

# Diffusion-FOF: Single-view Clothed Human Reconstruction via Diffusion-based Fourier Occupancy Field

Yuanzhen Li, Fei Luo\*, Chunxia Xiao\*

School of Computer Science, Wuhan University, China

yuanzhen@whu.edu.cn, luofei@whu.edu.cn, cx Xiao@whu.edu.cn

## Abstract

Reconstructing a clothed human from a single-view image has several challenging issues, including flexibly representing various body shapes and poses, estimating complete 3D geometry and consistent texture, and achieving more fine-grained details. To address them, we propose a new diffusion-based Fourier occupancy field method to improve the human representing ability and the geometry generating ability. First, we estimate the back-view image from the given reference image by incorporating a style consistency constraint. Then, we extract multi-scale features of the two images as conditional and design a diffusion model to generate the Fourier occupancy field in the wavelet domain. We refine the initial estimated Fourier occupancy field with image features as conditions to improve the geometric accuracy. Finally, the reference and estimated back-view images are mapped onto the human model, creating a textured clothed human model. Substantial experiments are conducted, and the experimental results show that our method outperforms the state-of-the-art methods in geometry and texture reconstruction performance.

## 1. Introduction

3D human reconstruction has wide applications in education, entertainment, and AR/VR [4, 5, 20]. Traditional methods can reconstruct a human’s geometry and texture by extracting adequate information from multi-view images [10, 23, 41]. However, multiple-view images for a human are not available in many scenarios. For example, photos of people in the smartphone’s album are usually shot on the single-view. Reconstructing a clothed human from a single-view image is a challenging task [24, 27]. Several issues need to be further dealt with, including flexibly representing various shapes and poses, robustly estimating complete 3D geometry and consistent texture appearance, and achieving more fine-grained details.

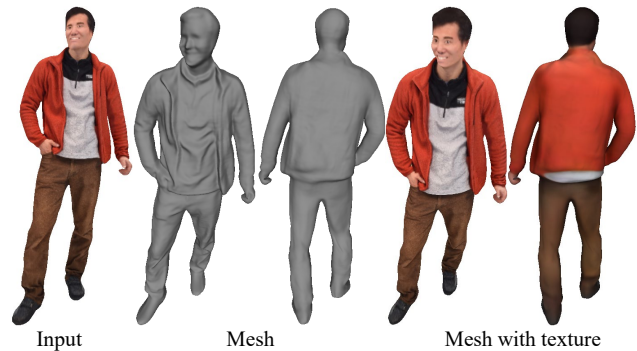


Figure 1. The 3D reconstruction example of our method for a single-view clothed human image.

Properly representing a human is one important factor, as it determines the scale of body shapes and poses that can be reconstructed. The widely used parametric model SMPL [21] is based on skinning and blend shapes and is learned from thousands of 3D body scans. Researchers introduced clothing displacement to SMPL to reconstruct clothing details [1, 2]. These methods have limitations in reconstructing loose-fitting clothes such as dresses and robes. The visual hull [24], the depth [11, 19], and the voxel [35, 47] have been also explored. They require significant computational resources. Besides explicit representation methods, researchers proposed implicit neural representation methods [27, 28], using the network to predict the geometry and texture of spatial sample points. Recently, Feng et al. [9] proposed a novel 3D geometric representation called Fourier occupancy field (FOF), representing 3D geometry as a multi-channel image. However, FOF directly utilizes a 2D Convolutional Neural Network (CNN) to estimate the occupancy field and loses high-frequency information. Such weakness may lead to geometric distortion or overly smoothing.

The powerful generative model is another important factor in determining how well the reconstruction results can approximate real humans. Diffusion model [8] has substantially succeeded in several computer vision tasks

\*Chunxia Xiao and Fei Luo are co-corresponding authors

[26, 33, 44]. We propose to combine the generation capability of the image-conditioned diffusion model and the flexibility of the Fourier occupancy field representation. In particular, we introduce the wavelet mechanism to handle the weaknesses of the diffusion model and the Fourier occupancy field. Briefly, the wavelet transform decomposes the high-frequency and low-frequency information, facilitating learning intricate details. The spatial dimensions of wavelet subbands are 1/4 of the original image, reducing computational resources and inference time.

We propose a novel single-view clothed human reconstruction method via a diffusion-based Fourier occupancy field. It takes several steps to realize reconstruction. First, we estimate the back-view image to provide more human prior knowledge. Current methods have not considered the texture consistency between the back-view and reference images. When wearing a black jacket with a white T-shirt, the clothing on the back view will likely be black. Thus, we introduce a style consistency constraint between the predicted back-view and reference images. Then, we extract multi-scale features of the reference image and the estimated back-view image. We design a diffusion model to generate the Fourier occupancy field in the wavelet domain based on the image features as conditional. Meanwhile, we refine the initial estimated Fourier occupancy field with image features as conditions to improve the geometric accuracy. Finally, the reference and estimated back-view images are mapped onto the model, producing the final textured clothed human model. Extensive comparative experiments and ablation studies verify the effectiveness of our method.

In summary, the main contributions of our method are summarized as follows:

- We propose a wavelet-based FOF diffusion model to reconstruct 3D clothed human from a single image. The wavelet transform facilitates the explicit learning of detailed information and reduces computational time.
- During the back-view image prediction, we introduce a style consistency constraint between the predicted back-view image and the reference image to enhance the style consistency of the texture.
- In the geometric prediction, we add the predicted back-view image as conditional, providing more human prior information to the geometric prediction network.

## 2. Related Work

**Single-view human reconstruction.** Only with 2D information of a single-view image, reconstructing the 3D human is inherently ill-posed. Some works introduced additional assumptions or prior knowledge. Previous research has proposed effective parametric models [3, 21] of the human body, which utilizes statistical methods to reduce the

variations in human body shape and pose to a compact set of parameters. With the rapid development of deep learning, methods [17, 18] attempt to estimate and regress the model parameters from a single image by deep neural networks. Human-parameterized models lack 3D details of clothes, hairstyles, and adornments. To generate the clothing details, methods [1, 2] added offsets on the top of parameterized model vertices. Although these methods can reconstruct certain clothing details, they often face challenges when dealing with loose-fitting garments, such as robes and dresses.

To address the constraints of loose-fitting clothing reconstruction, various 3D human representations have been explored, including the visual hull [24], the double depth maps [11, 13], and the voxel [36]. However, these methods need high memory requirements, limiting the spatial resolution of shape estimation.

To reconstruct high-resolution 3D clothed humans, Saito et al. [27] proposed a pixel-aligned implicit function for reconstructing 3D human geometry and texture called PIFu. They used neural networks to extract 2D image features and designed a deep implicit function to estimate the geometry and texture of 3D sampling points. PIFuHD [28] designed a coarse-to-fine framework to reconstruct high-resolution 3D human geometric with the normal as prior knowledge. These two methods could generate distorted shapes in complex poses due to the lack of regularization. To improve geometric stability, methods [40, 42, 46] utilized human parameterized models as prior information to guide implicit function learning. However, inaccuracies in parameterized model estimation would decrease reconstruction accuracy.

Recently, Feng et al. [9] proposed a novel 3D representation, the Fourier occupancy field, which converts the 3D occupancy value into a 2D vector field using Fourier series expansion. Different from [9], we aim to generate the Fourier occupancy field from the view of generative modeling implemented by a wavelet-based diffusion model.

**Denoising diffusion model.** The Diffusion model is a generative model that employs an iterative denoising process to generate high-quality results of target tasks [14]. It has demonstrated superior performance in various computer vision tasks. In 2D computer vision applications, it has been used for tasks such as image generation [33, 34], inpainting [25], and super-resolution [26]. In 2.5D computer vision tasks, the diffusion model has been applied to monocular depth estimation [15, 29] and depth refinement [30]. In the realm of 3D content generation, it finds application in tasks such as 3D shape generation [6, 48] and completion [7, 49].

## 3. Method

The pipeline of our method is shown in Figure 2. Given a single human image  $I_a$ , we first predict the back-view image  $I'_b$ . Then, we design a wavelet-based diffusion model to

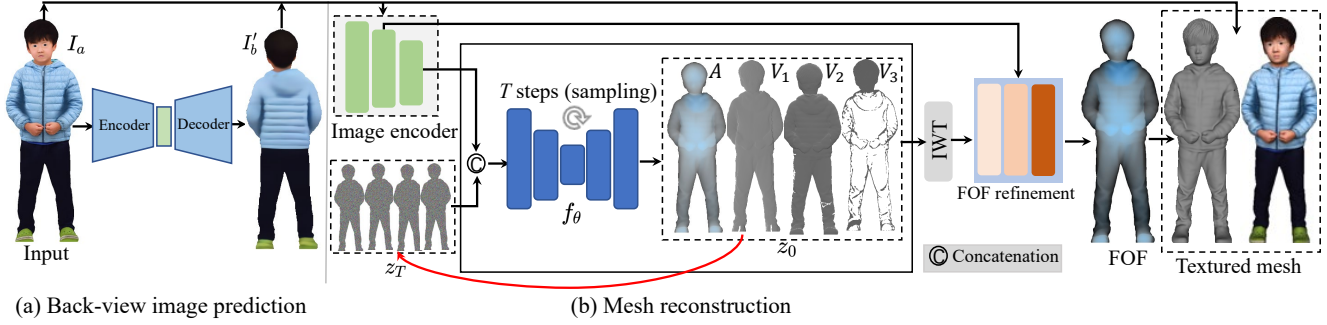


Figure 2. Overview of our method. Given the human image  $I_a$ , we first predict the back-view image  $I'_b$ . Then, we design a wavelet-based diffusion model to generate the Fourier occupancy field based on the two images as conditional. We transform the Fourier occupancy field to the 3D mesh. Finally, the two images  $I_a$  and  $I'_b$  are projected back to the 3D mesh, generating the textured model.

generate the Fourier occupancy field based on the two images as conditional. We transform the Fourier occupancy field to occupancy values and use the marching cubes [22] algorithm to generate the 3D mesh. Finally, the two images  $I_a$  and  $I'_b$  are mapped onto the human model through rasterization, creating the textured model.

### 3.1. Preliminaries

**Fourier occupancy field.** It encodes the 3D object geometry to a 2D vector field [9]. Each pixel  $(x, y)$  on the image  $I$  corresponds to a line in 3D space and can be used as an occupancy function  $f(z)$  represent. The occupancy function  $f(z)$  satisfies the Dirichlet conditions and can be expanded as a convergent Fourier series:

$$f(z) = \frac{a_0}{2} + \sum_{n=1}^{\infty} (a_n \cos(nz\pi) + b_n \sin(nz\pi)). \quad (1)$$

where  $\{a_n\}$  and  $\{b_n\}$  are coefficients of basis functions  $\{\cos(nx)\}$  and  $\{\sin(nx)\}$ , respectively. Approximate  $f(z)$  by a subspace spanned by the first  $2N + 1$  basis functions:

$$f(z) = b^\top(z)c, \quad (2)$$

where  $b(z) = [1/2, \cos(z), \sin(z), \dots, \cos(Nz), \sin(Nz)]^\top$  is the vector of the first  $2N + 1$  basis functions spanning the approximation subspace, and  $c = [a_0, a_1, b_1, \dots, a_N, b_N]^\top$  is the  $2N + 1$  Fourier coefficient vectors. This procedure can be extended to cover the entire  $xy$ -plane:  $F(x, y, z) = b^\top(z)C(x, y)$ , and  $C$  called Fourier occupancy field (FOF). In our experiment,  $N$  is settled as 15.

When FOF is estimated, the approximate occupancy field can be extracted according to Eq. 2. Then, we can use the marching cubes algorithm [22] to extract the 3D mesh from the occupancy field.

**Wavelet transform.** It is a classic technique extensively used in image compression. It is applied to separate the original image's low-frequency approximation and high-frequency details. The low sub-band corresponds to a

down-sampled version resembling the original image, and the high sub-bands capture local statistical information on vertical, horizontal, and diagonal edges. Haar wavelet [12] is a simple wavelet transform, including discrete wavelet transform (DWT) and inverse wavelet transform (IWT).

We use Haar wavelet to decompose the Fourier occupancy field  $C \in \mathbb{R}^{H \times W \times (2N+1)}$  into four wavelet sub-bands  $\{A, V_1, V_2, V_3\} \in \mathbb{R}^{\frac{H}{2} \times \frac{W}{2} \times (2N+1)}$ , representing the average of the source image and high-frequency information in the vertical, horizontal, and diagonal directions, respectively.

**Diffusion model.** It is divided into forward diffusion and inverse denoising phases [14]. The forward process is fixed to a Markov chain that gradually adds Gaussian noise to the target training data  $z_0 = z$ :

$$q(z_{1:T}) = \prod_{t=1}^T q(z_t|z_{t-1}), \quad (3)$$

$$q(z_t|z_{t-1}) = \mathcal{N}(z_t; \sqrt{1 - \beta_t}z_{t-1}, \beta_t\mathbf{I}), \quad (4)$$

where  $\beta_t$  is a variance schedule that increases from  $\beta_0 = 0$  to  $\beta_T = 1$  and controls how much noise is added in each step. We can obtain the sampling  $z_t$  at even arbitrary time step  $t$  from  $z_0$ :

$$q(z_t|z_0) = \mathcal{N}(z_t; \sqrt{\bar{\alpha}_t}z_0, (1 - \bar{\alpha}_t)\mathbf{I}), \quad (5)$$

where  $\bar{\alpha}_t = \prod_{s=0}^t \alpha_s = \prod_{s=0}^t (1 - \beta_s)$ . The reverse process aims to derive the posterior distribution for the less noisy image  $z_{t-1}$  given the more noisy image  $z_t$  using the denoising network  $f_\theta$ :

$$p_\theta(z_{0:T}) = p(z_T) \prod_{t=1}^T p_\theta(z_{t-1}|z_t), \quad (6)$$

$$p_\theta(z_{t-1}|z_t) = \mathcal{N}(z_{t-1}; \mu_\theta(z_t, t), \sigma_t^2\mathbf{I}), \quad (7)$$

where  $p(z_T) = \mathcal{N}(z_T; \mathbf{0}, \mathbf{I})$  is the random sampling of Gaussian noise,  $\mu_\theta(z_t, t)$  and  $\sigma_t^2$  are the mean and variance of the parametric denoising model, respectively. The objective is to minimize the distance between a true denoising distribution  $q(z_t|z_{t-1})$  and the parameterized  $p_\theta(z_{t-1}|z_t)$  through Kullback-Leibler (KL) divergence. DDPM [14] utilizes the network to predict the noise  $\epsilon$ .

### 3.2. Back-view Image Prediction

In the back-view image prediction, we propose a style consistency constraint between the predicted and reference images. We utilize a Siamese network training strategy to train the back-view image prediction network.

Given the human image  $I_a$ , we use a deep neural network to estimate the back-view image  $I'_b$ . We train the network using the L1 loss between the estimated image  $I'_b$  and the ground truth  $I_b$ :

$$\mathcal{L}_1(I'_b, I_b) = \|I'_b - I_b\|_1. \quad (8)$$

There is a significant correlation between the back-view and front clothes of the human. For example, when a person wears a black jacket with a white T-shirt, the clothing on the back side will be black. Consequently, the predicted back-view image  $I'_b$  and the reference image  $I_a$  have consistent style (texture). Inspired by the image style transfer [16], we propose a style consistency constraint between the predicted back-view image  $I'_b$  and the reference image  $I_a$ :

$$\mathcal{L}_s(I'_b, I_a) = \|G(\Phi_1(I'_b)) - G(\Phi_1(I_a))\|_2^2, \quad (9)$$

where  $G(\cdot)$  denotes the Gram matrix, and  $\Phi_1$  represents the latent space feature extracted from the first layer of the pre-trained VGG19 model [31], which is effective at capturing low-level color features of the reconstructed texture.

From the above analysis, the predicted back-view image  $I'_b$  correlates with the ground truth  $I_b$  and the reference image  $I_a$ . To enhance the effectiveness of network training, we adopt a Siamese network training strategy to train the back-view image prediction network.

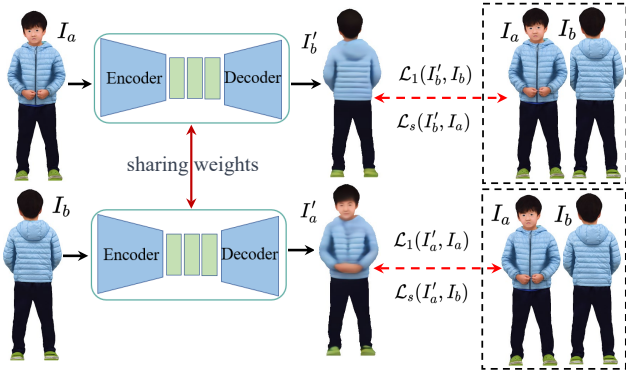


Figure 3. Training framework of the back-view image estimation.

The training framework is shown in Figure 3. The twin networks have the same parameters and sharing weights. During testing, only one network is used to predict the back-view image. We input a pair of images  $I_a$  and  $I_b$  into the twin networks and output their back-view image  $I'_b$  and  $I'_a$ , respectively. We establish constraints between the estimated and input images to train the network.

In summary, we train the back-view image prediction network with the following loss:

$$\mathcal{L}_{\text{color}} = \lambda_1(\mathcal{L}_1(I'_b, I_b) + \mathcal{L}_1(I'_a, I_a)) + \lambda_2(\mathcal{L}_s(I'_b, I_a) + \mathcal{L}_s(I'_a, I_b)), \quad (10)$$

where the hyper-parameters  $\lambda_1 = 1.0$  and  $\lambda_2 = 0.8$  control the relative weights of the different terms. We use HR-Net [37] as the back-view image prediction network.

### 3.3. Wavelet-based Diffusion FOF Prediction

The training framework is shown in Figure 4. We learn the conditional denoising process  $p_\theta(z_{0:T}|z_0, x)$  with the reference image  $I_a$  and the predicted back-view image  $I'_b$  as the condition  $x$ . In our work, the Eq. 6 is modified to:

$$p_\theta(z_{0:T}|x) = p(z_T) \prod_{t=1}^T p_\theta(z_{t-1}|z_t, x). \quad (11)$$

As our task involves optimizing Fourier occupancy fields, we train the denoising network  $f_\theta$  to predict  $z_0$  instead of the noise  $\epsilon$ . Once trained, at generation time, the model  $f_\theta$  can then approximate the mean  $\mu_\theta(z_t, t)$  of the posterior  $p_\theta(z_{t-1}|z_t, x)$  as:

$$\mu_\theta(z_t, t) \approx \frac{1}{\sqrt{\alpha_t}} \left( z_t - \frac{1 - \alpha_t}{1 - \bar{\alpha}_t} (z_t - \sqrt{\bar{\alpha}_t} f_\theta(z_t, t)) \right). \quad (12)$$

Thus, we can obtain the less noisy image  $z_{t-1}$  from the noisy image  $z_t$  by sampling the approximate posterior in each generation step.

We use DWT to decompose the FOF  $C$  into four wavelet sub-bands as the training data  $z_0$  in the diffusion model. At even arbitrary time step  $t$ , the sampling  $z_t$  is constructed by adding Gaussian noise to the ground truth  $z_0$  in the forward diffusion. The inverse denoising is to predict  $z_0$  with the condition  $x$ . We estimate the initial FOF in the wavelet domain and further refine it in the pixel domain.

Firstly, we design an image encoder module to extract multi-scale feature representations from the reference images  $I_a$  and predicted back-view image  $I'_b$ . We use the low-resolution image feature as the condition  $x$  in the conditional diffusion model. Then, we concatenate  $z_t$ ,  $x$  and  $t$  and feed them into the denoising network  $f_\theta$ , outputs wavelet coefficient  $\tilde{z}_0$ . The wavelet coefficient  $\tilde{z}_0$  is converted into the FOF  $C_{\text{init}}$  using IWT. Finally, We design a refinement module to refine the initial predicted FOF  $C_{\text{init}}$  with the high-resolution image feature as guidance and output a perfect FOF  $C_{\text{refine}}$ .

We formulate three objective functions to train the model

$$\mathcal{L}_{\text{geometric}} = \mathcal{L}_{\text{diffu}}(\tilde{z}_0, z_0) + \mathcal{L}_{\text{init}}(C_{\text{init}}, C_{\text{gt}}) + \mathcal{L}_{\text{refine}}(C_{\text{refine}}, C_{\text{gt}}). \quad (13)$$

The loss  $\mathcal{L}_{\text{diffu}}(\tilde{z}_0, z_0)$  represents the difference between the ground truth  $z_0$  and predicted  $\tilde{z}_0$ :

$$\mathcal{L}_{\text{diffu}}(\tilde{z}_0, z_0) = \|\tilde{z}_0 - z_0\|_1. \quad (14)$$

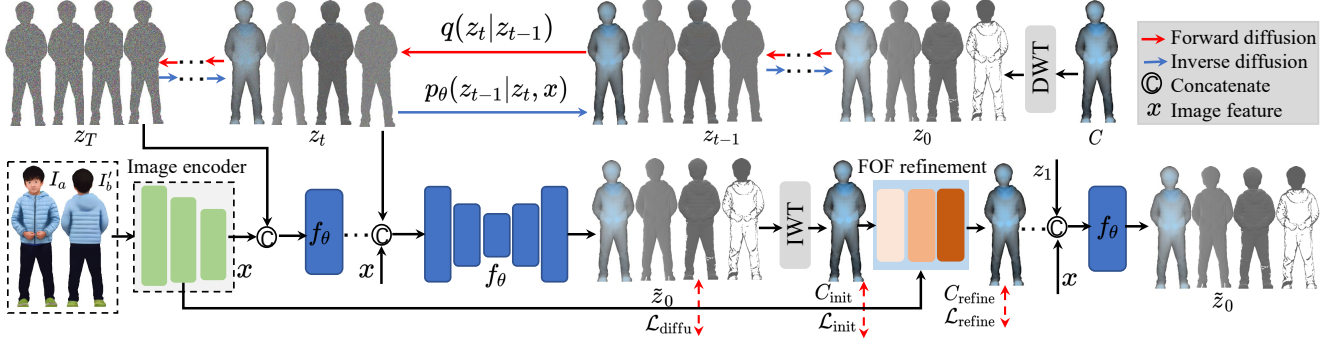


Figure 4. The training framework of the FOF prediction. FOF  $C$  is decomposed into sub-bands  $z_0$  using DWT. At even time step  $t$ ,  $z_t$  is obtained from  $z_0$  through forward diffusion. Multi-scale features of the images  $I_a$  and  $I_b$  are extracted using an image encoder network, with low-resolution features as condition  $x$ . The concatenation of  $z_t$ ,  $x$ , and  $t$  is input into the denoising network  $f_\theta$ , output  $\hat{z}_0$ . Subsequently, IWT is applied to  $\hat{z}_0$  to convert it into FOF. Finally, a refinement module enhances the predicted FOF guided by high-resolution features. Three loss functions,  $\mathcal{L}_{diffu}$ ,  $\mathcal{L}_{init}$ , and  $\mathcal{L}_{refine}$ , are designed to optimize the network.

The loss  $\mathcal{L}_{init}(C_{init}, C_{gt})$  represents the difference between the ground truth  $C_{gt}(C)$  and the initial predicted FOF  $C_{init}$ :

$$\mathcal{L}_{init}(C_{init}, C_{gt}) = \|C_{init} - C_{gt}\|_1. \quad (15)$$

The loss  $\mathcal{L}_{refine}(C_{refine}, C_{gt})$  represents the difference between the ground truth  $C_{gt}$  and the refined FOF  $C_{refine}$ :

$$\mathcal{L}_{refine}(C_{refine}, C_{gt}) = \|C_{refine} - C_{gt}\|_1. \quad (16)$$

Figure 5 presents the details of the image encoder network and refinement network. CBAM [38] is a lightweight attention module. We use the U-Net architecture [8] as our denoise network  $f_\theta$ .

In the inference process, given a human image and the predicted back-view image, we first extract the image feature as the condition. Then, we randomly sample the noisy map  $\tilde{z}_T$  from the Gaussian distribution  $\tilde{z}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  and iteratively predict  $\tilde{z}_0$  in the wavelet domain. We employ the DDIM update rule [32] for the sampling process. Finally, we use the inverse wavelet transform (IWT) to transform  $\tilde{z}_0$  to the FOF and refine it with the image feature. We provide the pseudo-code of the geometric training procedure and test procedure in the supplementary material.

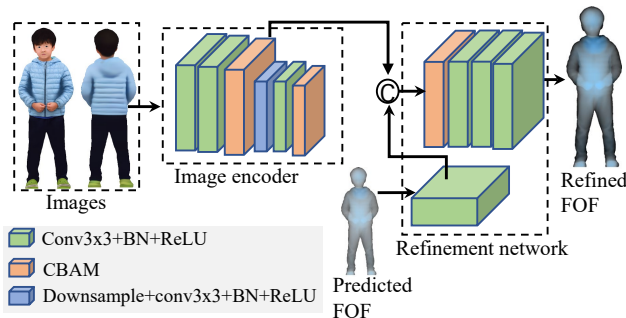


Figure 5. Image encoder network and refinement network.

Table 1. Quantitative comparison of texture on the 2K2K dataset.  $\uparrow$  means the larger the better while  $\downarrow$  means the smaller the better.

Methods	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$
SiCloPe [24]	17.579	0.844	0.281
Ours	<b>26.362</b>	<b>0.929</b>	<b>0.142</b>
PIFu [27]	14.334	0.821	0.269
GTA [45]	18.352	0.842	0.236
Ours	<b>25.252</b>	<b>0.925</b>	<b>0.157</b>

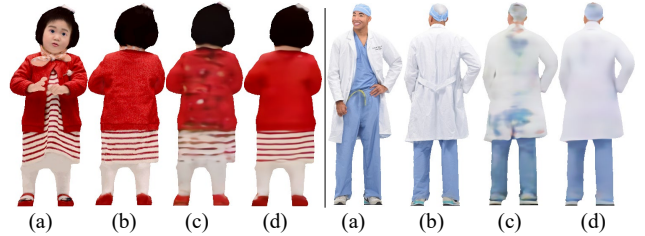


Figure 6. Qualitative comparison of back-view image estimation. (a) Input image. (b) Ground Truth. (c) SiCloPe [24]. (d) Ours.

## 4. Experiments

### 4.1. Experimental Settings

**Datasets.** We utilize three public 3D clothed human datasets: Thuman2.0 [43], 2K2K [13], and CLOTH4D [50], for training and evaluating our method. We randomly select 400 scans from Thuman2.0 and 1000 scans from 2K2K for our training dataset. The test set comprises 100 scans from Thuman2.0, 300 from 2K2K, and 300 from CLOTH4D. For each model, we render the FOF [9], front image, and back-view image as a training pair at each viewpoint of 300 different viewpoints around it utilizing the weak perspective camera model. Each render image resolution is  $512 \times 512$ .

**Metrics.** We evaluate texture performance using three metrics: peak signal-to-noise ratio (PSNR), structural similarity index (SSIM) and learned perceptual image patch

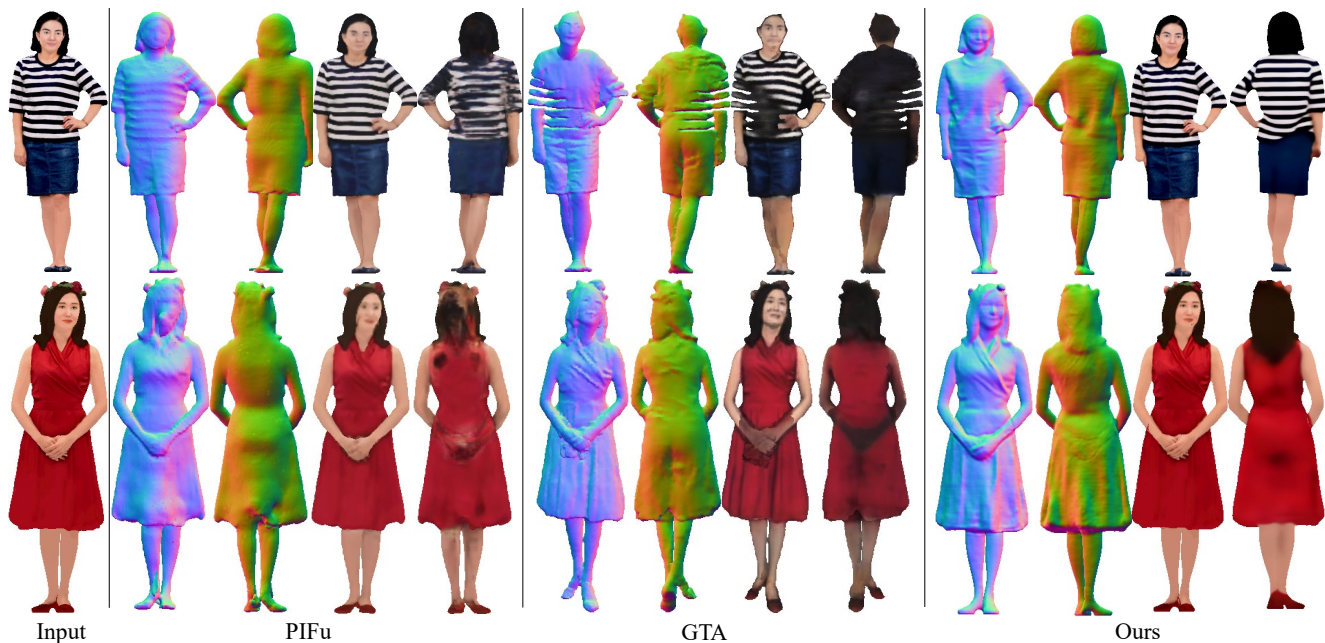


Figure 7. Qualitative comparison of geometric and texture with methods PIFu [27] and GTA [45].

Table 2. Quantitative evaluation of geometric on the Thuman2.0, 2k2k, and CLOTH4D datasets (cm). The best and second-best results are highlighted in **bold** and underlined on each dataset, respectively.

Methods	THuman2.0			2K2K			CLOTH4D		
	Chamfer↓	P2S↓	Normal↓	Chamfer↓	P2S↓	Normal↓	Chamfer↓	P2S↓	Normal↓
PIFu [27]	3.224	2.802	3.476	2.232	2.210	3.212	2.124	2.132	3.124
PIFuHD [28]	2.952	2.240	2.698	1.820	1.745	2.362	1.726	1.732	2.235
ICON [40]	2.378	1.820	2.792	1.142	1.012	2.242	1.114	1.198	1.854
FOF [9]	2.474	1.817	2.532	1.132	1.093	2.101	1.218	1.195	1.723
D-IF [42]	2.368	1.820	2.724	1.134	<u>0.912</u>	2.125	1.124	1.012	1.863
ECON [39]	2.312	1.878	2.584	1.174	1.192	1.885	1.132	1.098	1.684
2K2K [13]	2.523	1.914	2.532	<u>1.129</u>	1.107	<u>1.754</u>	1.146	1.132	1.647
GTA [45]	<u>2.298</u>	<u>1.793</u>	<u>2.475</u>	1.130	1.103	1.791	<u>1.102</u>	<u>0.963</u>	<u>1.594</u>
Ours	<b>2.131</b>	<b>1.635</b>	<b>2.031</b>	<b>0.934</b>	<b>0.872</b>	<b>1.502</b>	<b>0.906</b>	<b>0.927</b>	<b>1.517</b>

similarity (LPIPS). We use Chamfer distance and P2S distance [9] to evaluate the geometric quality, comparing reconstructed meshes with ground truth. We also measure L1 normal error between normal images from both meshes by rotating the camera at four fixed angles  $\{0^\circ, 90^\circ, 180^\circ, 270^\circ\}$  relative to the input view.

## 4.2. Comparison with the State-of-the-art Methods

**Texture evaluation.** We compare our method with methods: SiCloPe [24], PIFu [27], and GTA [45]. SiCloPe estimates the back-view image; thus, we compare the predicted back-view image. PIFu and GTA use the implicit function to estimate the color of 3D points. To evaluate our results, we render textured meshes by rotating the camera at four fixed angles ( $0^\circ, 90^\circ, 180^\circ, 270^\circ$ ) relative to the input view and compare the rendered images.

Table 1 presents the quantitative comparison results.

When evaluating the estimated back-view image, our result surpasses SiCloPe. Our method has also achieved the best results when evaluating rendered images. Figure 6 presents visual comparison results with method SiCloPe, where our results exhibit greater clarity. Figure 7 presents visual comparison results with methods PIFu and GTA. Our texture and geometric present greater clarity and realism in invisible areas. Quantitative and qualitative experiments verify the effectiveness of our texture estimation method.

**Geometric evaluation.** We compare our method with methods: PIFu [27], PIFuHD [28], ICON [40], D-IF [42], FOF [9], ECON [39], 2K2K [13], and GTA [45]. Table 2 reports the quantitative comparison results. We can see that our method excels over the compared methods on the three quantitative metrics.

Figure 8 and Figure 9 show qualitative comparison results. In Figure 8, the two input images are from the 2K2K

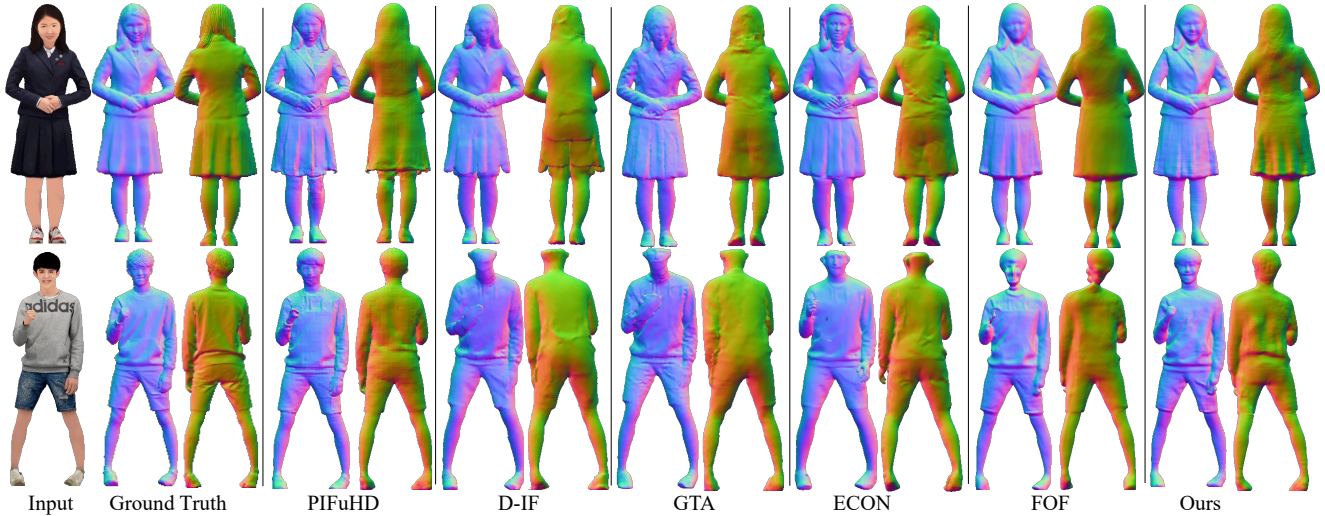


Figure 8. Qualitative comparison of geometric on the 2K2K dataset with state-of-the-art single-view human reconstruction methods: PIFuHD [28], D-IF [42], GTA [45], ECON [39], and FOF [9].

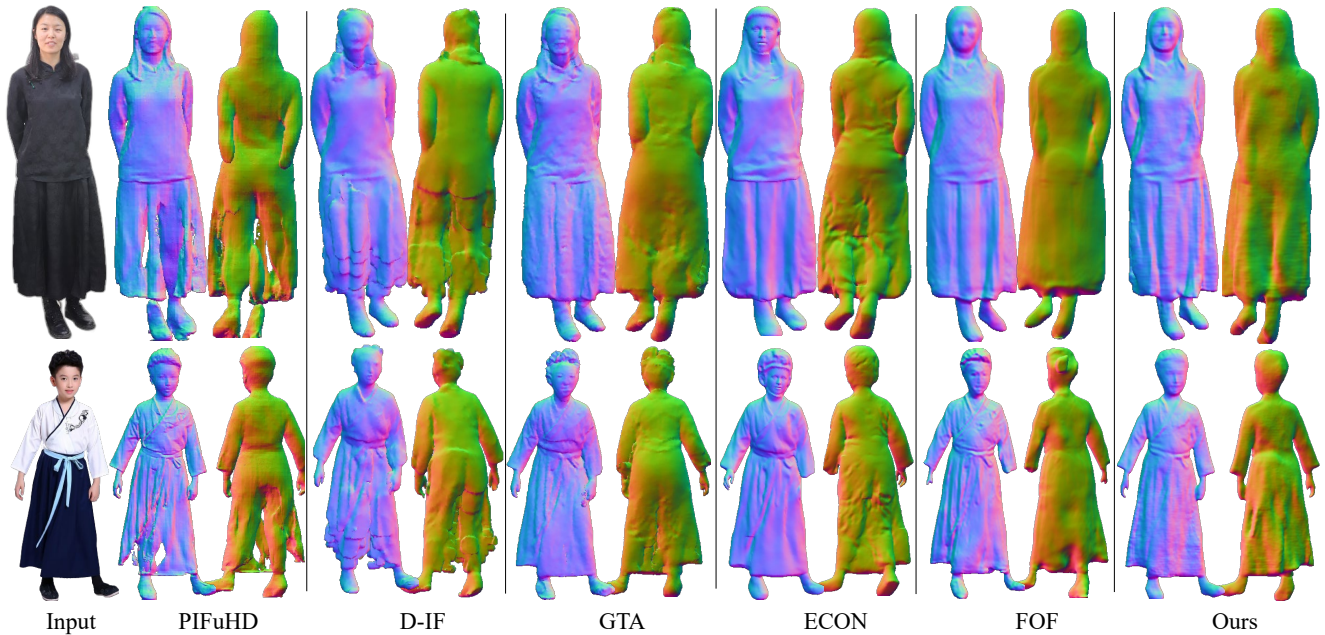


Figure 9. Qualitative comparison of geometric in-the-wild of images with state-of-the-art single-view human reconstruction methods: PIFuHD [28], D-IF [42], GTA [45], ECON [39], and FOF [9].

dataset. Our method can accurately reconstruct the geometry and capture more realistic wrinkle details. Figure 9 shows two examples of in-the-wild images. The first image is captured using a camera under natural lighting conditions; the second is from the Internet. Our method achieves outstanding results in reconstructing loose-fitting clothing and recovering more reasonable details in invisible areas. Figure 9 validates our method has robustness and generalization. From both quantitative and qualitative results, our geometric reconstruction method is effective.

### 4.3. Ablation Study

**Ablation on back-view image estimation.** To validate the effectiveness of the proposed style loss  $\mathcal{L}_s$  and Siamese network training strategy, we design the following three variants: (1) loss  $\mathcal{L}_1$ : L1 loss between the predicted back-view image and the ground truth back-view image. (2) loss  $(\mathcal{L}_1 + \mathcal{L}_s)$ : loss  $\mathcal{L}_1$  combines with the style consistency loss  $\mathcal{L}_s$  between the predicted back-view image and the input image. (3) loss  $(\mathcal{L}_1 + \mathcal{L}_s)$  with Siamese: loss  $(\mathcal{L}_1 + \mathcal{L}_s)$  combines with the Siamese network training strategy.

We train the three variants and evaluate the results on the 2K2K dataset. The comparison results of these three variants are summarized in Table 3. The results show that the style loss  $\mathcal{L}_s$  and Siamese network training strategy are two important factors for our back-view image prediction. We also present two qualitative results in Figure 10. Compared to only using the  $\mathcal{L}_1$  loss, incorporating the style loss  $\mathcal{L}_s$  yields more reasonable results.

Table 3. Ablation study on back-view image estimation.

Methods	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$
loss ( $\mathcal{L}_1$ )	18.427	0.886	0.247
loss ( $\mathcal{L}_1 + \mathcal{L}_s$ )	24.476	0.920	0.174
loss ( $\mathcal{L}_1 + \mathcal{L}_s$ ) with Siamese	<b>26.362</b>	<b>0.929</b>	<b>0.142</b>

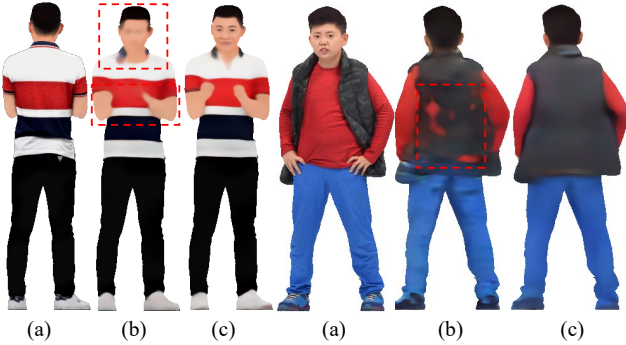


Figure 10. Ablation study for style loss  $\mathcal{L}_s$  in the back-view image prediction. (a) Input image, (b) w/o style loss. (c) w style loss.

**Ablation on geometric.** To validate the effectiveness of the predicted back-view image  $I'_b$ , diffusion model, and wavelet transform, we design the following eight variants: (1) FOF-M1: baseline method with the reference image  $I_a$  as input. (2) FOF-M2: baseline method with  $I_a$  and  $I'_b$  as input. (3) FOF-M3: FOF-M2 combines with refinement module. (4) Ours-W1: training on the diffusion model with  $I_a$  as condition. (5) Ours-W2: training on the diffusion model with  $I_a$  and  $I'_b$  as condition. (6) Ours-M1: training on the wavelet diffusion model with  $I_a$  as condition. (7) Ours-M2: training on the wavelet diffusion model with  $I_a$  and  $I'_b$  as condition. (8) Ours-M3: Ours-M2 combines with refinement module.

We train the eight variants and evaluate the results. The comparison results are summarized in Table 4. The results confirm that the predicted back-view image  $I'_b$ , the diffusion model, and the wavelet transform are three important factors for our geometric prediction. We also present qualitative results in Figure 11. The geometric quality of FOF-M2 is higher than that of FOF-M1, indicating that the back-view image contributes beneficially to geometric reconstruction. Compared to the baseline method, our approach achieves higher geometric accuracy in reconstruction, particularly in capturing details such as the scarves and facial features.

Table 4. Ablation study on 3D reconstruction (cm).

Methods	THuman2.0			2K2K		
	Chamfer $\downarrow$	P2S $\downarrow$	Normal $\downarrow$	Chamfer $\downarrow$	P2S $\downarrow$	Normal $\downarrow$
FOF-M1	2.474	1.817	2.532	1.132	1.093	2.101
FOF-M2	2.467	1.808	2.528	1.127	1.085	1.984
FOF-M3	2.462	1.803	2.522	1.122	1.078	1.971
Ours-W1	2.245	1.700	2.224	0.981	0.916	1.705
Ours-W2	2.243	1.695	2.221	0.978	0.912	1.700
Ours-M1	2.241	1.690	2.219	0.972	0.907	1.694
Ours-M2	2.138	1.642	2.114	0.942	0.887	1.584
Ours-M3	<b>2.131</b>	<b>1.635</b>	<b>2.031</b>	<b>0.934</b>	<b>0.872</b>	<b>1.502</b>

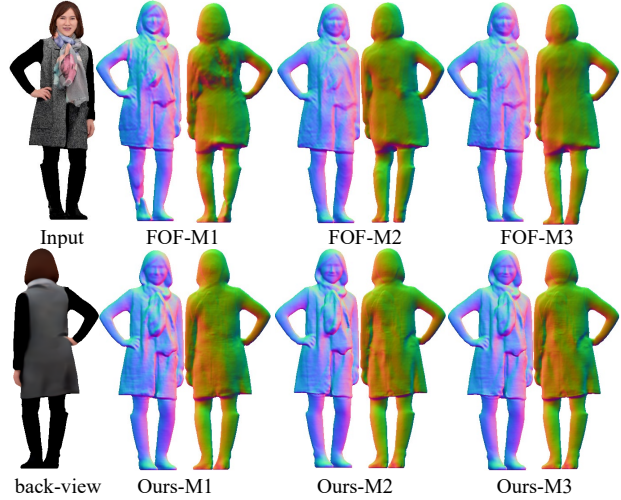


Figure 11. Qualitative comparison with PIFu [27].

**Limitation.** Our method can reconstruct the 3D clothed human model from a single image. However, the reconstructed geometric accuracy may be lower when the human self-occlusion is severe in the image.

## 5. Conclusion

We have proposed a diffusion model to reconstruct a 3D human model from a single image. First, we proposed a style consistency constraint between the back-view and reference images to effectively predict the back-view image. We then proposed a wavelet-based diffusion model in the geometric prediction to generate the FOF conditional on the two images. The two images are mapped onto the human model, creating a textured clothed human model. Experimental results indicated that our texture estimation and geometric reconstruction methods are effective.

## 6. Acknowledgments

This work is partially supported by the National Natural Science Foundation of China (No. 61972298 and No. 62372336) and Wuhan University-Huawei GeoInformatics Innovation Lab.



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