDhuman is a general rendering framework. Benefit from the generalization ability of pixel-aligned spatial transformer and geometry-guided feature integration, our method is able to perform high quality reconstruction and rendering for novel subjects without any fine-tuning. Experiments show that our general approach significantly improves the rendering quality compared with all the existing generic and specific works. In summary, our contributions are:

- We propose a new general neural rendering framework capable of rendering novel views of human performers with complex texture patterns at 2k image resolution from a sparse set of camera views.
- A pixel-aligned spatial transformer that is able to perform efficient feature fusion in human reconstruction, enabling us to reconstruct highly detailed human models from sparse views.
- A geometry-guided pixel-wise feature integration method for efficiently solving the severe occlusion problems that caused by the sparsity of input views.
- We demonstrate significant rendering quality improvements of our method compared to the prior works, especially for humans with loose clothes or complex texture patterns.

### 2 Related Work

**Human Reconstruction.** Human reconstruction has a long and overlapping history in both computer vision and graphics. In earlier years, multi-view stereo (MVS) is the most widely used method for human reconstruction. [11] proposes a continuous a depth map estimation method for improving the performances of MVS. Over the past decade, benefit from the development of hardware, many works [12], [13], [14], [15] take single or multi RGBD views as input to get amazing real-time high fidelity human reconstruction and rendering. However, the relied depth sensors are only able to capture humans or objects that are near the sensors. When humans move far from the sensors (farther than 3m), the depth sensors will fail capturing depth streams, which greatly limits their applications. In recent years, one of the most promising research directions for human reconstruction is pixel-aligned implicit function (PIFu) [16]. PIFu takes a single color image as input and encode the image to generate pixel-aligned image features. Based on the pixel-aligned features that contain the geometry details in the input image, they learns an implicit function over the 3D space. Following PIFu, PIFuHD [17] introduces a multi-level framework for high fidelity 3D reconstruction of clothed human. It uses an additional image translation network to predict normal maps from original color images. The predicted normal maps enable it to reconstruct more geometry details, such as clothing folds. Moreover, a fine-level is used in PIFuHD to recover more subtle details from the high resolution input images.

For multi-view human reconstruction, PIFu uses a naive average pooling operation for multi-view feature fusion, which is not efficient enough to fuse the geometry details that observed in the multi-view input images. [18] uses SMPL as the geometry prior to solve the occlusion problem in multi-person reconstruction, but the usage of SMPL not only makes the reconstruction results might be pixel-misaligned, but also makes it unable to reconstruct the human cases with loose clothes, such as long dress. In contrast, without using any geometry prior, we present a pixel-aligned spatial transformer for multi-view feature fusion, enabling us to produce pixel-aligned highly detailed reconstruction results.

**View Synthesis.** Many works [1], [19], [20] use the traditional image-based rendering or view synthesis pipeline for novel view rendering, i.e. proxy geometry reconstruction-warping-blending. To bridge the gap between reconstruction and rendering, [4] presents a point cloud based method to improve multi-view stereo algorithm for more realistic free view synthesis (FVV). Benefit from the significant research progress of deep learning in recent years, some works [11], [3] use neural networks to blend the novel views from the warped source views. However, these warping-based works need dense camera views as input to warp the source views to the novel view. If the input camera views are highly sparse, the performances of this classic method will degrade dramatically as the wide camera baselines will cause severe occlusion problems.

More recently, volume rendering is another method to achieve photo-realistic rendering. It uses volumes to rep-
resent the shape and appearance of a scene. Multi-plane images (MPIs) [21] is one of the most promising ways for this volumetric representation, which computes a separate RGBA image for each depth plane. The α channel and the RGB channels represent the shape and appearance of the scene respectively. Based on the MPIs-representation, [2] introduces a soft 3D representation of the scene geometry. This representation enables it to handle the depth uncertainty of the scene. Benefit from the significant research progress on neural networks, [22, 23] use neural networks to predict the MPIs for each input views. Another promising research direction for volume rendering is neural radiance fields (NeRF) [9], which uses a multi-layer perceptron (MLP) to represent the density and color fields of a scene and thus it is well-suited for differentiable rendering. However, both MPIs-based and NeRF-based works need dense camera views as input and always need to train or fine-tune an independent network of each scene. For human rendering on sparse views, [5] uses latent codes that anchored on SMPL vertices to integrate observations from a multi-view video, thus enabling it to reconstruct and render humans from sparse views. However, [5] is only able to render humans with relatively uniform textures. When human performers wear clothes with complex texture patterns, its rendering quality will degrade dramatically as the SMPL models do not contain any geometry details. Besides, it needs to train an independent network for a different human, which is extremely time-consuming. In our work, we introduce a new general framework for the high quality rendering of challenging human performers with complex texture patterns using spare views.

3 APPROACH

Given a sparse set of challenging human views as input, the goal of our method is to render high quality images on novel views. For 4D human rendering, our system pipeline can be divided into three parts: 1) a reconstruction network with pixel-aligned spatial transformer for highly detailed initial reconstruction (Sec. 3.1), 2) a skeleton-based tracking method for more robust and coherent 4D human reconstruction (Sec. 3.2), and 3) a rendering network with geometry-guided pixel-wise feature integration for novel view human rendering (Sec. 3.3). Note that the tracking step is only possible in 4D human reconstruction, so for static human rendering, we will use the reconstructed meshes from the reconstruction network as the geometry input of the rendering network.

3.1 Human Reconstruction

3.1.1 Preliminary

PIFu [16] introduces a pixel-aligned implicit function to reconstruct the underlining 3D human geometry from a single or multi-view images. The proposed pixel-aligned implicit function consists of a convolutional image encoder g and a continuous implicit function f that represented by a multi-layer perceptron. Concretely, the human surface is defined as

\[ f(g(I(x)), z(X)) = s : s \in \mathbb{R}, \]  

where \( X \) is the given 3D point, \( x = \pi(X) \) is its orthogonal 2D projection, \( g(I(x)) \) is the bilinear sampled image feature at \( x \). During the inference, 3D space is uniformly sampled to infer the occupancy and the final iso-surface is extracted with a threshold of 0.5 using marching cube algorithm.

To achieve high-fidelity 3D reconstruction of clothed human from a single image, recovering detailed information such as clothing folds, PIFuHD [17] proposes a coarse-to-fine framework for 3D clothed human reconstruction using images with resolution of \( 1024 \times 1024 \). It uses an additional network to predict normal maps from the input color images. Compared with PIFu, the predicted normal maps enable it to recover more details as the geometry information in normal maps is more explicit. Moreover, a fine-level is used in PIFuHD to recover details from high resolution images. Specifically, the fine level can be denoted as

\[ f^H(g^H(I_H, F_H, B_H, x_H), \Omega(X)) = s : s \in \mathbb{R}, \]  

where \( I_H, F_H, B_H \) are the input color images and the predicted front and back normal maps at resolution of \( 1024 \times 1024 \). \( \Omega(X) \) is the feature extracted from the coarse level.

For multi-view reconstruction, PIFu [16] uses a naive average pooling operation to fuse multi-view features. This average operation regard each view equally, but in fact, for each 3D point in world space, different views should have different weights for the occupancy estimation of the 3D point. [18] uses human shape and pose prior SMPL [6] for multi-person reconstruction using sparse views. The usage of SMPL enables it to solve the occlusion problems caused by the interaction of multi-human.

Limitations. 1. To recover the subtle details of clothed humans, PIFuHD needs to use images with a high resolution of \( 1024 \times 1024 \) as the input of fine-level, in which the memory usage is large. As we have multi-view images, if we are able to aggregate the geometry details that observed in the multi-view input images, we will also be able to produce highly detailed reconstruction results without high resolution images as input. Therefore, for memory efficiency, we need an efficient way to aggregate the details in the multi-view input images, enabling us to use images at a lower resolution of \( 512 \times 512 \) to produce highly detailed reconstruction results with only a single level. 2. The average pooling operation in PIFu is not efficient enough to aggregate geometry details that observed in the input images as it regard each view equally, resulting in losing subtle geometry details, which will finally limit the rendering quality. Therefore, we need to find a way that is able to calculate the correlations between the input views, providing high-level information for feature aggregation and enabling us to preserve the subtle details. 3. Though the usage of SMPL model makes the reconstruction results of [18] more robust, it will cause two problems: 1) the reconstruction results might be pixel-misaligned as the SMPL models do not contain any geometry details, this misalignment will result in artifacts in the rendering results; 2) it will be difficult to reconstruct humans with loose clothes, such as long dress. For this end, we have to find a way to robustly reconstruct humans without using any geometry prior, enabling us to produce pixel-aligned
reconstruction results and handle the humans cases with loose clothes.

3.1.2 Pixel-aligned Spatial Transformer

To achieve the goal of high quality human rendering, highly detailed reconstruction of humans is essential. The key to this reconstruction problem is how to preserve the geometry details that observed in the input multi-view images. For this end, we propose a pixel-aligned spatial transformer in the reconstruction network for highly detailed human reconstruction. See Fig. 2 for an illustration.

Following [17], we firstly predict frontal normal maps from color images, and encode each color image using a Hourglass encoder $g$. Our observation is that in multi-view reconstruction, the coarse level network in [17] is enough to reconstruct high-frequency details with frontal normal maps as input. So, for memory efficiency, we only use a single level for reconstruction.

To efficiently preserve the geometry details that observed in the input views, we use a spatial transformer to calculate the correlations between the input multi-view pixel-aligned features. Specifically, for a 3D point $X$, given $N$ views encoded features, we will stack them together to get $Φ_{mv} \in \mathbb{R}^{N \times D}$, where $D$ is the feature dimensions. And then we embed it with three learnable different linear layers: $Φ_q = Φ_{mv}W_q, Φ_k = Φ_{mv}W_k, Φ_v = Φ_{mv}W_v$, where $W_q, W_k, W_v \in \mathbb{R}^{D \times d_k}$ and $Φ_q, Φ_k, Φ_v \in \mathbb{R}^{N \times d_k}$. $d_k$ is the embedded feature dimension. Then, a spatial transformer will be applied:

$$Φ_{mv, att} = Transformer(Φ_q, Φ_k, Φ_v) = softmax\left(\frac{Φ_qΦ_k^T}{\sqrt{d_k}}\right)Φ_v,$$

where $Φ_{mv, att} \in \mathbb{R}^{N \times d_k}$ is the transformer-aware multi-view features. To counter the gradient vanishing problem caused by the softmax operation, we scale the dot-product operation by $\frac{1}{\sqrt{d_k}}$. Different from the feature before transformer calculation, which only contains the geometry details observed in a single view, the transformer-aware feature contains all the geometry details that observed in multi-view images. Compared with the average pooling operation in [16], the transformer-based fusion operation calculates the correlations between the multi-view features, which provides a high-level information for fusion, allowing the network to preserve more geometry details.

To query the depth value of point $X$ with the encoded features, we need to normalize the depth value for each view. Given multi-view human images and the corresponding calibrated camera parameters as input, we will estimate each view’s human 2D skeleton using Openpose [24], and then obtain 3D skeleton $S_w \in \mathbb{R}^{3 \times J}$ in world space through triangulation. $J$ is the number of joints. We use the hip position $H_w \in \mathbb{R}^3$ and neck position $N_w \in \mathbb{R}^3$ to normalize the depth. Specifically,

$$H_i^c = R_iH_w + t_i = (H_{c_i}^1, H_{c_i}^2, H_{c_i}^3),$$

$$X_i^c = R_iX + t_i = (X_{c_i}^1, X_{c_i}^2, X_{c_i}^3),$$

$$z_i(X_{c_i}^j) = \frac{X_{c_i}^j - H_{c_i}^j}{\lambda\|H_w - N_w\|_2},$$

where $H_i^c, X_i^c$ are the hip position and the point $X$ position in view $i$’s camera space respectively. $R_i, t_i$ are camera $i$’s rotation and translation. $\lambda$ is a constant value to make sure the normalized depth always lies in $(0, 1)$, and we set it to $4/\sqrt{3}$ in all our experiments.

Finally, we use a multi-layer perceptron to predict the 3D occupancy and use marching cube algorithm to extract the surface from the predicted occupancy, resulting in the final reconstructed mesh.

![Architecture of our reconstruction network](image)

**Fig. 2. Architecture of our reconstruction network.** For memory efficiency, we only use a single level for reconstruction. The pixel-aligned spatial transformer enable us to preserve the geometry details that observed in the input views, resulting in highly detailed reconstruction. Our framework doesn’t use any geometry prior, so our reconstruction results are fully pixel-aligned.
This misalignment, we will refine each frame's kinematic caused by the skeleton estimation errors. In order to relieve and the reconstructed mesh might be misaligned, which is Rigid refinement. After animation, the animated mesh and is initialized as $\theta_f^{ani}$. $m_{refine}^f$ is the animated refined mesh using the refined parameters. $Dist$ is a function that calculates the distance between the refined mesh and reconstructed mesh, i.e. for every vertex in the refined mesh, we found its nearest neighbor in the reconstructed mesh and calculate their euclidean distance and add the distances for all the vertices. After the rigid refinement, we will get a refined mesh sequence $M_{refine} = \{m_{refine}^1, ..., m_{refine}^m\}$.

**Deformation.** After animation and refinement, the tracked mesh sequence $M_{refine}$ doesn’t contain the reconstructed geometry details. We will apply a non-rigid deformation to the refined mesh sequence $M_{refine}$ to recover the geometry details.

$$E_{deform}(\delta^f) = (m_{deform}^f - m_{recon}) + \lambda \text{Reg}(m_{deform}^f), \quad (10)$$

where $\delta^f$ is the translation for the vertices of the mesh $m_{refine}^f$. $N$ is the number of vertices. $(m_{deform}^f - m_{recon}) \in \mathbb{R}^{N \times 3}$ is the distance between each vertex of $m_{deform}^f$ and its nearest neighbor in $m_{recon}^f$. $\text{Reg}(m_{deform}^f) \in \mathbb{R}^{E \times 3}$ is the regular term: for each edge in mesh $m_{deform}^f$, we calculate the translation difference of the two vertices in the edge. $E$ is the number of edges. lambda is a hyper-parameter that balances the deform term and regular term. We set it to 100 in all our experiments. We solve all the energy functions using Gaussian-Newton solver. After deformation, we get a deformed mesh sequence $M_{deform} = \{m_{deform}^1, ..., m_{deform}^m\}$. Compared with the reconstructed mesh sequence $M_{recon}$, $M_{deform}$ solves the artifacts caused by occlusion and normal maps inconsistency while maintaining the geometry details.

**Novel View Rendering.** Given a sparse set of input images $\{I_0, ..., I_N\}$, the corresponding calibrated camera parameters and the reconstructed meshes, we use a rendering network to render high quality novel view images of human performers. To achieve
the goal of high quality rendering, the core is to solve the occlusion problems caused by the sparsity of input views. For this end, we present a geometry-guided pixel-wise feature integration method in the rendering network for solving the occlusions. The architecture of rendering network is shown in Fig. 4. In summary, we use a encode-integration-render framework for novel view rendering, which mainly consists of three parts: 1) encoding each input image to feature space using an encoder-net $e$, 2) pixel-wise visibility reasoning and feature integration using the reconstructed human geometry, 3) render the novel view image using a render-net $r$.

**Image encoding.** For each input image $I_n \in \mathbb{R}^{H \times W \times 3}$, we firstly encode it to a high-dimensional feature space and get feature map $F_n = e(I_n) \in \mathbb{R}^{H \times W \times D}$ at the same resolution. Following [25], the encoder $e$ uses a Res-UNet architecture, where the encoding part is an ImageNet-pretrained ResNet [27] and the decoding part upsamples the feature map using nearest-neighbor interpolation, concatenating it with the corresponding feature map (of the same resolution) from the encoding part.

**Geometry-guided pixel-wise feature integration.** To render high quality novel view images from sparse views, the core is solving the occlusion problems caused by the sparsity of views. However, traditional IBR methods always use warping operation to map the source views to the novel view, in which the warping operation will warp the pixels or areas that are not visible in the novel view, resulting in rendering artifacts or blurring. Therefore, we argue that this warping operation is not suitable for solving the occlusion problems.

For each pixel in a novel view, the visible input views are different. So we perform visibility reasoning and get the visible source views for each pixel in the novel view. And then only integrate features from visible source views to the novel view pixel, the source views that are not visible will be abandoned. Concretely, given input views’ calibrated camera parameters (including intrinsic and extrinsic parameters) $\{C_1,...,C_N\}$, the novel view camera $C_{novel}$ and the reconstructed human mesh, we will render depth maps of the input views $\{D_1,...,D_N\}$ and novel views $D_{novel}$ using OpenGL or Taichi. And then, for each pixel $p \in \mathbb{R}^2$ with valid depth value ($d_{render} > 0$) in the novel view, we will unproject it to the world space, getting point $P \in \mathbb{R}^3$, and then project it to each input view’s image space using the corresponding cameras, getting the reprojected pixel and depth and rendered depth in each view $\{(p_{reproj_1}, d_{reproj_1}, d_{render_1}), ..., (p_{reproj_N}, d_{reproj_N}, d_{render_N})\}$.

$$
(p_{reproj_n}, d_{reproj_n}, d_{render_n}) = C_n(C_{novel}^{-1}(p, d_{render})),
$$

where $d_{render_n} = D_n(p_{reproj_n})$. If the difference between the rendered depth and reprojected depth is lower than a threshold, we will regard view $n$ is visible for pixel $p$:

$$
|d_{render_n} - d_{reproj_n}| < \lambda \cdot \min(d_{render_n}, d_{reproj_n}),
$$

where $\lambda$ is a hyper-parameter and we set it to 0.01 in all our experiments.

After the visibility reasoning, we will sample features from all the visible views’ using bilinear sampling, i.e. $f_n = F_n(p_{reproj_n})$, and getting $\{f_1,...,f_K\}$, where $K$ is the number of visible source views for pixel $p$. And then, a direction average operation will be performed to integrate...
source view features to the novel view pixel:

\[
s_{\text{fusion}} = \frac{1}{W} \sum_{k=1}^{K} \max(0, \cos(\text{dir}_{\text{novel}}, \text{dir}_k)) \cdot f_k,
\]

where \(\text{dir}_{\text{novel}}, \text{dir}_k\) are the novel view direction and the visible source view \(k\)'s direction respectively. The fused novel view feature is divided by \(W = \sum_{k=1}^{K} \max(0, \cos(\text{dir}_{\text{novel}}, \text{dir}_k))\) for normalization.

**Novel view rendering.** After getting the feature map \(F_{\text{novel}}\) of the novel view, we will use a convolutional render-net \(r\) to render the novel view’s color image i.e. \(I_{\text{novel}} = r(F_{\text{novel}})\). The architecture of render-net is a stacked U-Net, where each stack \(L\) learns the residual of \(F_{\text{novel}}\), i.e. \(r(F_{\text{novel}}) = r^L(F_{\text{novel}} + r^{L-1}(F_{\text{novel}} + ...)))\).

### 4 Experiments

#### 4.1 Training

**Dataset.** We collect 1700 high quality textured human meshes from Twindom [28] as a large scale dataset for the training and evaluation of our reconstruction network and rendering network. The collected models have a wide range of clothing, poses and shapes. We randomly split the models into a training set of 1500 subjects and a testing set of 200 subjects.

**Reconstruction network training.** For each subject in dataset, we generate 360 virtual perspective cameras in yaw axis (1 camera for each degree) and each camera has a random pitch angle. And then we render 360 images at a resolution of 512 \(\times\) 512 using Taichi. During training, we randomly pick 4 views over the 360 images as the input for each iteration. We use Adam optimizer with a learning rate of \(1 \times 10^{-4}\) and train the reconstruction network for nearly 300000 iterations for convergence. The training procedure costs 3 days with a batch size of 1 in a single Nvidia TitanXp GPU.

**Rendering network training.** The rendering network needs reconstructed meshes as input, but we didn’t use the ground truth geometry. Instead, we randomly picking 5 views

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**Fig. 5. Qualitative results of reconstruction.** The top two rows are the results on twindom dataset, with 6 views as input. The bottom two rows are the results on real-world data, with 8 views as input. We strongly recommend the readers to zoom the pages for a better visualization of the reconstructed details.
over the 360 images and use the reconstruction network to generate a coarse mesh for each subject. With coarse meshes as input, the rendering network will have greater generalization ability and have more robust performances. We use the generated perspective cameras to render 360 images and depth maps at a higher resolution of 1024×1024 for each subject in our dataset. We divide the yaw axis degrees into 6 parts, each part has a range of 60 degrees. During training, we randomly pick 1 views in each part, resulting in 6 images as input. Then, we randomly select 1 view as the novel view and other views are the source views. We use Adam optimizer with a learning rate of $1 \times 10^{-4}$ and train for nearly 400000 iterations for convergence. The training procedure costs nearly 2 days with a batch size of 1 using a single Nvidia RTX3090 GPU.

### 4.2 Evaluation Settings

In this section, we will introduce our evaluation metrics, compared methods and the settings for each compared method. The evaluation will be performed both on static human performers (synthetic data) and dynamic human performers (real-world data). We highly recommend readers to refer to the webpage [29] for a better visualization of the reconstruction and rendering results of our methods.

**Metrics.** For reconstruction, we use Chamfer distance and Point-to-Surface distance (P2S) for quantitative evaluation. For rendering, we will quantitatively evaluate our method using three most widely used metrics: peak signal-to-noise ratio (PSNR), structural similarity index (SSIM) and learned perceptual image patch similarity (LPIPS).

**Compared methods.** We compare our method with both generic and specific rendering methods [2], [5], [10]. 1) Neural texture [10] introduces differentiable latent neural texture maps for novel view rendering. It needs to train an independent network for each a different subject. Note that to evaluate [10] on dynamic humans, topological consistent reconstruction of human performers is necessary. The deformed sequence $M_{deform}$ after tracking in our method is a topological consistent mesh sequence, so we use it as the input meshes to evaluate [10]. 2) Soft3D [2] is a MPI-based method for view synthesis, which uses multi-plane images (MPI) to handle the uncertainty of depth maps. It is a generic view synthesis method that doesn’t need to train any network. Note that [2] doesn’t use any geometry prior, so it needs to use MPI to estimate an initial depth map for each input image, which is extremely coarse, making the quality of synthetic images very low. For fairness, we will use the rendered depth maps in our method as the initial depth maps for an additional input of [2], which improves its performance. 3) Neural body [5] proposes a NeRF-based implicit neural representation for human novel view rendering, it needs to train a separate network for each human. Note that reconstruction results are only available on neural body [5], so we will perform comparisons with it for reconstruction evaluation.

### 4.3 Results on Static Human Rendering (Synthetic Data)

For static human rendering, tracking is impossible, so we use the meshes from the reconstruction network as the input of the rendering network. We select 5 models in the testing set of Twindom for the evaluation on synthetic data. For each model, we render 36 images in a circle arrangement at a resolution of 2048×2048. And we use 6 uniformly distributed views as input and the remaining 30 views for evaluation. Table 2 shows the quantitative reconstruction comparisons of our method with neural body [5]. For both P2S distance and Chamfer distance, our method outperforms [5] by extremely large margins. Some qualitative reconstruction results are shown on the top two rows of Fig. 5. The reconstruction results are produced with only 6 views as input, showing that our method is able to perform highly detailed reconstruction of challenging humans using only a sparse set of camera views.

For novel view rendering, quantitative results are shown in Table 3. Our method achieves the best performances among all the methods in LPIPS metric and SSIM metric. Fig. 6 shows some qualitative rendering results. The results show that our method is able to rendering high quality images on challenging humans with complex texture patterns or loose clothes, such as long dress.

### 4.4 Results on 4D Human Rendering (Real-World Data)

For 4D human rendering, we use the full pipeline of our method, reconstruction-tracking-rendering. To evaluate our method’s performance on 4D rendering, we create a multi-view dataset, which captures 5 dynamic human videos at a resolution of 2660 × 2300 using a multi-camera system that has 24 calibrated synchronized cameras in a circle arrangement. In contrast to the dataset of NeuralBody [5], which only captures humans with relatively uniform textures, our captured human performers with complex texture patterns or loose clothes. We select 8 uniformly distributed cameras for each input image, which is extremely coarse, making...
as the source input views and use the remaining 16 cameras for testing. All sequences have a length of 150 frames.

Some qualitative results are shown on the bottom two rows of Fig. 2. Compared with neural body, our reconstruction results have more high-frequency details, such as clothing folds. Achieving great performances on real-world data means that the proposed pixel-aligned spatial transformer is robust and efficient.

The quantitative results is shown on Table 4. Our method outperforms all other methods on all the measured metrics. Fig. 7 illustrates some qualitative results. The novel views rendered by our method contains more texture details compared with other methods. Benefit from the geometry-guided pixel-wise feature integration, we efficiently solve the occlusion problems caused by the sparsity of input views, resulting in the robust high quality rendering on real-world data.

5 CONCLUSION AND DISCUSSION

In this paper, we introduce HDhuman, a generic method that uses pixel-aligned spatial transformer and geometry-guided pixel-wise feature integration for high quality human reconstruction and rendering using sparse views. Experiments show that our rendering quality significantly outperforms both the generic and specific methods. Our method demonstrates that high-quality human rendering in sparse views is possible without any network fine-tuning, which can serve as an important baseline in the area of human rendering.

However, the geometry representation we used are meshes, so the geometry-guided pixel-wise feature integration used in our method is indistinguishable with the reconstructed geometry, making us unable to refine the geometry if we fine-tune our networks. Instead, we can only optimize the parameters in the rendering network, which will result in blur in the areas that have artifacts. So the fine-tuning operation can not significantly improve...
TABLE 4
Quantitative rendering results on our multi-view videos dataset. “NB” means neural body. “D+S3D” means Soft3D with our depth maps as input. “NT” means neural texture. For each frame, we use 8 views as input and 16 views for evaluation. Each sequence has a length of 150 frames.

|        | LPIPS (lower better) | SSIM (higher better) | PSNR (higher better) |
|--------|----------------------|----------------------|----------------------|
|        | Ours NB [5] | D+S3D [2] | NT [10] | Ours NB [5] | D+S3D [2] | NT [10] | Ours NB [5] | D+S3D [2] | NT [10] |
| Sequence1 | 0.1455 | 0.2680 | 0.1502 | 0.2949 | 0.823 | 0.732 | 0.722 | 0.687 | 24.14 | 21.08 | 21.11 | 17.61 |
| Sequence2 | 0.1961 | 0.2894 | 0.2516 | 0.3914 | 0.787 | 0.659 | 0.671 | 0.649 | 22.36 | 20.60 | 19.13 | 17.11 |
| Sequence3 | 0.1217 | 0.2132 | 0.1788 | 0.3191 | 0.887 | 0.831 | 0.811 | 0.790 | 25.04 | 22.76 | 22.10 | 19.81 |
| Sequence4 | 0.2396 | 0.4246 | 0.2651 | 0.4377 | 0.872 | 0.832 | 0.797 | 0.796 | 26.90 | 24.35 | 24.42 | 22.88 |
| Sequence5 | 0.1304 | 0.2723 | 0.1723 | 0.3055 | 0.880 | 0.822 | 0.800 | 0.751 | 26.47 | 24.32 | 23.45 | 17.59 |
| Average  | 0.1647 | 0.2931 | 0.2096 | 0.3493 | 0.850 | 0.775 | 0.760 | 0.735 | 24.98 | 22.92 | 22.04 | 19.00 |

Fig. 7. Novel view rendering on our captured multi-view videos dataset. We use 8 views as input. We strongly recommend the readers to zoom the pages for a better visualization of the rendered details.

the rendering performances, which is a limitation of our method.

In future, a research direction that is worthy to explore is to use a geometry representation that is differentiable in our framework. For example, we could encode the reconstructed mesh to a volume, and then perform differentiable geometry-guided visibility reasoning for each voxel and finally use volume rendering techniques to render novel views. In this way, the geometry will be differentiable, enabling us to refine the geometry in the procedure of fine-tuning.

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